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A COMPARISON BETWEEN SWITCHING INTENTION AND SWITCHING BEHAVIOUR IN THE SOUTH AFRICAN MOBILE TELECOMMUNICATIONS INDUSTRY

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Rapid growth in the mobile telecommunications industry has resulted in near-saturated markets and thus intense competition. Due to high new customer acquisition costs, mobile network operators (MNOs) provide attractive offers to competitors' existing customers to encourage switching. Consequently, MNOs currently face accelerated switching rates, despite using contracts as a means of customer lock-in. Therefore preventing switching in this industry has become vital.

The study develops and tests a conceptual switching intention model using switching intention data. Switching antecedents investigated are relational switching costs, perceived value and alternative attractiveness. Subsequently, actual switching behaviour data is compared to the conceptual switching intention model. Finally, the role of relationship characteristics in both switching contexts is investigated.

Primary data was collected via an online self-administered survey using a cross-sectional online panel. A contract with a South African MNO was a prerequisite for survey participation. Parameter estimates were obtained using maximum likelihood (ML) in AMOS and bootstrapping was conducted to confirm the stability of the ML estimates. EQS was used to obtain robust ML indices. The switching intention model fit indices obtained were

as follows: $\chi^2/df = 6.004$ ($\chi^2 = 966.61$; $df = 161$; $p < 0.000$); RMSEA = 0.070 [0.066; 0.074]; NNFI = 0.943; CFI = 0.952.

In the switching behaviour context, the three antecedents explained only 12% of variance; whereas the same antecedents explained 52% of variance for switching intention. The results suggest that factors other than the antecedents investigated drive switching behaviour. Relationship depth weakly influenced switching intention, while the influence of relationship length and breadth was negligible. None of the relationship characteristics influenced switching behaviour.

The strongest predictor of switching intention was alternative attractiveness. The relationship strength of the dependent variable and antecedent variables was stronger in the switching intention context than in the switching behaviour context. Findings suggest that switching intention and switching behaviour are intrinsically different. Moreover, customers may perceive an increase in their monthly bill as a reason to switch. However other factors may influence customers when their actual switching decision is made.

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Soli Deo Gloria!
Glory to God alone

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TABLE OF CONTENTS

CHAPTER 3

CHAPTER 5

APPENDICES

LIST OF FIGURES

LIST OF TABLES

KEYWORDS

Keywords: relationship marketing, churn, switching intention, switching behaviour, relational switching costs, perceived value, alternative attractiveness, mobile telecommunications, mobile network operators

LIST OF KEY TERMS

Table A below provides a list of abbreviations that are used throughout the chapters and their meanings.

Table A: Abbreviations used in this document

Abbreviation	Meaning
B2B	Business-to-business
B2C	Business-to-consumer
GDP	Gross domestic product
ICT	Information and Communications Technology
ITU	International Telecommunications Union
MNO	Mobile Network Operator
MNP	Mobile Number Portability
MVNO	Mobile Virtual Network Operator

CHAPTER 1

INTRODUCTION AND OVERVIEW

1.1 INTRODUCTION

Rapid growth in the telecommunications industry since the 1990s has resulted in this industry becoming an important sector for economic development (Keramati & Ardabili, 2011:344; Shukla, 2010:467; Srinuan, Bohlin & Madden, 2012:453; Totten, Lipscomb, Cook & Lesch, 2005:14). Technological progress and an increase in the number of mobile network operators (MNOs) worldwide have caused intense competition in the mobile telecommunications industry (Gerpott, Rams & Schindler, 2001:249; Totten *et al*., 2005:14). Furthermore, innovative wireless technologies and progressive improvement of mobile handsets, development of applications for mobile handsets and an increasing variety of services offered have played a role in the rapid growth of the mobile telecommunications industry (Keramati & Ardabili, 2011:344; Kim & Yoon, 2004:752; Malhotra & Malhotra, 2013:13; Nysveen, Pedersen & Thorbjørnsen, 2005:330; Ranganathan, Seo & Babad, 2006:269). Due to the economic importance of the telecommunications industry worldwide and this industry's alarmingly high churn rates, an urgent need has arisen to establish how to retain customers and to subsequently determine factors that cause customer switching (Kim, Park & Jeong, 2004:148; Shukla, 2010:467).

1.2 BACKGROUND

As markets become more competitive and/or market growth slows, maintaining market share by protecting the customer base is essential for organisations to remain competitive (Aydin, Özer & Arasil, 2005:90). Research shows that costs associated with customer acquisition are up to six times higher than the cost of retaining current customers (Keaveney & Parthasarathy, 2001:375; Rosenberg & Czepiel, 1983 in Aydin & Özer, 2005:141; Shukla, 2010:471). Hence, customer retention is vital for an organisation's survival, which has lead to the increased interest in relationship marketing over the last few decades (Ahn, Han & Lee, 2006:553; Blery, Batistatos, Papastratou, Perifanos, Remoundaki & Retsina, 2009:27; Chen & Cheng, 2012:807; Chuang, 2011:128; Keramati & Ardabili, 2011:344; Wong, 2011:37).

Research findings indicate that loyal customers increase their spending over time (Eshghi, Haughton, Teebagy & Topi, 2006:179; Ganesh, Arnold & Reynolds, 2000:65; Wong 2011:38). Furthermore, research also shows that for every additional year that the business-customer relationship is successful, the customer becomes less costly to serve, due to learning effects and decreased servicing costs (Ganesh *et al*., 2000:65). In addition, satisfied long-term customers spread positive word-of-mouth, thereby drawing new customers with fairly little cost to the organisation (Wong, 2011:38). Therefore, considering the importance of past and future relational exchange, relational contracting theory (Macneil, 1987) is an important foundation for relationship marketing (Hunt, Arnett & Madhavaram, 2006:77; Macneil, 1987: 274).

Conversely, switching decreases profitability and market share, and has a significant negative financial impact on organisations, especially service organisations (Ahn *et al*., 2006:552; Bansal & Taylor, 1999a:75). Should a customer decide to terminate the usage of the organisation's services, that organisation not only loses current earnings, but future revenue is also jeopardised (Hughes, 2008:17). Due to high customer acquisition costs, the organisation from which customers switched will have to make large investments to attract new customers in order to replace customers that defected (Rosenberg & Czepiel, 1983 in Aydin & Özer, 2005:141).

Furthermore, customer switching is detrimental to organisations that rely on contract customers as a primary source of income (Keaveney & Parthasarathy, 2001:375). Thus contract law, which guides exchange relationships by applying the legal rights of parties in the exchange, is relevant to the study, since many customers have a contractual agreement with their MNO (Gundlach & Murphy, 1993:38).

Due to the severe negative consequences of switching, marketing practitioners attempt to understand how customers make their switching decisions in order to predict behaviour, thus "understanding consumer behaviour lies at the heart of marketing" (Lovelock & Wirtz, 2011:58). Various models have been developed to predict behavioural intention, for example the well-known Theory of Reasoned Action (Fishbein & Ajzen, 1975; Ajzen & Fishbein, 1980) and the Theory of Planned Behaviour (Ajzen, 1991:181). Attempts have also been made to develop switching models (Keaveney, 1995; Bansal & Taylor, 1999b; Bansal, Taylor & St. James, 2005). However, to date, no specific set of switching antecedents have been identified (Bansal & Taylor, 1999b; Keaveney, 1995).

Thus, taking into consideration that abundant research is available concerning the factors that influence customer switching, albeit that no specific set of switching antecedents have been identified; and considering that certain antecedents have not as yet received much attention in the literature, Bansal *et al*.'s (2005:108) suggestion to find more significant switching intention antecedents was followed. Thus relational switching costs, perceived value, alternative attractiveness and relationship characteristics were chosen as the switching antecedents to be investigated in the current study.

1.2.1 Switching antecedents

The first antecedent to be investigated, namely relational switching costs, refers in particular to the emotional or psychological discomfort, brand relationship loss and/or loss of social bonds that customers experience once the relationship with their service provider is terminated (Burnham, Frels & Mahajan, 2003:112; Chuang, 2011:131; Jones, Reynolds, Mothersbaugh & Beatty, 2007:337). Customers remain in an exchange relationship provided the rewards of the relationship outweigh the costs (Edward & Sahadev, 2011:329; Roberts, 1989:20). Thus, in the context of this study, social exchange theory (Blau 1964) is applicable to relational switching costs, since social exchange theory evaluates benefits compared to costs of remaining in the service provider-customer relationship.

Furthermore, relational exchanges are continuous exchanges over a long or possibly indefinite period of time between parties that are known to one another. The purpose of relational exchange is to develop a long-term relationship between buyers and sellers (Schakett, 2009). Relational exchange also takes into consideration past and possible future transactions each time an interaction occurs (Dwyer, Schurr & Oh, 1987:12; Gundlach & Murphy, 1993:36; Hunt *et al.*, 2006:77). Continuous relational exchange is based on relational exchange theory which uses a foundation of relational norms that serve as moral controls which encourage behaviours that are beneficial to the relationship, for example commitment, and discourage behaviours that will undermine the relationship, such as opportunism (Joshi & Stump, 1999:335, 339).

For an exchange to take place, both the buyer and the seller must receive something of value (Lamb, Hair, McDaniel, Boshoff, Terblanche, Elliott & Klopper, 2010:10; Lovelock, 1996:460). Value is often described as the trade-off between benefits received and sacrifices made (McDougall & Levesque, 2000:394; Yang & Peterson, 2004:803). Perceived value, then, indicates the perceived tangible and intangible benefits and costs that customers incur in an exchange, whether monetary or non-monetary (Ballantyne, Christopher & Payne, 2003:161; Kotler & Keller, 2006:25). Equity theory is at the core of perceived value. Equity theory considers how individuals in an exchange relationship compare their ratio of inputs and outputs to determine whether the exchange was fair (Glass & Wood, 1996:1191; Lapidus & Pinkerton, 1995:108). Similarly, perceived value compares customer's outcome/input to the service provider's outcome/input (Yang & Peterson, 2004:802).

Customers often have several service providers to choose from. Thus customers may switch to an alternative service provider, should they feel that their current service provider does not meet their needs (Chuang, 2011:135; Sharma & Patterson, 2000:475). Therefore the third antecedent, alternative attractiveness is also included in the study.

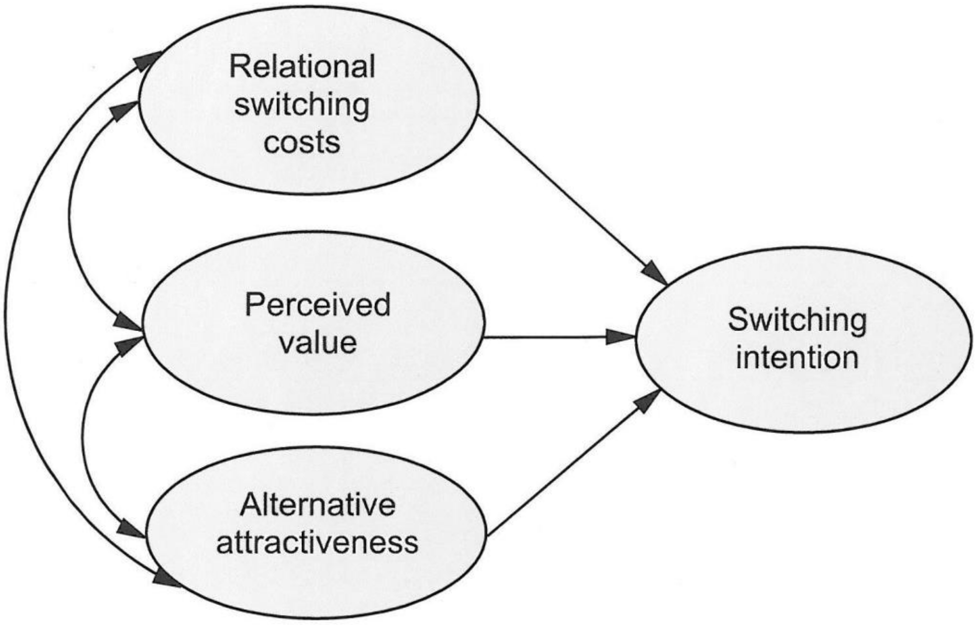
Lastly, relationship characteristics also play a role in switching (Ahn *et al.*, 2006:564; Keaveney & Parthasarathy, 2001:378; Keramati & Ardabili, 2011:352; Lopez, Redondo & Olivan, 2006:564; Ranganathan *et al.*, 2006:274). Relationship characteristics include relationship length, depth and breadth. Relationship length refers to the length of time that a customer remains with their service provider (Bolton, Lemon, Verhoef, 2004:273). Relationship depth is the frequency and intensity of service usage over time (Liang & Chen, 2009:219; Polo & Sesé, 2009:123). Relationship breadth reflects the purchase of additional products or services over time (Bolton *et al*., 2004:273; Lopez *et al.*, 2006:561).

Taking into consideration the literature regarding switching, a conceptual model was developed to guide the study.

1.2.2 Conceptual model

The conceptual model in Figure 1.1 presents the proposed direct influence of the three switching antecedents (relational switching costs, perceived value and alternative attractiveness) on switching intention, and the proposed relationships among the switching antecedents. The relationships are discussed at length in Chapter 3.

Figure 1.1: The conceptual switching intention model



Due to the highly competitive mobile telecommunications industry and the damaging effects of switching, the research problem, explaining the importance of investigating switching antecedents, is formulated in the next section.

1.3 RESEARCH PROBLEM

Research has been conducted to identify customer characteristics that may predict customer switching behaviour (Bansal *et al.*, 2005; Cronin, Brady & Hult, 2000; Eshghi *et al.*, 2006; Keaveney, 1995). Extensive research has also been conducted regarding switching determinants in the mobile telecommunications industry (Ahn *et al.*, 2006; Chuang, 2011; Hu & Hwang, 2006; Kim & Yoon, 2004; Min & Wan, 2009; Ranganathan *et al.*, 2006; Roos & Gustafsson, 2007; Shin & Kim, 2008; Shukla, 2010; Wong, 2011). However, to date, most switching studies have focussed on the predictive accuracy of switching intention and not on actual switching behaviour (Ahn *et al.*, 2006:553). Furthermore, few researchers have investigated alternative attractiveness as a predictor of switching behaviour (Chuang, 2011; Min & Wan, 2009). Even fewer studies have investigated switching cost components separately (Vasudevan, Gaur & Shinde, 2006:346).

In addition, monitoring customer relationship characteristics may assist organisations to predict switching behaviour. Relationship characteristics include relationship length, depth and breadth (Lopez *et al*., 2006:556). Counterintuitive results have been found concerning the relationship between switching intention and the three relationship characteristics (Ahn *et al*., 2006:564; Keramati & Ardabili, 2011:352; Madden, Savage & Coble-Neal, 1999:205).

Moreover, previous research conducted in South Africa relating to the mobile telecommunications industry has focussed on customers' attitudes toward mobile marketing (Beneke, Cumming, Stevens & Versfeld, 2010; van der Waldt, Rebello, & Brown, 2009), mobile marketing acceptance (Petzer, 2011), and cellphone banking (Brown, Cajee, Davies & Stroebel, 2003). Kruger and Mostert (2012) investigated young adults' relationship intentions towards their MNO. Furthermore, predictors of brand loyalty among cell phone users was recently investigated (Petzer, Mostert, Kruger & Kuhn, 2014). Notably, to date no studies that investigated switching antecedents in the mobile telecommunications industry in South Africa could be found.

Consequently, the following research objectives and hypotheses were compiled to explore switching predictors as well as actual switching behaviour in the mobile telecommunications industry in South Africa.

1.4 RESEARCH OBJECTIVES, HYPOTHESES AND CONCEPTUAL MODEL

1.4.1 Primary research objectives

This study has three primary research objectives:

1. to develop and empirically test a conceptual switching intention model (RO1),
2. to compare the conceptual switching intention model and actual switching behaviour data by fitting the switching behaviour data to the conceptual switching intention model (RO2), and
3. to explore the role of relationship characteristics, and their influence on both switching intention and switching behaviour (RO3).

1.4.2 Secondary research objectives

Secondary objectives following from research objective one (RO1) are:

Firstly, to investigate the direct influence of switching antecedents on switching intention, that is:

- to investigate the relationship between relational switching costs and switching intention,
- to investigate the relationship between perceived value and switching intention, and
- to investigate the relationship between alternative attractiveness and switching intention.

Secondly, to investigate the interrelationships between the switching intention antecedents, specifically:

- to investigate the relationship between relational switching costs and perceived value,
- to investigate the relationship between relational switching costs and alternative attractiveness, and
- to investigate the relationship between perceived value and alternative attractiveness.

Secondary objectives following from research objective two (RO2) are:
Firstly, to investigate the direct influence of switching antecedents on switching behaviour, that is:

- to investigate the relationship between relational switching costs and switching behaviour,
- to investigate the relationship between perceived value and switching behaviour, and
- to investigate the relationship between alternative attractiveness and switching behaviour.

Secondly, to investigate the interrelationships between the switching behaviour antecedents, that is:

- to investigate the relationship between relational switching costs and perceived value,
- to investigate the relationship between relational switching costs and alternative attractiveness, and
- to investigate the relationship between perceived value and alternative attractiveness.

Secondary objectives for research objective three (RO3) are:

- to investigate the influence of relationship length on switching intention,
- to investigate the influence of relationship depth on switching intention,
- to investigate the influence of relationship breadth on switching intention, and
- to investigate the influence of relationship length on switching behaviour,

- to investigate the influence of relationship depth on switching behaviour,
- to investigate the influence of relationship breadth on switching behaviour.

Alternative hypotheses were formulated for the above objectives and are presented in the next section.

1.4.3 Hypotheses

In order to investigate the secondary objectives listed in Section 1.4.2, the following alternative hypotheses (presented in Table 1.1) were formulated:

Table 1.1: Alternative hypotheses

Alternative hypotheses
H_{1a}: There is a negative relationship between relational switching costs and switching intention.
H_{1b}: There is a negative relationship between relational switching costs and switching behaviour.
H_{2a}: There is a negative relationship between perceived value and switching intention.
H_{2b}: There is a negative relationship between perceived value and switching behaviour.
H_{3a}: There is a positive relationship between alternative attractiveness and switching intention.
H_{3b}: There is a positive relationship between alternative attractiveness and switching behaviour.
H_{4a}: There is a relationship between relational switching costs and perceived value in a switching intention context.
H_{4b}: There is a relationship between relational switching costs and perceived value in a switching behaviour context.
H_{5a}: There is a relationship between relational switching costs and alternative attractiveness in a switching intention context.
H_{5b}: There is a relationship between relational switching costs and alternative attractiveness in a switching behaviour context.
H_{6a}: There is a relationship between perceived value and alternative attractiveness in a switching intention context.
H_{6b}: There is a relationship between perceived value and alternative attractiveness in a switching behaviour context.
H_{7a}: There is a negative relationship between relationship length and switching intention.
H_{7b}: There is a negative relationship between relationship length and switching behaviour.

Alternative hypotheses
H_{8a}: There is a negative relationship between relationship depth and switching intention.
H_{8b}: There is a negative relationship between relationship depth and switching behaviour.
H_{9a}: There is a negative relationship between relationship breadth and switching intention.
H_{9b}: There is a negative relationship between relationship breadth and switching behaviour.

The research design used for the study is summarised below. A detailed explanation of each aspect of the research design is provided in Chapter 4.

1.5 RESEARCH DESIGN

The following section presents an outline of the research design, sampling, data collection method and data analysis procedures used in the study.

Empirical research was used to conduct the study. Conducting empirical research implies that new data is collected (Cooper & Schindler, 2014:66). Both descriptive and explanatory research were conducted to identify characteristics and explore and explain relationships between the constructs being researched in the study (Cooper & Schindler, 2014:22). The research was cross-sectional (Cooper & Schindler, 2014:128), and an *ex post facto* design was used to investigate whether relationships exist between dependent and independent variables (Leedy & Ormrod, 2010:238-239).

Consulta Research, a South African-based market research company, kindly granted the researcher permission to use their cross-sectional online panel as the sample for data collection (see Consulta Research's letter of permission in Appendix A). Quantitative research was used to collect the primary data. Survey research with the aid of an online, structured, self-administered questionnaire, was used for data collection. The constructs were measured using existing Likert scales from previous research. Separate questionnaires were constructed to measure switching intention and switching behaviour.

After obtaining ethical clearance from the Research Ethics Committee of the Faculty of Economic and Management Sciences at the University of Pretoria, pre-testing was conducted in three phases using a live pre-test procedure. Informed consent was obtained from all potential participants before completing the survey. Emails with a cover letter inviting panel members to participate in the study were sent to potential respondents. The survey was sent to 54,924 panel members. In total, 1,668 surveys were returned. After data editing, switching intention observations totalled N_1 = 1,025 and switching behaviour observations totalled N_2 = 135. Note that for the remainder of the discussion, the switching intention sample will be referred to as N_1 and the switching behaviour sample will be referred to as N_2.

The univariate descriptive statistics were analysed using the IBM SPSS Statistics version 22 package. Descriptive statistics were used to compile a sample profile for both the switching intention sample and the switching behaviour sample, and to evaluate measurement scale validity and reliability. Various multivariate data analyses, including exploratory factor analysis (EFA), path analysis and multiple regression, were also conducted using the SPSS package. The AMOS package was used to conduct Structural Equation Modeling (SEM) and hypothesis testing. Parameter estimates and goodness-of-fit indices were obtained using maximum likelihood (ML). Since AMOS cannot estimate robust maximum likelihood, further analysis of the SEM model was conducted to obtain these results, with the use of the EQS package.

1.6 PROPOSED CONTRIBUTION

The study contributes toward the scholarly discussion on switching intention and behaviour and investigates constructs that have been neglected in the switching literature. Scant information is available regarding alternative attractiveness and perceived value, hence their inclusion in the study. Likewise, relational switching costs as a separate switching cost has not received much attention in the literature. Furthermore, the three aforementioned antecedents were previously not tested in one model and thus their interrelationships, until now, were unknown. The study also provides insight concerning the counterintuitive results that have been found regarding relationship length, depth and breadth in recent studies.

Apart from the aforementioned contributions, the most unique contribution of the research concerns the comparison of switching intention and switching behaviour. Previous studies have presumed that intention can act as a proxy for actual behaviour. In this study, actual behaviour data was investigated and compared to intended behaviour. The results provide managers with helpful insight as to whether intention can in fact be used as a proxy for behaviour.

Managers will benefit greatly if insight is gained as to the reasons why customers switch. Gaining an understanding of the antecedents of switching will allow managers to make better predictions when considering the possible causes of customer churn. Such information is particularly valuable in the mobile telecommunications industry, which has seen a dramatic rise in churn rates and intense competition (Kim *et al*., 2004:148).

Consequently, this research will make a contribution to managers in MNO organisations in South Africa and will contribute to the exploration of switching predictors as well as actual switching behaviour in the mobile telecommunications industry in South Africa.

1.7 DEMARCATION

The mobile telecommunications industry can be divided into residential and business customers (Gerpott *et al*., 2001:252; Srinuan *et al*., 2012:454). Business customers use mobile telecommunications to earn an income. The decision regarding which MNO to subscribe to typically depends on the employer and not the individual user. The employer usually pays the phone bill in part or in full. Residential customers, on the other hand, use mobile telecommunications to upkeep personal relationships; decide which MNO to subscribe to; and are personally responsible for the phone bill. For these reasons, residential customers were the focus of the research.

Customers can choose to be a contract (post-paid) subscriber or a pre-paid ('pay-as-you-go') subscriber (Corrocher & Zirulia, 2005:3; Malhotra & Malhotra, 2013:14). In contrast to pre-paid subscribers, post-paid subscriptions require customers to enter into a long-term contract with the service provider (Lee, Murphy & Dickinger, 2006a:1; Malhotra & Malhotra, 2013:14; Minges, 1999:589). The research concentrated on contract subscribers, since they are committed to a specific MNO for an extended period of time. A recent study conducted in a South African context indicated that the majority respondents (77.8%) had contracts with their MNO (Kruger & Mostert, 2012:45), providing support for the decision to include only contract customers.

The current study was conducted in the context of relationship marketing, and thus concentrated on the relationship between the customer (subscriber) and the MNO, that is, business-to-consumer (B2C) behaviour, and not the relationship between the customer and the actual mobile handset. Studies have been conducted to investigate consumer acceptance and use of smartphones (Chen, Yen & Chen, 2009), how mobile handsets are used to access mobile internet services (Pihlström & Brush, 2008:733), and general patterns of mobile handset usage among college students (Totten *et al*., 2005). However, the interaction between the consumer and the product that was purchased was not the focus of the current study.

Studies have also been conducted to determine how mobile handsets are used as a platform for an array of marketing communication, known as mobile marketing (Sultan, Rohm & Gao, 2009:308). Mobile marketing is a rapidly emerging trend which is also becoming widely researched (Gao, Rohm, Sultan, Huang, 2012; Petzer, 2011; Varnali & Toker, 2010). Although marketing communication can be used as a relationship marketing tool, mobile marketing falls outside the scope of the current study.

The marketing discipline experienced a paradigm shift, resulting in the movement from a goods-dominant to a service-dominant view (Vargo & Lusch, 2004:2). In addition, the service industry contributes approximately 65% of the gross domestic product (GDP) in most developed countries (Fahy & Jobber, 2012:174). Thus services marketing research has expanded tremendously, and is an important aspect of marketing to research.

Since services are intangible, purchasing services carry greater risks for customers than purchasing tangible products. Relationship marketing intends to reduce these risks by creating a bond with the customer (Kaur, Sharma & Mahajan, 2012:280). Due to acquisition costs far outweighing retention costs (Keaveney & Parthasarathy, 2001:375; Shukla, 2010:471), establishing a relationship between the customer and the service provider is important to retain the current customer base Berry (2002:60).

1.8 CHAPTER OUTLINE

The current chapter is an introduction to the study. The chapter comprises a brief literature review which summarises the importance of the mobile telecommunications industry and highlights the significance of preventing switching, and how switching affects the mobile telecommunications industry. The problem statement and research objectives are provided. An outline of the research design is also provided. Furthermore, the contribution of the study, the scope of the study and the chapter layout of the study are also discussed.

Chapter 2 commences with the literature review presenting an overview of mobile telecommunications and the mobile telecommunications industry. The chapter then describes mobile network operators (MNOs) that are specific to South Africa. An explanation of different types of contracts and mobile handsets concludes the mobile telecommunications section in the chapter. Services marketing, relationship marketing and their associated theories are elaborated upon in Chapter 2, and the need for and influence of exchange in relationship marketing is explained.

The next chapter, Chapter 3, continues the literature review with a discussion regarding switching. The importance of retention is discussed, followed by an explanation of the purchase process and post-purchase behaviour. In the ensuing section of the chapter, the switching intention and three switching antecedents, namely relational switching costs, perceived value and alternative attractiveness are conceptualised. Following the conceptualisation of each construct, relationships between the dependent variable (switching intention) and the independent variables are explained. Furthermore, the interrelationships between the independent variables are explored. Therefore the conceptual switching model is presented and industry-specific switching influencers are also mentioned. The influence of relationship characteristics, namely relationship length, depth and breadth on switching intention, are discussed in the final section of the chapter. Hypotheses formulated for the study are stated after each explanation of the relationships between constructs.

After the literature review, the research methodology section – Chapter 4 – follows. The chapter explains the research design chosen, the sample frame, and the questionnaire design process. A discussion of the data collection procedure is followed by an explanation of the data analysis techniques to be used. Various descriptive and multivariate data analysis techniques are explained. Following an explanation of the SEM model building and refinement process, hypothesis testing is discussed.

Chapter 5 provides the results of the study. Firstly, the sample profile of both the switching intention and switching behaviour samples are provided using descriptive statistics. Next, the scale validity and reliability tests are explained, followed by the measurement scale interpretations. The procedure followed to develop the conceptual switching intention model precedes the comparison of switching intention with switching behaviour. Next, the influence of relationship characteristics, namely relationship length, depth and breadth, on switching intention and switching behaviour are explored. Lastly, the hypothesis test results are discussed.

The final chapter, Chapter 6, summarises the findings of the study. Furthermoe, managerial implications and conclusions regarding the results are drawn. Lastly, the limitations of the study and recommendations for future research are provided.

1.9 CONCLUSION

The purpose of the first chapter is to provide an overview of the study by placing the industry in context, summarising the constructs and core theories which form the foundation of the study and formulating the research problem and research objectives. Further objectives of the chapter are to describe the research design, the proposed contribution and demarcation of the study, and provide an outline of the subsequent chapters.

To establish the context of the study in further detail, Chapter 2 begins with an overview of the mobile telecommunications industry, followed by a description of mobile network operators (MNOs) in South Africa. Since the mobile telecommunications industry can be considered part of the services sector, the fundamental concepts on which services marketing is based and the development of services marketing is also discussed in the following chapter. To facilitate customer retention, relationship marketing has become an integral part of services marketing. Thus Chapter 2 concludes with a discussion regarding the development of relationship marketing, the importance of customer retention in general, and the importance of customer retention in the mobile telecommunications industry in particular.

CHAPTER 2

MOBILE TELECOMMUNICATIONS, SERVICES MARKETING AND RELATIONSHIP MARKETING

2.1 INTRODUCTION

Mobile telecommunication has become an important sector for economic development. This sector of the telecommunications industry has grown rapidly, resulting in a large number of mobile network operators (MNOs) worldwide, and thus intense competition (Keramati & Ardabili, 2011:344; Shukla, 2010:467; Srinuan *et al*., 2012:453; Turel, Serenko & Bontis, 2007:63). Thus the study was conducted in the contet of mobile telecommunications. The chapter begins with an overview of the mobile telecommunications industry, followed by a description of mobile network operators (MNOs) in South Africa.

As markets become more competitive, protecting the current customer base is essential (Aydin, Özer & Arasil, 2005:90). Since customer acquisition costs are up to six times higher than customer retention costs, customer retention is a vital consideration for organisations in order to remain competitive (Keaveney & Parthasarathy, 2001:375; Shukla, 2010:471). Thus relationship marketing has become a topic of interest to researchers and marketing practitioners. In marketing literature, relationship marketing is one of the facets of services marketing. Thus fundamental concepts on which services marketing is based are discussed, followed by a discussion regarding the development of relationship marketing, and its role in customer retention.

2.2 MOBILE TELECOMMUNICATIONS

Telecommunication is defined as “the transmission of messages, over significant distances, for the purpose of communication” (Alam, 2011:6). After the advent of electricity and electronics, first the telephone, then other forms of telecommunication such as radio, television, telegraphs, fibre optics, orbiting satellites and the internet became popular (Alam, 2011:6). One of the main factors attributing to the considerable growth rate of mobile telecommunication is the substitution of fixed telephony for mobile telephony (Minges, 1999:586; Totten *et al*., 2005:15; van der Wal, Pampallis & Bond, 2002:324), since mobile telephony has many features and benefits that fixed telephony lacks.

Mobile telecommunication has been the fastest growing sector in the telecommunications industry since the 1990s, and as a result has become an important sector for economic development (Keramati & Ardabili, 2011:344; Shukla, 2010:467; Srinuan *et al*., 2012:453). The demand for mobile telecommunication "has grown exponentially" (Ranganathan *et al.*, 2006:269).

Rapid development of hardware and software and substantial infrastructure investment contributed toward immense growth in the mobile telecommunications industry (Malhotra & Malhotra, 2013:13). Other reasons for the accelerated growth of the mobile telecommunications industry were the abundant innovative wireless technologies, the constant improvement of mobile handsets and the numerous applications for mobile handsets (Keramati & Ardabili, 2011:344; Kim & Yoon, 2004:752; Malhotra & Malhotra, 2013:13; Nysveen *et al*., 2005:330; Ranganathan *et al*., 2006:269). Furthermore, the introduction of innovative services such as pre-paid contributed substantially to the tremendous growth of the mobile telecommunications industry (Corrocher & Zirulia, 2005:2).

2.2.1 <u>The mobile telecommunications industry</u>

Technological progress and a worldwide increase in the number of mobile network operators (MNOs) resulted in intense competition in the mobile telecommunications industry (Gerpott *et al*., 2001:249-250; Turel *et al.*, 2007:63). Consequently, continuously innovation to develop better products and services became essential (Srinuan *et al*., 2012:453), resulting in shortened product life cycles (Aydin & Özer, 2005:141).

Mobile telephony in most countries, whether developed or developing, has reached a level of maturity (Min & Wan, 2009:106; Negi, 2009:31; Govan-Vassen, 2014). According to the International Telecommunications Union (ITU), approximately 60% of the world's population are mobile subscribers (Srinuan *et al*., 2012:453). Certain countries are experiencing high mobile phone penetration rates (Chuang, 2011:128) and some countries have more mobile handsets than inhabitants (Glotz, Bertschi & Locke, 2006:3; Shukla, 2010:467). By the end of the first quarter of 2006, 30 countries had exceeded 100% mobile handset penetration (Wallace, 2006). Mobile penetration in Europe is saturated (Srinuan *et al*., 2012:453). Taiwan reached saturation in 2003 (Kuo, Wu & Deng, 2009:887).

Saturation has resulted in intense competition among MNOs (Shukla, 2010:467). Consequently MNOs are attempting to attract customers from their competitors by using attractive offers to encourage switching (Malhotra & Malhotra, 2013:14; Ranganathan *et al*., 2006:269; Shukla, 2010:467). Studies conducted in the United States in the early 2000s found that customer acquisition costs were between US$300 and US$475 (Brown, 2004:6; Sharma & Ojha, 2004:110). These high acquisition costs reflect the necessity to retain current customers, especially since research has shown that acquiring customers is more expensive than retaining current customers (Berry, 2002:60; Reicheld, 1996:57).

An overview of the South African mobile telecommunications industry is provided in the next section.

2.2.2 The South African mobile telecommunications industry

South Africa is considered to have the most modern fixed-line and mobile telecommunications system in Africa (CIA World Factbook: Communications, 2014). The South Africa Yearbook 2013/14 (2013:81) estimates that the Information and Communications Technology (ICT) industry in South Africa makes a contribution of approximately 7% toward gross domestic product (GDP).

Results published in 2012 by the International Telecommunications Union (ITU) indicated that South Africa was the 15th largest telecommunications market in the world in terms of revenues received from telecommunications services (Deloitte Digital SA, 2013). Despite approximately half of South Africa's population living "below the poverty line" (South Africa Yearbook 2013/14, 2013:87), South Africa had 128% mobile penetration by 2012 (Deloitte Digital SA, 2013).

2.2.2.1 Mobile network operators (MNOs)

Mobile network operators (MNOs) act as retailers of airtime to the public. MNOs sell mobile communications services and own a network structure (Banerjee & Dippon, 2009:72). Choosing a MNO is largely determined by price paid for obtaining access to a network and price paid for using the network (Gerpott *et al.*, 2001:257).

Four MNOs currently operate in South Africa, namely: Vodacom, MTN, Cell C and Telkom Mobile (South Africa Yearbook 2013/14, 2013:87). In August 2013, MNO market share estimates were: Vodacom (43%), MTN (36.8%), Cell C (17.1%) and Telkom Mobile (2.3%) (Bronkhorst, 2013). As indicated by their majority market share, Vodacom still enjoys first-mover advantage. The two dominant MNOs (Vodacom and MTN) are multinationals (SouthAfricaInfo, n.d.). Both were launched in 1994 (Hodge, 2005:495). Cell C, the third largest MNO, has been in operation since November 2001 (Cell C, n.d.). In 2010 Telkom, the former fixed-line parastatal monopoly, launched their mobile arm Heita (8ta). In 2013 8ta was rebranded to Telkom Mobile (Telkom, 2013).

South Africa currently has one mobile virtual network operator (MVNO). Virgin Mobile (founded in 2006) is the only MVNO in South Africa at present (Ferreira, 2013) and currently uses Cell C's network (McLeod, 2014a). MVNOs offer mobile services but do not own a bandwidth licence, nor their own network infrastructure. Instead MVNOs use the MNOs' existing wireless network infrastructure (Ferreira, 2013; McLeod, 2014a). MVNOs purchase the MNOs services at a wholesale price and sell their services at a retail price (Banerjee & Dippon, 2009:72; Cricelli, Grimaldi & Ghiron, 2012:1; Ferreira, 2013). MVNOs also offer their own products and services (McLeod, 2014a). Virgin Mobile's estimated market share is 0.7% (Bronkhorst, 2013).

2.2.2.2 Type of subscription

MNOs typically offer two types of subscription plans, either pre-paid or post-paid services. These subscription plans include a variety of calling plans, which differ for each MNO. A pre-paid subscription, also known as 'pay-as-you-go', allows customers to purchase airtime on an ad hoc basis (Gillwald, 2005:477; Lee *et al*., 2006a:1; Malhotra & Malhotra, 2013:14; Minges, 1999:589). Airtime is pre-purchased and reduces upon actual usage (Lee *et al.*, 2006a:1; Nikbin, Ismail, Marimuthu & Armesh, 2012:310). Airtime is the variable amount that is charged per minute of talking time (Bolton, 1998:52). Once depleted, the customer can 'top up' buy purchasing more airtime, hence the description 'pay-as-you-go' (Malhotra & Malhotra, 2013:14). Pre-paid subscription is appropriate for individuals with an unstable income or a tight budget (Nikbin *et al*., 2012:310), because a fixed amount of airtime is pre-purchased enabling subscribers to precisely control their spending. Another advantage is that there is no customer lock-in as with long-term contracts (Malhotra & Malhotra, 2013:14; Minges, 1999:589).

A post-paid subscription requires customers to enter into a long-term contract with the MNO (Lee *et al*., 2006a:1; Malhotra & Malhotra, 2013:14). Contract subscribers pay a start-up fee and a monthly access fee, contributing a fixed monthly charge that allows customers to use the mobile telecommunications network (Bolton, 1998:52; Gerpott *et al.*, 2001:251). The MNO requires a fixed minimum monthly spend, which customers pay at the end of every month (Lee *et al*., 2006a:1). Over and above those costs, customers also pay per minute of airtime, depending on their type of calling plan.

MNOs are the link between the handset manufacturer and the customer (Dedrick, Kraemer & Linden, 2011:506). MNOs generally subsidise the cost of the mobile handset in a post-paid subscription "in exchange for a period of exclusivity from the manufacturer" (Dedrick *et al*., 2011:506). Consequently customer retention is essential. Due to subsidy implications, MNOs charge an early termination fee. MNOs recover subsidy costs by having customers commit to a 24-month contract, thereby guaranteeing an income for 24 months, wherein the customer essentially pays back the subsidy (Dedrick *et al*., 2011:506).

2.2.2.3 Mobile handsets

Mobile handsets are the devices used for mobile telecommunication. At the outset, mobile phones were a compliment to fixed line telephony (Hodge, 2005:493). However, the current trend is that customers no longer have fixed-lines (land-lines) but use only mobile phones (Totten *et al.*, 2005:15).

Initially, mobile handsets were designed for voice communication, specifically to make and receive calls (much like fixed-line telephones). As technology progressed, a number of functions were added, for example text messages, internet connectivity, multimedia transmissions (which enables users to send and receive photos and videos) and cameras (Chen *et al*., 2009:241; Ketola & Röykkee, 2001:1; Kim *et al*., 2004:145; Lim, Widdows & Park, 2006:208; Mathieson, 2005:231; Ranganathan *et al*., 2006:269; Totten *et al*., 2005:15). Other uses of mobile handsets include entertainment, information retrieval and other miscellaneous functions. Entertainment can take the form of music playback (MP3), games, ringtones, video recording, watching streaming videos or downloading videos for later viewing. Information regarding sport, news, the weather, entertainment, events, banking and social media is obtained via an internet connection. Lastly, miscellaneous functions include memo recording, personal organisers, call registers and an address book are available (Mathieson, 2005:233).

Recent technological developments have resulted in mobile handsets evolving into multi-purpose smartphones providing users with a single solution for all communication needs (Chen *et al.*, 2009:241). A multi-function smartphone is a mobile phone that has the ability to access the internet and store data. Smartphones also have a variety of customer applications and are able to play music and videos (Dedrick *et al*., 2011:505).

Mobile handsets have changed the way people communicate, and the manner in which information is accessed and shared (Malhotra & Malhotra, 2013:13). Although mobile handsets were mainly used for voice communication, using a mobile device to access the Internet is rapidly increasing (Malhotra & Malhotra, 2013:13). The advent of smart phones is shifting the paradigm of the mobile telecommunications industry from being voice-driven to being data-driven (Malhotra & Malhotra, 2013:13).

Customers derive increased value from their mobile devices as a result of software and applications that are constantly being improved (Malhotra & Malhotra, 2013:13). MNOs have partnered with organisations that develop hardware and software (Malhotra & Malhotra, 2013:13). These partnerships have led to faster and more reliable mobile devices and attractive data capabilities (Malhotra & Malhotra, 2013:13).

There is high market demand for mobile connectivity, whether it be voice or data (Malhotra & Malhotra, 2013:13). As a result, MNOs must ensure that their infrastructure can manage the 'high volumes of usage', and still ensure clarity of voice calls and [rapid] data transfer (Malhotra & Malhotra, 2013:13). MNOs that are not able to continually maintain and upgrade their base infrastructure are bound to forfeit customers, as clarity of voice calls and rapid data transfer are essential requirements (Gerpott *et al.*, 2001:257; Malhotra & Malhotra, 2013:13).

Now that the industry in which the study takes place has been described, the marketing context, namely services marketing, and more specifically relationship marketing, are discussed in the sections to follow.

2.3 SERVICES MARKETING

The marketing discipline evolved over many decades, during which a variety of different marketing orientations came to the fore (Bruhn, 2003:1). From the time of the industrial revolution, large organisations concentrated on production efficiency and later, product development. Thus at the time the marketing discipline was 'goods' orientated (Bruhn, 2003:2; Lamb *et al.*, 2010:10; Rathmell, 1966:32). Authors such as Rathmell (1966) and

Shostack (1977) had the foresight to encourage researchers to shift their focus toward services marketing. Both researchers regarded services marketing as a separate discipline to goods marketing (Rathmell 1966; Shostack 1977). Considerable research in the field of marketing by the likes of Kotler (1972), Grönroos (1984) and Zeithaml, Parasuraman and Berry (1985) caused a paradigm shift resulting in the movement from a goods-dominant to a service-dominant view (Vargo & Lusch, 2004:2). The new paradigm led to the rapid growth of services marketing research and the recognition of services marketing as a discipline in the field of marketing (Lovelock, 1996:5).

Early economists considered the service sector to have an insignificant contribution toward the economy (Palmer, 2008:4). However, the service industry has grown to such an extent that 60% to 70% of the gross domestic product (GDP) of most developed countries is accounted for by the service industry, far exceeding manufacturing and agriculture (Fahy & Jobber, 2012:174). Even in emerging economies, services represent at least half of the GDP (Lovelock & Wirtz, 2011:29). Though classified as a developing country, South Africa is also regarded as having one of the most progressive economies on the African continent (African Telecoms News, n.d.; Southern African Development Community, 2012). South Africa was the only African country ranked in the top 15 worldwide emerging economies rankings in 2012 (South Africa Yearbook 2013/14, 2013:95). The well-developed service sector in South Africa is responsible for generating 68.4% toward the GDP (CIA World Factbook: Economy, 2014). Consequently the services industry is extremely important not only in South Africa, but also worldwide.

The service industry is based on the service-dominant logic comprising three fundamental concepts: intangible resources, relationships and co-creation of value by producers and customers (Baron, Conway & Warnaby, 2010:12). Therefore the aforementioned three aspects form the outline of this chapter and are discussed in three sections: services marketing (intangible resources), relationship marketing (relationships) and value through exchange (co-creation of value). Services marketing is defined and described in the next section.

2.3.1 Defining services marketing

Before further elaboration on intangible resources, to better understand services marketing a service is first defined. Kotler and Keller (2006:402) provide the following definition of a service: "…any act or performance that one party can offer to another that is essentially intangible and does not result in the ownership of anything. Its production may or may not be tied to a physical product". Intangible market offerings, abstract ideas and processes are marketed using services marketing (Boshoff, 2007:41). Thus a service can be described as a deed, meaning that a service is experienced or consumed and can not be kept (Perreault & McCarthy, 2006:195).

Furthermore, services "…are economic activities that create value and provide benefits for customers…" (Lovelock & Wright, 2002:6). It is important to note that while one party performs a deed for another, the service is provided in exchange for money and in addition the customer expects value from their access to the service, whether it be professional skills, facilities or labour (Lovelock & Wirtz, 2011:37).

Given that a service is often tied to a physical product, a distinction between products and services is also necessary before elaborating upon intangible resources. In general, tangible goods can be seen, touched, heard, smelled or tasted (Rathmell, 1966:32), whereas services are considered intangible, inseparable, perishable and heterogeneous (Palmer, 2008:9). However, among the researchers that proposed a service-dominant view, Shostack (1977:77) clearly differentiated between tangible-dominant and intangible-dominant market offerings. Shostack (1977:73) argued that the classification of products and services could not merely be made by stating that products are tangible and services, intangible, but instead felt strongly that different degrees of tangibility exist.

Shostack's view of combining tangible-dominant and intangible-dominant market offerings has been reiterated in definitions of a product. For example, Levitt (1981:98) defined a product as, "a promise, a cluster of value expectations of which its nontangible qualities are as integral as its tangible parts". Kotler and Keller (2006:372) and Palmer (2008:26) also recognise that a product combes tangible and intangible elements which satisfy needs and wants, and can be in the form of goods, services, ideas, experiences, events, information, places, people, organisations or any combination of these. Hereafter the terms 'product' and 'service' will refer to the market offering of the organisation, which is a combination of the tangible and intangible benefits that are sold to customers.

2.3.2 Distinguishing characteristics of services marketing

Four distinctive characteristics of services, namely intangibility, inseparability, heterogeneity and perishability, differentiate services from products (Hoffman, Bateson, Wood & Kenyon, 2009:26; Kasper, van Helsdingen & Gabbott, 2006:58; Kotler & Keller, 2006:405; Lamb *et al*., 2010:468; McColl, Callaghan & Palmer, 1998:47). Each characteristic is briefly described in the paragraphs to follow.

2.3.2.1 Intangibility

Intangibility of a service refers to the fact that services can not be seen, tasted, felt, heard nor smelled (Hoffman *et al*., 2009:26; Lamb *et al.*, 2010:468). Due to the intangible nature of services, testing or evaluating a service prior to purchase is rarely possible (Levitt, 1981:96; Sharma & Patterson, 2000:474). As a result, purchasing services carry greater risks for customers than purchasing tangible products. According to risk theory, individuals intend to keep their subjectively perceived risks as low as possible to avoid negative outcomes (Bruhn, 2003:27).

To reduce the uncertainty that customers experience, service providers use tangible cues to allude to the quality that customers can expect from the service (Kasper *et al*., 2006:58; Lamb *et al.*, 2010:469). Tangible cues include people (how the staff are dressed; the demeanour of the staff), place (the physical setting in which the service is delivered), communication material (letterheads, business cards), symbols (the organisation's logo) and price (Kotler & Keller, 2006:405; Lamb *et al.*, 2010:469).

2.3.2.2 Inseparability

Unlike products, which are mostly manufactured in factories a long distance from customers, in most cases the customer has to be present for some or all of the service production and consumption (Hoffman *et al*., 2009:32; Palmer, 2008:13; Perreault & McCarthy, 2006:195). Thus it can be said that production and consumption of the service occur simultaneously (Hoffman *et al*., 2009:32; Kasper *et al*., 2006:58). Furthermore, customers also participate in the production of the service (Kasper *et al*., 2006:58; Lamb *et al.*, 2010:469). As a result, the term 'interactive consumption' was coined (Kasper *et al*., 2006:58).

Given that the customer has to be present during the service delivery process, the service provider must ensure that the customer has a pleasant service encounter (Palmer, 2008:13), thus a positive service provider-client interaction experience is imperative (Kotler & Keller, 2006:406). However, production and delivery of a service is highly people-intensive and therefore a greater possibility of errors during service encounter exists, which may cause customer dissatisfaction (Levitt, 1981:98). Furthermore, not only does service delivery depend on the quality of the organisation's employees (Lamb *et al.*, 2010:469), the cooperation of the customer and the presence of other customers also influence the service encounter (Fahy & Jobber, 2012:176). Inseparability then, according to Hoffman *et al*. (2009:31), "reflects the interconnection between the service provider, the customer involved in receiving the service and other customers sharing the same experience."

2.3.2.3 Heterogeneity

Heterogeneity refers to the "variation in consistency from one service transaction to the next" (Hoffman *et al*., 2009:38). Considering that employees differ in personality, interpersonal skills, mood and technical skills, the service provided will vary to a degree with each service encounter (Hoffman *et al*., 2009:39; Lamb *et al.*, 2010:469). In certain instances, since the customer participates in the service process, the customer could well be the cause of the inconsistency (Hoffman *et al*., 2009:39).

Service quality control is challenging, because the service can not be delivered in exactly the same manner every time (Hoffman *et al*., 2009:39). The reason being that services are delivered by human beings and not machines that are programmed to produce the exact same product in the exact same manner each time production takes place (Kasper *et al*., 2006:60). However, services can be standardised to a degree to reduce variation in the service process (Lovelock & Wright, 2002:31). Standardisation can be achieved by following standardised procedures, providing standard service offerings and through extensive staff training.

Even though standardisation is often a requirement for business success, the service characteristic of heterogeneity can be considered a competitive advantage, since services can be customised to the exact needs of customers, thereby satisfying individual needs and wants, which is extremely valuable to customers (Pride & Ferrell, 2010:362).

2.3.2.4 Perishability

Perishability refers to the fact that services can not be stored nor inventorised, and unused capacity can not be reserved for future use (Lamb *et al.*, 2010:470; Pride & Ferrell, 2010:366). On the contrary, products can be stored and sold in the future (Hoffman *et al*., 2009:43). Consequently, balancing supply and demand is much more challenging for services than products (Kasper *et al*., 2006:60; Perreault & McCarthy, 2006:195). When demand is higher than supply, more customers require the service than the organisation is equipped to serve at that specified point in time. Whereas low demand implies that resources (such as employees) are underutilised because not enough customers require the service at that point in time (Hoffman *et al*., 2009:44-45). Service providers constantly strive to find equilibrium between supply and demand and often offer discounts during off-peak times, make use of appointment systems or increase prices during peak times in an attempt to establish a balance (Kotler & Keller, 2006:407; Lamb *et al.*, 2010:470; Pride & Ferrell, 2010:366-367).

Now that services have been defined and the core distinguishing characteristics of services have been discussed, the means by which services have been categorised is explained in the section to follow.

2.3.3 Categorisation of services

Since services are so diverse, classification of services is complicated due to the diversity of services (Blythe, 2006:407; McColl *et al*., 1998:56; Palmer, 2008:18). Suggestions have been made to classify services according to industry, however such a classification scheme would be imprudent, since many different industries share common service delivery challenges (Hoffman *et al*., 2009:66). Classification of services according to similar service operation activities has become the accepted means of service categorisation, since similar service delivery challenges are common across numerous industries (Hoffmann *et al*., 2009:66; McColl *et al*., 1998:56). Although a variety of classification categories have been proposed, for the purpose of the current study only the following categories are considered: the degree of tangibility; the level of customer involvement; how customers evaluate quality; and the means of service delivery.

2.3.3.1 The degree of tangibility

Services can be categorised according to their degree of tangibility. As originally proposed by Shostack (1977), goods and services can be placed on a tangible-dominant – intangible-dominant continuum. The continuum indicates whether the service offering has a large or a small service component (Kotler & Keller, 2006:403; Lovelock & Wirtz, 2011:37). Using the five degrees of tangibility is a simplified means of categorising the degree of tangibility along the continuum. The five degrees of tangibility are: pure tangible goods; a tangible good with accompanying services; a hybrid with equal parts of goods and services; a major service with accompanying minor goods and services; and pure services (Blythe, 2006:407; Kotler & Keller, 2006:403-404; McColl *et al*., 1998:59). Organisations in the services industry typically fall within the last three categories.

2.3.3.2 The level of customer involvement

Secondly, services can be classified according to the level of customer involvement. Customer involvement refers to the actions, resources and inputs supplied by the customer during production and delivery of the service (Lovelock & Wirtz, 2011:237). In some cases, the service can only be provided if the customer is present; at other times the customer only initiates the process (McColl *et al*., 1998:60). The customer is seen as a co-producer of the service if the customer is present during the service delivery process (Lovelock & Wirtz, 2011:48). Low customer involvement implies that the employees and systems perform tasks, and requires services to be standardised. Moderate customer involvement requires customer input to create and deliver the service, and some degree of customisation. High levels of customer involvement require customers to actively participate with the service provider to co-produce the service. Failure on the customer's part to perform certain tasks will jeopardise the quality of the service outcome (Lovelock & Wirtz, 2011:237).

2.3.3.3 How customers evaluate quality

Customers experience high risk when purchasing services because services are high in experience and credence qualities (Bruhn, 2003:21). Experience qualities indicate that customers are only able to evaluate the service during or after consumption (Bruhn, 2003:21; Lovelock, 1996:165-166). Credence qualities are characteristics of a service which are not easy to evaluate even after the purchase (Bruhn, 2003:21; Edward, George & Sarkar, 2010:168-169; Lovelock, 1996:166). Therefore service aspects such as price, personnel and tangible cues are used to judge quality (Blythe, 2006:410; Lamb *et al*., 2010:423).

High prices are often used to signify high quality (Lamb *et al*., 2010:423). Well-trained employees, and the manner in which personnel are groomed, are also crucial aspects of the service delivery process (Lovelock & Wirtz, 2011:46). Tangible cues in the servicescape – the physical environment in which the service is delivered – give clues as to the quality of service to expect (Bitner, 1992:57). Therefore attention should be paid to tangible cues such as décor and restroom facilities, to indicate the level of service quality and customer needs. In contrast, if the customer is not expected to be present, operational processes and the needs of employees are considered important (Bitner, 1992:58; Kotler & Keller, 2006:404; McColl *et al*., 1998:60-61).

2.3.3.4 The means of service delivery

Lastly, the means of delivery of the service can be either equipment-based or people-based. Equipment-based services use equipment to mainly provide the service. The equipment could be automated or monitored by skilled or unskilled operators. In the case of people-based services, the service is provided by unskilled, skilled or professional workers (Kotler & Keller, 2006:404; McColl *et al*., 1998:59). People-based services are usually customised to meet the exact needs of each individual customer, whereas equipment-based services are mostly standardised (Pride & Ferrell, 2010:363).

Similar to tangible products, marketing practitioners that deliver services also need to identify and segment target markets, position the service and consider the appropriate combination of marketing mix elements that will best suit the target market. In order to develop a suitable marketing mix, the 7 Ps of services marketing should be considered.

2.3.4 <u>The services marketing mix (7 Ps)</u>

The marketing mix, usually referred to as the ‘4 Ps’ of marketing, consists of product, place, promotion and price (Lamb *et al.*, 2010:28). The marketing mix is used to develop strategies to market manufactured goods (Lovelock & Wirtz, 2011:44). The ‘4 Ps’ were found to be lacking with regards to services, due to the distinct service characteristics of intangibility, inseparability, heterogeneity and perishability (Lovelock & Wirtz, 2011:44; McColl *et al*., 1998:18). Subsequently three ‘Ps’ were added to make the marketing mix relevant to services, resulting in the services marketing mix or ‘7 Ps’. The three additional elements added were people, processes and physical evidence (Lovelock & Wirtz, 2011:44). Each element of the services marketing mix is briefly discussed in the paragraphs to follow.

2.3.4.1 The service offering (product)

The service offering is the 'product' that the organisation offers to potential customers to satisfy needs (McColl *et al*., 1998:19). The service offering must create value for customers to entice them to purchase it (Lovelock & Wirtz, 2011:44). The service offering can be described using three levels, where each level acts in a hierarchy adding more value than the previous level (Lovelock & Wirtz, 2011:106). The core service level is the central problem-solving benefit that the customer derives from purchasing the service (Lovelock & Wirtz, 2011:106). The next level is the supplementary service which facilitates use of the core service and enhances its value. The third level, the delivery process, includes the processes used to deliver the core service and each supplementary service (Lovelock & Wirtz, 2011:106). In the mobile telecommunications industry the core service level is communication, while the supplementary service is all the means in which communication is facilitated. For example, network quality, connectivity, voice quality and mobile handsets. The delivery process includes the number of contact points available to customers, for example websites, call centres, retail outlets and repair centres.

2.3.4.2 Pricing services

Price is described as that which is given up in an exchange to acquire a product or service (Zeithaml, 1988:10). In the service sector, 'price' is often replaced with terms such as commission, rates, tariffs, premiums, rent, interest, fares or service charges (Kasper *et al*., 2006:417-418; Lovelock & Wirtz, 2011:158).

Customers incur both monetary and non-monetary costs when making a purchase (Kasper *et al*., 2006:418; Lovelock & Wirtz, 2011:46). Monetary costs are the actual price paid for the service. Non-monetary costs include time costs when searching for a product. Psychological costs refer to the mental effort to collect information and compare various products and the physical effort to go and purchase the product (Kasper *et al*., 2006:418; Lovelock & Wirtz, 2011:46). The high experience and credence attributes of services may also increase psychological costs such as fear, perceived risk and cognitive dissonance (Lovelock & Wirtz, 2011:164). Should the costs (monetary and non-monetary) outweigh the benefits, there is a high likelihood that customers will not purchase the product. Therefore a balance has to be achieved between the maximum amount that the customer is prepared to pay for the service, and the minimum amount that the organisation needs to receive in order to cover costs and reach financial objectives.

Due to the intangible nature of services, customers rely heavily on price as an indicator of quality (Lamb, 2010:423; McColl *et al*., 1998:19; Palmer, 2008:39; Pride & Ferrell, 2010:367). Since customers are not able to easily judge quality, price will most likely affect the choice of service provider, should customers perceive the quality of competing service providers to be similar (Pride & Ferrell, 2010:367). In the mobile telecommunications industry pricing is perceived as complicated. MNOs offer a variety of packages that are very similar, but not easily comparable. Consequently, increased mental effort to collect information and compare various packages could influence the customer’s decision to remain with their current MNO.

2.3.4.3 Promotion of services (marketing communication)

Marketing communication is used to convey the benefits (value proposition) that a service may provide to potential customers (Lovelock & Wirtz, 2011:46; McColl *et al*., 1998:19). In ‘goods’ marketing, the conventional marketing communication elements, also known as the promotion mix (or marketing communications mix) include advertising, sales promotion, personal selling and public relations (Lamb *et al*., 2010:375-399). A wide variety of marketing communications elements have since developed. Lovelock and Wirtz (2011:196-200) classify marketing communications elements as those transmitted through traditional marketing channels, such as advertising, sales promotion, personal selling and public relations, direct marketing, trade shows and the internet (including the organisation’s website and online advertising). The second category are marketing communications transmitted through service delivery channels, such as service outlets, frontline employees, self-service points and where applicable, customer training (Lovelock & Wirtz, 2011:203-203). Lastly, marketing communications messages originating outside the organisation include word-of-mouth, media coverage and social networks (Lovelock & Wirtz, 2011:206-208).

In addition to using the aforementioned promotion mix elements in services marketing, greater emphasis is placed on increasing the tangibility of the service in all services marketing communication (McColl *et al*., 1998:20). When promoting a tangible product, the actual product can be shown in the promotional material, whereas the actual performance of a service can not be depicted (Pride & Ferrell, 2010:365). Consequently tangible cues such as facilities, service personnel and equipment are mostly used in services marketing communication. Symbols and tangible expressions of customer lifestyles are also used as a means to indicate the benefits derived from using the service. Communicating the organisation's affiliation with accreditation organisations and the qualification of personnel are other cues to make the service seem more tangible. (Pride & Ferrell, 2010:365). Furthermore, including service personnel in service marketing communication is also common practise (McColl *et al*., 1009:20).

Services can not be experienced nor sampled before being purchased. In some cases, service providers are able to offer customers a trial period, however, in most cases, word-of-mouth or the organisation's reputation are the only indicators available to customers to decide whether or not to use the service provider (Pride & Ferrell, 2010:366). For this reason, stimulating positive word-of-mouth communication, using satisfied customer testimonials and customer referrals are often used for services marketing communication.

MNOs in South Africa use traditional forms of advertising, sales promotions and sponsorships, and also have websites and social media platforms. A variety of service outlets are also available, where customers interact directly with frontline employees. The service outlets are an opportunity to add a tangible component to an otherwise intangible service. Thus the décor of the stores and the staff at the service outlets are important. With customer complaints platforms available to customers, such as Hellopeter.com, monitoring negative word-of-mouth is essential.

2.3.4.4 Distribution of services (place)

The purpose of distribution is to connect the customer and service provider (Kasper *et al*., 2001:400). Services are delivered (distributed) in three main ways, namely customers go to the service provider, the service provider goes to the customer, and no face-to-face contact with the customer is required (Lovelock & Wirtz, 2011:134; Pride & Ferrell, 2010:364).

Service delivery usually uses short marketing channels since the service provider is often in direct contact with the customer, however, intermediaries are used in some instances (Pride & Ferrell, 2010:364). Different marketing channel options include: direct channels, where the service is performed directly by the service provider (especially when complex or tailor-made services are required); indirect channels, where one or more intermediaries assist in connecting the service provider to the customer (either due to social, psychological or geographical issues); and multi-channels, which use two or more channels to either offer customers more choice or to reach different market segments (Kasper *et al*., 2006:404). The distribution channel chosen will determine how many intermediaries will be involved in the service delivery process. Intermediaries include the service providers (direct channels), retailers or service outlets, wholesalers, agents or brokers or franchised service deliverers (Kasper *et al*., 2006:404-405; Lovelock & Wirtz, 2011:144).

MNOs in the mobile telecommunications industry use multi-channel distribution. Some direct outlets are available to consumers, for example online stores. Other outlets include franchises, for example Vodacom 4u stores. MNOs also make use of approved distributors and have contracts with intermediaries such as Altech Autopage.

2.3.4.5 Physical evidence

An important addition to the services marketing mix is physical evidence. Due to the intangible nature of services, judging a service prior to consumption is problematic. Physical evidence thus provides tangible cues and thereby reduces the risk that customers experience when purchasing services that can not be evaluated beforehand (McColl *et al*., 1998:21). Furthermore, due to simultaneous production and consumption of services, the customer is often in the 'factory' (the place where the service is produced) whilst experiencing the service (Bitner, 1992:57). Thus the surroundings in which the service is produced (the servicescape) also impact the customer's experience.

Service organisations differ regarding the degree of physical evidence that is required. Taking into consideration the five degrees of tangibility, if the organisation offers a pure service, more physical evidence will be necessary than an organisation offering a major service with accompanying minor goods and services. The type of physical evidence required also depends on who will be using the service. If self-service is appropriate, the servicescape should greatly enhance customer satisfaction and be attractive. If an interpersonal service is needed, the servicescape should satisfy both the customer and employee's needs. Lastly, for organisations using a remote service, the servicescape should be designed to suit the employees, since customers will have limited, if any, access to the environment in which the service is being provided (Bitner, 1992:58). Should the servicescape be absent or not important (for example gardening or office cleaning services), tangible cues could be conveyed through business cards, account statements, equipment or staff uniforms (Lamb *et al.*, 2010:471). Due to the intangible nature of mobile telecommunications, MNOs convey tangibility to their customers via the look and feel of their service outlets. Thus the staff, décor and store layout are important elements in the stores.

2.3.4.6 Process

The service encounter refers to "the period during which a service provider … and a service buyer interact in a face-to-face situation" (Boshoff, 2007:41). Keaveney (1995:76) defines the service encounter as "personal interactions between customers and employees in service firms". The service delivery process comprises a combination of sub-systems which work together in order to provide the overall service (Kasper *et al*., 2006:380). Since the service is produced and consumed during the service encounter and in the presence of the customer, the flow of the process is crucial to the success of the service encounter (Lamb *et al.*, 2010:471; McColl *et al*., 1998:22).

To enhance the flow of the service delivery process, service organisations typically use blueprinting – an operation-management technique which uses flowcharts to plan, manage and analyse each service encounter and identify possible errors and bottlenecks in the process (Kasper *et al*., 2006:388). Both front stage and backstage activities of employees should be included in the service blueprint. A distinction can be made between activities and employees that are visible to customers (front stage activities) and those activities and employees that are not directly visible to the customer (backstage activities). Often front stage and backstage activities take place simultaneously, hence the contribution of both are crucial to the success of the service encounter (Fahy & Jobber, 2012:179; Lamb *et al.*, 2010:471). In terms of mobile telecommunications service outlets, MNOs can ensure that each service being provided is clearly indicated using signage in each section of the store, for example, helpdesk or repairs. An assistant could be available on the floor to guide customers to the correct section of the store. In the case of call centres, MNOs should ensure that the instructions are clear, so that customers are directed to the correct call centre agent.

2.3.4.7 People

Often the only interaction customers have with the organisation is through a single contact employee. During the first service encounter, customers form an opinion of the organisation, the quality of the service and the employees and decide whether or not to do business with the organisation in future (Kasper *et al*., 2006:374). Therefore suitable staff should be recruited and continuous staff training and development are essential (Lovelock & Wirtz, 2011:48). The adage, 'happy employees lead to happy customers' certainly holds true for the 'people' element of the services marketing mix. Research has shown that when employees feel that the organisation is treating them well, they are more likely to treat customers well, which ultimately leads to superior profitability (Fahy & Jobber, 2012:178). For this reason internal marketing has gained popularity in service organisations. Customers also influence service delivery, depending on whether or not they participate and co-operate with service employees (Lamb *et al.*, 2010:470). Similarly, other customers can also enhance or negatively influence the service encounter through their behaviour. Regarding employees, MNOs could consider incentive programmes to encourage employees to strive toward target service levels. MNOs should also implement appropriate employee development programmes. Ideally such programmes should be aligned to the organisation's culture and overall strategy.

According to risk theory, customers prefer to avoid risk (Bruhn, 2003:27). However, customers experience high risk when purchasing services, due to the intangibility of services (Bruhn, 2003:21). Therefore, building a relationship with customers is important because a relationship with an individual in the organisation makes the intangible service seem slightly more tangible, and thereby decreases risk (Berry, 2002:62). The lower the customer's perceived risk, the lower the likelihood that the customer will seek an alternative service provider (Sharma & Patterson, 2000:474). Furthermore, since research has shown that acquiring customers is more expensive than retaining current customers (Berry, 2002:60; Reicheld, 1996:57), fostering relationships with customers has become an essential strategy for successful organisations. In addition, once an organisation has formed a relationship with their customers, they are able to gain a better understanding of what their customers perceive as valuable. As a result, the organisation is able to provide a product offering that creates more value than those offered by competing organisations (Berry, 2002:65). The likes of Grönroos (2002:138) consider relationship marketing to be the underlying approach used in services marketing. The following section elaborates upon the concept of relationship marketing.

2.4 RELATIONSHIP MARKETING

Although Berry (1983) coined the term 'relationship marketing' over 30 years ago (Hunt *et al*., 2006:74), the relationship phenomenon is as old as any trade relationship (Ballantyne *et al*., 2003:159; Möller & Halinen, 2000:31). Due to rapid growth of many organisations worldwide, maintaining personal contact with customers has become challenging (Palmer, 2008:252). Large organisations are in sharp contrast to mom-and-pop stores in which case shopkeepers knew individual customers and offered each individual customer a personalised service (Ackerman & Schibrowsky, 2007:317; Stevens, 2000). Consequently, relationship marketing has become an important tool to assist organisations to remain competitive since identifying, developing and nurturing relationships leads to competitive advantage and superior financial performance (Hunt *et al.*, 2006:76).

Berry (2002:60) noted that protecting the customer base has become an extremely important strategy for organisations. This point of view has led to the current interest in relationship marketing as a research area. The next section will define relationship marketing, discuss the existence of a theory of relationship marketing and the paradigm shift toward relationship marketing. The ensuing section is a discussion regarding exchange in marketing and an explanation of the role of relational exchange and building customer-service provider relationships.

2.4.1 Defining relationship marketing

Much debate exists regarding a definition and the conceptualisation of relationship marketing (Hunt, 1997:431; Palmer, 2008:250). Gummesson (2000:1) is of the opinion that relationship marketing has three essential components – relationships, networks and interactions. Grönroos (2004:101) incorporated these three elements into his definition of relationship marketing: "the process of identifying and establishing, maintaining, enhancing, and when necessary terminating relationships with customers and other stakeholders, at a profit, so that the objectives of all parties involved are met, where this is done by a mutual giving and fulfilment of promises".

Ballantyne *et al.* (2003:163) however, challenge the three components and propose that relationships, networks and value exchanges (instead of mere interactions) are likely to define relationship marketing in the near future. Hunt (1997:431) is of the opinion that the common element in all relationship marketing definitions is the fact that organisations that wish to remain competitive place great emphasis on building long-term relationships with stakeholders, whether customers, employees, suppliers or competitors.

2.4.2 A theory of relationship marketing

Even though there has been wide interest in relationship marketing, to date, a 'Theory of Relationship Marketing' is yet to be developed (Ivens & Blois, 1994:240; Möller & Halinen, 2000:34; Shrivastava & Kale, 2003:61). Many researchers feel strongly about the development of a more substantial theoretical base for relationship marketing literature (Ivens & Blois, 1994:240). Hunt *et al.* (2006:76) and Hunt (2010:359) strongly argue that resource-advantage theory should be used as the theoretical foundation of relationship marketing, whereas Gummesson (1995) proposed a single general theory for relationship marketing (Möller & Halinen, 2000:44).

Relationship marketing literature has developed from a variety of theories, paradigms and frameworks. Some have originated in the marketing discipline, while numerous theories from other disciplines, including economics, psychology and sociology, have been incorporated into the marketing literature (Bruhn, 2003:19; Grönroos, 2002:129; Ivens & Blois, 1994:240; Möller & Halinen, 2000:34). Taking into consideration the wide variety of theories that relationship marketing has been based on, the development of a single relationship marketing theory is unlikely. The purpose of the next discussion is not to develop relationship marketing theory, but to take cognisance of the on-going scholarly debate in this field.

2.4.3 A paradigm shift toward relationship marketing

As mentioned in the services marketing discussion, marketing was originally goods-dominant with a focus on production (Rathmell, 1966:32). Aggressive sales techniques were used in an attempt to sell the abundant build-up of stock which resulted from testing production procedures and improving products. Since customers were unhappy that they had been coerced into purchasing products they did not need or could not afford, customers did not want any further interaction with the organisation, resulting in limited repeat sales (Lamb *et al.*, 2010:10-12). A major paradigm shift resulted in an attempt to generate repeat business. Organisations became customer-orientated instead of production or sales orientated. Hence the marketing concept was 'born'. The marketing concept is a customer-orientated philosophy pertaining to the satisfaction of customer needs and wants (Lamb *et al.*, 2010:12). The marketing concept prescribes that in order for an organisation to be successful, customer satisfaction through satisfying customer needs and wants should be the primary focus to achieve long term profitability and sustainability (Lamb *et al.*, 2010:13; Perreault & McCarthy, 2006:20). Organisations that subscribe to the marketing concept have recognised the importance of building enduring exchange relationships with customers (Kotler & Keller, 2006:17; Pride & Ferrell, 2010:47) and therefore strive to continually satisfy customer needs and provide customer value before and after the purchase (Perreault & McCarthy, 2006:20).

Enduring exchange relationships occur if customers receive value and their needs are satisfied, resulting in repeat purchases from one organisation. In turn, the organisation is able to make a profit because of continued customer purchases. To ensure future purchases, the organisation continually seeks ways in which to provide customer value that is better than the competitors' offerings, resulting in satisfied customers and thus the likelihood that customers will remain loyal (Perreault & McCarthy, 2006:21; Pride & Ferrell, 2010:15). The above cycle is mutually beneficial to both parties, thus the field of relationship marketing evolved to build long-term exchange relationships with customers (Lamb *et al.*, 2010:10). Since exchange plays an important part in building customer relationships, a brief overview of the role of exchange in marketing follows.

2.4.4 Marketing and exchange

Exchange is a fundamental principle in business, since without exchange, a business can not survive. During the exchange process, the buyer gives up something of value (usually money) to receive something perceived as valuable in return (Kotler & Keller, 2006:6; Lamb *et al*., 2010:9; Pride & Ferrell, 2010:9). Exchange can take place without money, for example bartering (Lamb *et al.*, 2010:9). However, most often a monetary value (price) is attached to the item being sold. Zeithaml (1988:10) notoriously defined price as "what is given up or sacrificed to obtain a product".

2.4.4.1 Evolution of exchange in marketing

Exchange in marketing evolved from exchange principles in economics (Vargo & Lusch, 2004:1). Many authors argue in favour of the notion that exchange is at the core of marketing (Araujo, 2007:211; Bagozzi, 1975:32; Houston & Gassenheimer, 1987:3; Kotler & Keller, 2006:6). Interestingly, some definitions of marketing include the exchange paradigm (Lamb *et al.*, 2010:5; Pride & Ferrell, 2010:4), reinforcing the importance of exchange in marketing. The exchange theory is thus a relevant core theory of marketing.

Bagozzi (1975:32) is of the opinion that marketing exchanges are more complex than economic exchanges. Bagozzi noted that marketing exchanges often involve indirect exchanges, include more than two parties and the exchange may take place for intangible goods and symbolic aspects of the product or service. This is contrary to economic exchanges that are said to be a direct transfer of tangible goods between two parties. Marketing exchange is considered a mixed exchange, since both economic exchange and symbolic exchange take place. Economic exchange occurs when goods are given in return for money or other goods, for a profit, whereas symbolic exchange involves "… the mutual transfer of psychological, social or other intangible entities between two or more parties" (Bagozzi, 1975:36). It follows then that people and organisations engage in exchange to satisfy needs (Bagozzi, 1975:35). Need satisfaction is the force that drives exchange (Houston & Gassenehimer, 1987:16) and is driven by the value derived from need satisfaction, hence a discussion regarding value follows.

2.4.4.2 The role of value in exchange

Ballantyne *et al.* (2003:161) and Kotler and Keller (2006:25) are of the opinion that value is a core concept in marketing, since value is an indicator of the perceived tangible and intangible benefits and costs that customers incur in an exchange, whether monetary or non-monetary. Value is widely considered to be the difference between benefits that customers derive from a market offering and the costs of obtaining the benefits (Perreault & McCarthy, 2006:19). If the benefits received exceed costs, customers are generally satisfied. On the contrary, if the costs exceed the benefits, the customer is likely to consider alternatives (other competitors). Similarly value theory posits that the greater the product's usage value to a customer, the higher the likelihood that the customer will demand the product from the organisation (Bruhn, 2003:19). Value theory is thus closely related to perceived value (Bruhn, 2003:20). Thus value can be considered to be at the core of marketing activities (Yang & Peterson, 2004:803).

When evaluating an exchange relationship, parties have preconceived expectations regarding the performance of the other party (Gundlach & Murphy, 1993:37). Should the other party's performance meet original expectations, there is the perception that value has been derived from the exchange relationship. Various value-evaluation theories are applicable to all exchange relationships, namely equity theory, expectancy-value theory and social exchange theory. Each theory is briefly described below.

2.4.4.3 Equity theory

Equity theory explains how individuals in an exchange relationship compare their ratio of inputs and outputs in an exchange situation to determine whether a fair exchange has taken place (Glass & Wood, 1996:1191; Huppertz, Arenson & Evans, 1978:250; Lapidus & Pinkerton, 1995:108). Equity is the evaluation of fairness (Bolton & Lemon, 1999:173), thus inequity occurs when the ratio of input to output are perceived to be unequal, resulting in dissatisfaction (Glass & Wood, 1996:1191; Lapidus & Pinkerton, 1995:108). The dissatisfied party will be motivated to restore equity, that is, restore the balance between inputs and outputs or benefits and costs (Glass & Wood, 1996:1191; Huppertz *et al.*, 1978:250). The degree of equity that needs to be restored will depend on the value that the individual placed on the exchange (Glass & Wood, 1996:1192), known as value equity, that is, the customer's perception of the market offering's corresponding benefits and costs (Kotler & Keller, 2006:151). Equity theory is at the core of perceived value, since perceived value compares customer's outcome/input to the service provider's outcome/input (Yang & Peterson, 2004:802).

2.4.4.4 Expectancy-value theory

In expectancy-value theory, each party has an expectation of the risk involved in the exchange and would prefer to decrease risk as far as possible. To alleviate uncertainty (or avoid costs), customers often make purchases which carry the lowest risks. A popular expectancy-value theory by Edwards (1954) states that when faced with a decision, a person will choose the alternative that is most likely to have a favourable outcome (Thong, 2007:20), that is, the least risk. Some expectancy-value models, for example expected utility theory, calculate the actual monetary value of risks, whereas others determine customers' attitudes toward products, most notably the theory of reasoned action (Kardes, Cline & Cronley, 2011:168). Expected value can be positive or negative, since evaluations can have a negative value (East, Wright & Vanhuele, 2008:120).

2.4.4.5 Social exchange theory

According to Blau (1964), social exchange is described as the voluntary interaction of customers and organisations for the purpose of economic exchange to satisfy a common goal, namely profit generation (Schakett, 2009:13). Customers will remain in an exchange relationship is dependent on the satisfaction which that customer experiences in the existing relationship (Edward & Sahadev, 2011:329). Customer need satisfaction implies that customers will pursue rewards, but avoid costs (Roberts, 1989:20; Schakett, 2009:13).

Social exchange theory evaluates the benefits versus costs of remaining in a relationship. Willingness to remain in an exchange relationship is in direct proportion to the level of satisfaction derived from the existing relationship (Edward & Sahadev, 2011:329). Social exchange relationships should lead to mutual goal realisation for both parties (Whitten & Wakefield, 2006:227). Social exchange theory incorporates the development, growth and dissolution of social and business (both B2C and B2B) relationships (Patterson, 2004:1305).

When customers weigh benefits versus cost to decide whether to maintain a relationship with their service provider, social exchange theory applies. As a result, a service encounter can be viewed as a social exchange (Patterson, 2004:1305). Therefore interactions between customers and service providers are essential elements in determining customer satisfaction. In a services context, depending on the customer's level of involvement, the customer and service provider interact in order for the service to be performed. Thus the success of the interaction (service encounter) will determine whether the relationship will continue. Consequently Patterson (2004:1305) is of the opinion that switching can be theoretically based on social exchange theory.

Taking the above-mentioned exchange relationships into consideration, Antón, Camarero and Carrero (2007a:511) describe relationship marketing as a relational approach to exchange.

2.4.5 Relational exchange

Hunt *et al.* (2006:72) mention that one of the important facets of relationship marketing is to distinguish between the duration of two types of exchange relationships. This is because the duration of the exchange relationship determines whether a transactional or relational exchange take place. Transactional (discrete) exchanges have a distinct beginning and ending whereas relational exchanges comprise a series of transactions that are linked in some manner and take place over an extended period of time (Dwyer *et al.*, 1987:12; Gundlach & Murphy, 1993:36; Hunt *et al.*, 2006:72). As such, relational exchange is applicable to relationship marketing, since both strive toward an on-going relationship.

Dwyer *et al.* (1987:12) used Macneil's (1980) theory of contract law to describe the difference between discrete and relational exchange. Transactional exchange is a once-off transaction, usually of short duration, and takes place between anonymous parties, thereby excluding all relational elements (Dwyer *et al.*, 1987:12; Hunt *et al.*, 2006:77). Transactional exchange also assumes that once the customer has bought a product, there is no guarantee that the customer will use the service provider again in future (Gummesson, 2000:11). On the contrary, relational exchanges are continuous exchanges over a long or possibly indefinite period of time between parties that are known to one another. The purpose of relational exchange is to develop a long-term relationship between buyers and sellers (Schakett, 2009). Relational exchange also takes into consideration past and possible future transactions each time an interaction occurs (Dwyer *et al.*, 1987:12; Gundlach & Murphy, 1993:36; Hunt *et al.*, 2006:77). Continuous relational exchange is based on relational exchange theory which uses a foundation of relational norms that serve as moral controls which encourage behaviours that are beneficial to the relationship, for example commitment, and discourage behaviours that will undermine the relationship, such as opportunism (Joshi & Stump, 1999:335, 339).

Relationship marketing builds on relational contracting theory (Hunt *et al.*, 2006:77). Macneil defines relational contract theory as, "relations among people who have exchanged, are exchanging, or expect to be exchanging in the future" (Macneil, 1987:274). Since relational exchange considers past and future purchases, Dwyer *et al.* (1987:12) are of the opinion that future interactions are determined by trust between the customer and service provider. Ballantyne *et al.* (2003:160) and Morgan and Hunt (1994:24) argue that mutual trust is essential to successfully build a relationship with customers. Morgan and Hunt's (1994) commitment-trust theory found that the presence of trust and commitment are central components in successful relational exchanges and thus relationship marketing. The commitment-trust theory implies that both parties will do what they promised to do (Dwyer *et al*., 1987; Morgan & Hunt, 1994).

Relational exchange is also facilitated by a variety of legal theories, including contract law, so as to guide exchange and apply the legal rights of parties in the exchange (Gundlach & Murphy, 1993:38). Subscription markets use a form of contract to keep customers for a certain amount of time. The subscription is either an annually renewable contract or a tenure contract which continues indefinitely until cancelled (East *et al.*, 2008:97). Thus, relational contracting theory applies to business-to-customer (B2C) relationships where a long-term contract is involved (Ivens & Blois, 2004:242). Customer switching is particularly damaging in industries where organisations rely on long-term relationships with customers through contracts or subscriptions (Antón, Camarero & Carrero, 2007b:136), for example the mobile telecommunications industry. Taking into consideration that in a services context, many customers have subscriptions or contractual agreements with the service provider, Ultsch (2002:315) describes switching behaviour as the 'discontinuation of a contract with a business'.

Notwithstanding the necessity of contracts, the purpose of relationships is to build mutually beneficial partnerships with customers to provide value to both parties. The next section discusses various approaches to building relationships between customers and service providers.

2.4.6 Building customer–service provider relationships

Forming and maintaining a relationship is beneficial to both the service provider and the customer (Lopez *et al*., 2006:558). One benefit for the customer, linked to risk theory and Expectancy-value theory (Edwards, 1954), is reduced risk. If the customer repeatedly uses the same service provider, they will know what to expect and experience lower risk (Bruhn, 2003:27). Another benefit is that of customisation, where once the service provider knows the customer, special individual needs can be provided for. A third customer benefit is that time and effort to find a new service provider, termination fees and emotional loss are avoided (Fahy & Jobber, 2012:184; Hunt *et al.*, 2006:76).

The longer an organisation maintains a relationship with a customer, the more value the customers create for the organisation (Reichheld, 1996:57; Zeithaml, 2000:76). Research shows that for every additional year that the business-customer relationship is successful, the customer becomes less costly to serve because of learning effects and decreased servicing costs (Ganesh *et al*., 2000:65). As mentioned before, research has also shown that serving existing customers is less costly than serving new customers (Wong, 2011:38). In addition, satisfied long-term customers spread positive word-of-mouth (Wong, 2011:38), thereby drawing new customers with fairly little cost to the organisation. Further benefits for the service provider include decreased price sensitivity, use of a broader range of the firm's services, increased responsiveness to new products offered by the firm, resistance to switching attempts initiated by competitors and the spread of positive word-of-mouth (Fahy & Jobber, 2012:184; Ganesh *et al*., 2000:65; Lopez *et al*., 2006:558; Reichheld, 1996:57).

On the contrary, if a customer terminates usage of the organisations' services, the organisation not only loses earnings, but acquisition costs and future revenue are also lost (Hughes, 2008:17). Consequently, the organisation from which customers switched will have to invest resources to attract new customers so as to replace former customers. Therefore establishing a relationship between the customer and the service provider is important because relational bonds between an organisation and a customer often lead to repeat business (Dwyer *et al*., 1987:12).

Research has suggested the use of two strategies to retain customers: outperform competitors or use relationship marketing to create a special bond with the customer (Kaur, Sharma & Mahajan, 2012:280; Reicheld & Sasser, 1990:106). Social bonds enable more intimate relationships with customers and often lead to customer loyalty (Liang & Chen, 2009:221).

Through understanding and gaining knowledge about the customer, the service provider is likely to establish a bond with the customer, thus social bonding theory also applies to relationship marketing. Social bonds are developed through repeated personal interactions and continuous communication with customers (Ackerman & Schibrowsky, 2007:323; Liang & Chen, 2009:221). Bonds exist on a hierarchy of different levels of intensity (Berry, 2002:62; Fahy & Jobber, 2012:184; Palmer, 2008:250). Types of bonds include: financial bonds, at which level loyal customers are rewarded with discounts or loyalty points; social bonds, where customers become familiar to the service provider and receive a customised service with personalisation and frequent communication; and structural bonds, which occur when the customer becomes tied to the service provider through a unique service delivery system that no other service provider offers, thereby increasing switching costs and locking in the customer (Ackerman & Schibrowsky, 2007:322-327; Berry, 2002:62; Fahy & Jobber, 2012:184; Liang & Chen, 2009:220-221).

2.4.7 Importance of retention in the mobile telecommunications industry

Following from the many benefits of building a relationship with the customer, maintaining the relationship is imperative, especially in competitive markets. In a saturated and highly competitive industry such as mobile telecommunications, customer retention is even more important (Keramati & Ardabili, 2011:344). Understanding customer retention and retention antecedents is also central to relationship marketing (Polo & Sesé, 2009:119). The purpose of customer retention is to maintain the business relationship established between a service provider and customer (Gerpott *et al*., 2001:253). Retention can be achieved by either extending a customer's contract, or through the customer intending to make future purchases from the service provider (repurchase intention). If the relationship is maintained due to the customer's desire to continue the relationship, loyalty results. However, if the customer is forced to remain in the relationship, either due to contractual obligations or high switching barriers (mobility barriers), false loyalty is often the outcome (Gerpott *et al*., 2001:253).

Due the economic importance of the telecommunications industry worldwide (Shukla, 2010:467) and the alarmingly high churn rates in this particular industry (Kim *et al*., 2004:148), an urgent need has arisen to establish how to retain customers and subsequently also to determine what factors causes customers to switch. Much relationship marketing research has motivated that building customer relationships contributes toward organisation's success (Antón *et al*., 2007a:511). Furthermore, much research has investigated creation of relationships, loyalty and commitment (Antón *et al*., 2007a:511-512). However, very little research has investigated why relationships end (Antón *et al*., 2007a:512), even though the research results showed alarming disadvantages for organisations. Therefore the next chapter investigates switching and predictors of switching.

2.5 CONCLUSION

The chapter commenced with an overview of telecommunication and the global mobile telecommunications industry. Mobile telecommunication has become an important sector for economic development, taking into consideration that approximately 60% of the world's population are mobile subscribers (Keramati & Ardabili, 2011:344; Shukla, 2010:467; Srinuan *et al*., 2012:453). In terms of revenues received from telecommunications services, South Africa was the 15th largest telecommunications market in the world in 2012

(Deloitte Digital SA, 2013). Furthermore, despite approximately half of South Africa's population living "below the poverty line", South Africa had 128% mobile penetration by 2012 (Deloitte Digital SA, 2013; South Africa Yearbook 2013/14, 2013:87). Due to a high market demand for mobile connectivity (Malhotra & Malhotra, 2013:13), and rife competition in the saturated South African market, this industry is "prone to switching"

Moreover, the service industry accounts for 60% to 70% of the gross domestic product (GDP) of most developed countries, far exceeding manufacturing and agriculture (Fahy & Jobber, 2012:174). Similarly, the South African service sector generates 68.4% toward the GDP (CIA World Factbook: Economy, 2014). Consequently the services industry is extremely important not only in South Africa, but also worldwide. Thus a discussion defining services marketing and describing the distinguishing characteristics of services was included.

Protecting the customer base has become an extremely important strategy for organisations (Berry, 2002:60). Thus relationship marketing as a research area has generated much interest. Therefore the final section in the chapter explains the concept of relationship marketing and discusses the paradigm shift toward relationship marketing.

Long-term customers create value for the organisation (Reichheld, 1996:57; Zeithaml, 2000:76). Hence the chapter concludes with an discussion of the importance of customer relationship building and retention.

Considering the importance of customer retention, the next chapter explores the purchase process, specifically repurchase intention, which may result in favourable outcomes (loyalty) or unfavourable outcomes (switching). Taking into account the many benefits of customer retention, organisations ideally seek favourable purchase outcomes. However, the purpose of the current study is to explore unfavourable purchase outcomes, namely, switching intention. Thus various switching antecedents are discussed. The chapter then explores in-depth each construct chosen for the study, and also explains the development of the conceptual switching intention model.

CHAPTER 3

SWITCHING IN THE MOBILE TELECOMMUNICATIONS INDUSTRY

3.1 INTRODUCTION

Due to the importance of building and maintaining customer relationships, particularly in contractual service settings such as mobile telecommunications, this chapter commences with a brief discussion of the purchase process and the role of post-purchase evaluation. Customers may consider switching to an alternative service provider if an unfavourable opinion is formed during post-purchase evaluation. Thus the purpose of Chapter 3 is to place switching intention – the core context of the study – in perspective, and to explain switching in the context of mobile telecommunications.

3.2 THE PURCHASE PROCESS

Marketing practitioners intend to understand customer behaviour in order to understand how their purchase decisions are made (Lovelock & Wirtz, 2011:58). Marketing practitioners are also interested to know how customers utilise their products or services after the purchase (Lovelock & Wirtz, 2011:58). Marketing practitioners intend to discover how to create value for customers in order to satisfy their needs better than competitors would (Ballantyne *et al.,* 2003:161). After understanding what determines customer satisfaction before, during and/or after the purchase, an attempt can be made to create products/services that meet or even exceed customer satisfaction levels (Lovelock & Wirtz, 2011:58). The three phases of the purchase process, namely pre-purchase, purchase and post-purchase, are discussed in the following section.

3.2.1 Pre-purchase

A customer's intended purchase behaviour is described as behavioural intention. The study of behavioural intention assists organisations to determine the likelihood that a customer will behave in a predictable manner (Han, Kim & Hyun, 2011:621; Zeithaml, Berry & Parasuraman, 1996:33). Even though customers' behavioural intention occasionally differs from their actual behaviour (Antón *et al.*, 2007a:523; Athanassopoulos, Gounaris & Stathakopoulos, 2001:692), predicting how customers may possibly respond in a purchase situation is more advantageous than having no knowledge whatsoever concerning what behaviour to expect.

Various models have been developed to predict behavioural intention. The well-known attitude models include the Theory of Reasoned Action (TRA), the Theory of Planned Behaviour (TPB) and the Technology Acceptance Model (TAM) (Ajzen, 1991; Bansal & Taylor, 1999b; Belleau, Summers, Xu & Pinel, 2007; Chen & Chao, 2011:128; Liu, Marchewka, Lu & Yu, 2005; Turel *et al*., 2007). These models measure a variety of variables, including attitudes, subjective norms, perceived behavioural control, perceived usefulness and perceived ease of use (Wang, Lin & Luarn, 2006:160). However, since the focus of the current research is not based on attitudes that determine behavioural intention, but rather on comparing behavioural intention and behaviour, the above-mentioned attitude models are not incorporated into the current research. Nonetheless, the models are recognised for their valuable input regarding behavioural intention.

Section 3.5 conceptualises a model for switching intention, but first, the purchase process, post-purchase evaluation and repurchase intention are explained in the next section.

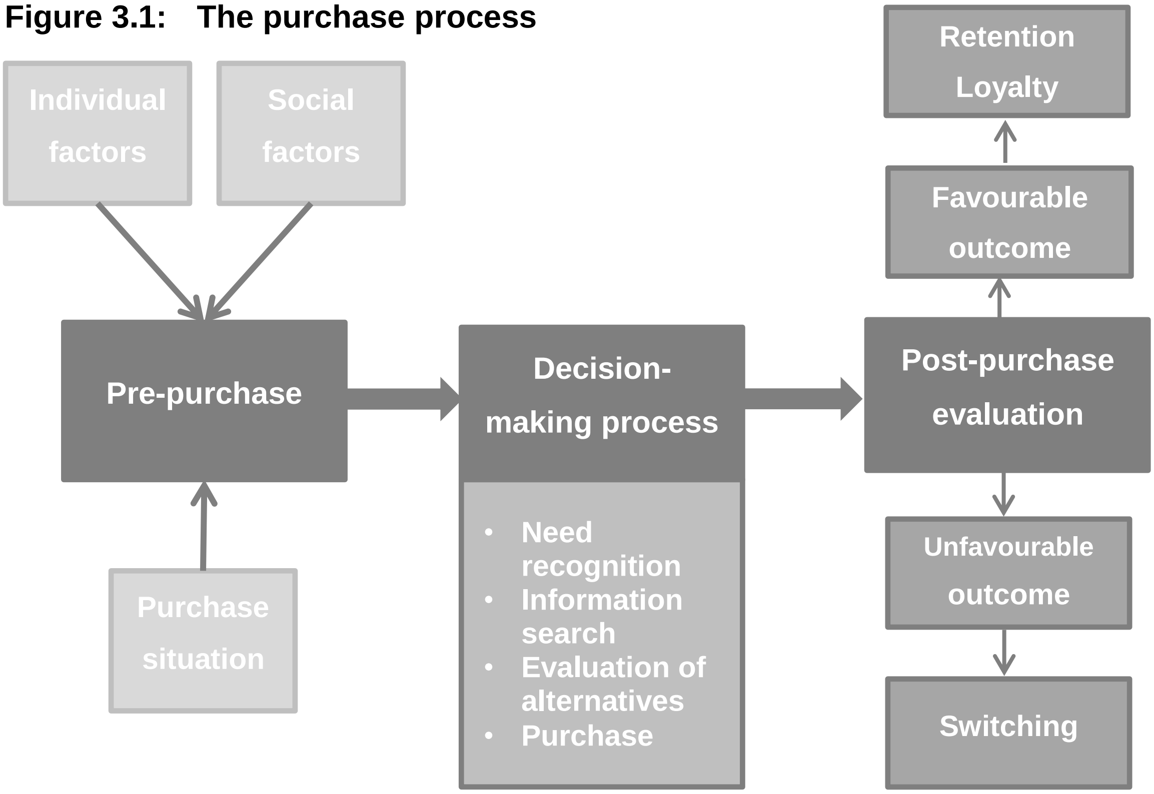
3.2.2 The purchase process

Various factors simultaneously influence the customer's decision to purchase or not to purchase a product (Perreault & McCarthy, 2006:114). In the pre-purchase phase, individual factors, social factors, as well as the purchase situation influence the purchase decision (Lamb *et al*., 2010:76; Perreault & McCarthy, 2006:113). Individual factors include, amongst others, the customer's motivation for the purchase, the customer's personality and lifestyle, and the customer's values, beliefs and attitudes. Influences due to culture, social class or reference groups are social factors which influence the purchase decision. Factors which influence the purchase situation are the reason for the purchase, the surroundings in which the purchase is made and whether the purchase is impulsive or planned (Lamb *et al*., 2010:76; Perrault & McCarthy, 2006:113).

The three aforementioned factors influence the decision-making process and thus cause customers with different purchase motivations and customers with varying social and individual factors, to make different decisions. During the decision-making process, customers typically recognise a need and strive to satisfy the need by purchasing the appropriate product. For complex purchases that require a high capital investment or long-term commitment, a thorough information search is generally conducted (Lamb *et al*., 2010:84). Subsequently, all available alternatives are considered, and should one of the alternatives appeal to the customer, a purchase is made (Pride & Ferrell, 2010:198).

Following the purchase transaction, the customer enters the post-purchase evaluation phase (Lamb *et al*., 2010:82; Mitchell & Boustani, 1994:58; Perreault & McCarthy, 2006:128) also known as post-consumption reaction (Babin & Harris, 2013:301) or purchase outcome (Bansal & Taylor, 1999b:200). After the post-purchase evaluation, the customer could be satisfied with the purchase, which leads to favourable outcomes such as customer retention and loyalty. In contrast, should the result of the post-purchase evaluation be negative, the customer may consider switching when purchasing the product in future (Antón *et al*., 2007:137b; Bansal & Taylor, 1999b:200; Han *et al*., 2011:621). A summary of the purchase process is shown in Figure 3.1.

Figure 3.1: The purchase process



Source: Adapted from Howard & Sheth (1969:471) and Lindquist & Sirgy (2006:115).

Lindquist and Sirgy (2006:114) suggest that analysing the factors that influenced the customer's purchase decision may enable the service provider to predict the possible outcome of the next purchase. If future purchases can be anticipated, marketing practitioners could possibly influence the customer's future actions (Lindquist & Sirgy, 2006:18), for example, prevent the customer from switching. Therefore, besides investigating the customer's actual post-purchase behaviour, researching the customer's intended repurchase behaviour is also an important consideration.

3.2.3 Post-purchase evaluation

After the purchase, customers could react to their purchase by having either favourable or unfavourable intentions (Zeithaml *et al.*, 1996:34). Favourable intentions include customers verbalising positive emotions toward the organisation by recommending the organisation or service offering to others, remaining loyal, increasing spending with the organisation, being willing to pay a price premium and purchasing more than one type of product from the organisation (cross-selling). The opposite is true for unfavourable intentions, which lead to customers speaking negatively about the organisation, complaining to others and external agencies about the organisation, conducting less business with the organisation or possibly switching to another organisation (Altuna & Konuk, 2009:46; Kaur *et al.*, 2012:281; Zeithaml *et al*., 1996:34).

Due to the wide variety of behavioural intentions mentioned in the literature, Zeithaml *et al.* (1996:37) developed a 13-item battery in an attempt to simplify the numerous intentions. Zeithaml *et al.*'s (1996:38) study led to five behavioural intention categories, namely, loyalty (to the organisation), propensity to switch, willingness to pay more, external responses to problems (complaining to other customers and external agencies or switching to a competitor) and internal responses to problems (complaining to the company's employees). The findings categorised loyalty and willingness to pay more as favourable behavioural intentions, whereas propensity to switch and external response to the problem were classified as unfavourable behavioural intentions (Zeithaml *et al.*, 1996:37-38). Unfortunately no clarity was obtained in their study as to whether internal response is a favourable or unfavourable outcome. The current research focuses on unfavourable behavioural intentions, in particular, the customer's propensity to switch. For the remainder of the current research, propensity to switch will be referred to as switching intention.

After post-purchase evaluation, the customer may intend to repurchase the product/service. Preceding the discussion regarding repurchase intention is an explanation regarding certain industry-related strategies can be used to influence switching. The mobile telecommunications industry inherently has industry-specific switching strategies, as discussed below.

3.2.4 <u>Strategies that influence switching in mobile telecommunications</u>

Switching costs and lock-in strategies coerce customers to remain with their current service provider. Nonetheless, developing strong relationships with customers has been suggested as a switching prevention strategy (Shah & Schaefer, 2006:76).

3.2.4.1 Lock-in strategies in mobile telecommunications

Switching costs are prevalent in markets characterised by customer lock-in (Aydin & Özer, 2005:144). Lock-in is a state in which the customer feels bound to a service provider and feels unable and/or unwilling to leave the relationship (Harrison, Beatty, Reynolds & Noble, 2012:392). Lock-in occurs when significant switching costs are imposed by a service provider (Büschken, 2004:1). Thus lock-in inhibits switching (Harrison *et al*., 2012:392). Lock-in differs from loyalty in that loyalty is voluntary, whereas lock-in is "a fixed state in which a customer feels firmly entrenched in the relationship" (Harrison *et al*., 2012:393).

Much previous research has suggested that organisations strategically build high switching costs into their products (whether actual or perceived) to create lock-in and thereby ensure customer retention (Aydin & Özer, 2005:142; Dick & Basu, 1994:104; Fornell 1992:10; Klemperer, 1987b:376; Patterson, 2004:1312; Seo, Ranganathan & Babad, 2008:184). The organisation benefits if customers are locked in, because customer price sensitivity decreases, customer sensitivity to satisfaction levels is reduced and the perception is created that functionally homogeneous service offerings are heterogeneously differentiated (Aydin & Özer, 2005:142; Klemperer, 1987b:376; Maicas, Polo & Sesé, 2009a:161; Shin & Kim, 2008:858). In other words, service offerings that are essentially the same are perceived to be different, due to the different switching costs present. Another benefit is that demand and revenue can be forecasted because of contractual lock-in. For example, in the mobile telecommunications industry, contract duration is usually 24 months, enabling the organisation to forecast demand and revenue for at least a two-year period (Malhotra & Malhotra, 2013:14).

Customers' switching intention reduces considerably if the possibility of experiencing switching costs exists (Lee, J., Lee, J. & Feick, 2001:38). Conclusive evidence in the literature has indicated that many customers remain in a relationship with their service provider, whether or not they are satisfied, if they are locked-in by switching costs (Aydin & Özer, 2005:144; Jones *et al*., 2007:335; Kim *et al*., 2004:157; Lee *et al*., 2001:38; Liu *et al*., 2011:76; Malhotra & Malhotra, 2013:14; Patterson, 2004:1304; Shy, 2002:71). Researchers caution that often the result of lock-in is false loyalty, which leads to an economic hostage situation in which customers remain with the service provider against their will (Antón *et al*., 2007b:141; Büschken, 2004:14; Lee *et al*., 2001:38). False loyalty, is also known as spurious loyalty (Malhotra & Malhotra, 2013:14), passive loyalty (Kaur *et al.*, 2012:283), or polygamous loyalty (Dowling & Uncles, 1997:74). This situation is confirmed by Kruger & Mostert (2012:47) who found that young adults remained with the MNO due to contractual lock-in or inconvenience, but not necessarily because they had a desire to do so.

Jones *et al*. (2007:336) suggest that a lock-in strategy is restricted. Most researchers have not considered that locked-in customers may have strong negative reactions toward the organisation, even though they remain with the organisation (Jones *et al*., 2007:336). Being locked-in could cause begrudgement against the MNO, due to the customer's feelings of powerlessness, often resulting in switching as retaliation (Malhotra & Malhotra, 2013:15). The long-term consequences of "forced lock-in" may be negative word-of-mouth, sabotage or hostility toward the organisation (Jones *et al*., 2007:336). Lock-in could be either positive or negative (Harrison *et al*., 2012:392), and can be described as either hard or soft lock-in (Malhotra & Malhotra, 2013:14). Hard lock-ins, such as financial switching costs, are considered to be negative switching barriers, whereas soft lock-ins, for example relational benefits that customers derive from an enduring relationship with the service provider are regarded as positive switching barriers (Malhotra & Malhotra, 2013:14).

I) Hard lock-in

Various hard and soft lock-in strategies exist. In mobile telecommunications, hard lock-in could be the result of procedural switching costs such as contractual agreements (Ranganathan *et al.*, 2006:270), start-up fees (Gerpott *et al.*, 2001:251), product-specific learning costs (Seo *et al*., 2008:184), service bundling (Shin, 2007:3) or incompatibility of the organisation' service offering with competing products (Shy, 2002:72).

In the case of a contractual agreement, the customer is obliged to remain with the organisation until the contract period expires (Büschken, 2004:14). Contracts act as an effective lock-in strategy due to high premature termination fees which penalise customers that switch before the contract ends (Shin & Kim, 2008:857; Wong, 2011:41). Also, in an attempt to retain hard lock-in customers, service providers offer very appealing incentives to entice existing customers to renew their contract (Malhotra & Malhotra, 2013:14; Shin & Kim, 2008:857).

Polo and Sesé (2009:130) found that customers with a contract (post-paid customers), have higher switching costs than pre-paid customers. However, upon investigating the relationship between the type of subscription and customer switching behaviour, Maicas *et al*. (2009a:169) found that post-paid subscribers are more likely to switch than pre-paid subscribers. The finding is surprising, since the expectation is that pre-paid subscribers are more likely to switch because they are not locked into long-term contracts and have much lower switching costs. Maicas *et al*. (2009a:169) speculate that competitors often target their aggressive marketing strategies at post-paid subscribers since these subscribers tend to be more profitable. In contrast, Wong (2011:41) found that post-paid customers are 96% less likely to switch, possibly because service contracts serve as a switching barrier and because many organisations have implemented high early-contract termination fees.

Subscription duration is commonly related to customer lock-in (Kim & Yoon, 2004:762). Jones *et al*. (2007:350) suggest that organisations should cautiously make use of procedural switching costs, because of the potentially harmful outcomes such as negative emotions, which inevitably lead to negative word-of-mouth. Malhotra and Malhotra (2013:18) found that using unreasonable contract length as a hard lock-in strategy significantly increased customer's propensity to switch. However, as mentioned previously, other researchers reported that a lock-in strategy does not necessarily increase customer's propensity to switch (Lee *et al*., 2001:38).

Due to the severe lock-in strategies in the industry, an attempt was made to encourage switching in the mobile telecommunications industry. Subsequently mobile number portability (MNP) was introduced.

i) Mobile number portability (MNP)

Apart from contractual agreements and locked handsets, customers lost their mobile numbers if they switched (Shin, 2007:2). The person being contacted usually identifies the caller by their number and many people filter incoming communication due to an increasing number of unsolicited calls and telemarketing. Thus the possibility exists that a call may be rejected if the receiver does not recognise the caller (Sutherland, 2007:12). A change in number also necessitates new business cards and updating contact information with various service providers, which is time consuming. Customers also incur costs in having to inform people of their new number (Gerpott *et al*., 2001:254). Consequently, the perception was created that switching costs are high in the mobile telecommunications industry if customers could not retain their mobile numbers.

After the introduction of Mobile Number Portability (MNP), switching costs significantly decreased (Buehler, Dewenter & Haucap, 2006:393; Lee, Kim, Lee & Park, 2006b:110). MNP allows customers to keep their mobile number (including the prefix) when switching from one MNO to another (Buehler *et al*., 2006:386; Maicas *et al*., 2009a:162; Shin & Kim, 2007:38; Srinuan *et al.*, 2012:453). MNP allows more flexibility in the market (Gerpott *et al*., 2001:266) and reduces the tedious burden of switching MNOs (Shi, Chiang & Rhee, 2006:27). MNP also encourages competition (Buehler *et al*., 2006:386; Shin, 2007:1; Shin & Kim, 2007:38), and has in turn encouraged lower prices for customers. Even though MNP was introduced to assist customers with enhanced service offerings at better prices, the impact that regulators and researchers predicted MNP would have on the industry did not actualise (Shin, 2007:2). Disappointingly, MNP has had no significant impact on churn rates (Shin & Kim, 2007:39).

Despite the introduction of MNP in South Africa, MNOs currently use an alternative hard lock-in strategy, namely network locking.

ii) Network locking

Network locking is a technical restriction which prevents subscribers' handsets from functioning on an alternative mobile network (Maicas *et al*., 2009a:163; Nakamura, 2010:739; Vermeulen, 2015). Thus, should customers decide to switch, they are obliged to purchase a new handset (Xavier & Ypsilanti, 2008:17). Due to high handset costs, customers avoid purchasing a new handset, thus handset lock-in creates a financial switching cost, with the result that customers remained with their current service provider.

To summarise, hard lock-in customers often continue business with an organisation even though they are not satisfied with the service provider, because of high perceived switching costs (Aydin & Özer, 2005:144; Lee *et al*., 2001:38; Malhotra & Malhotra, 2013:14; Patterson, 2004:1304; Shy, 2002:71). On the contrary, soft lock-in has resulted in relationally loyal customers that intend to continue the relationship with the service providers because of the value derived from the continued relationship (Malhotra & Malhotra, 2013:14).

II) Soft lock-in

The soft lock-in approach is a more positively-perceived alternative. Malhotra and Malhotra (2013:18-19) found that soft lock-in significantly decreased switching intention. Examples of soft lock-in are network effects and loyalty programmes. Network effects include subsidised or discounted rates for calls made to people on the same network (that is, people that subscribe to the same service provider). In some cases, free airtime is given as an incentive (Maicas *et al*., 2009a:162; Malhotra & Malhotra, 2013:15). Research has shown that customers spend significantly more airtime communicating with persons who are on the same network (Edward *et al*., 2010:156). Therefore, network effects decrease the customer's propensity to switch (since they act as a soft lock-in strategy), while simultaneously creating a positive attitude toward the MNO (Malhotra & Malhotra, 2013:15).

Gerpott *et al*. (2001:266) suggest that a loyalty programme could reward customers for the amount of services used and the duration of the contract. Research has indicated that loyalty programmes have a positive influence on relationship duration (Bolton *et al*., 2004:273). Similarly, Ahn *et al*. (2006:562) found that loyalty points decrease switching intention, since more points are gained as the relationship duration increases, confirming that loyalty programmes are a successful soft lock-in strategy.

A number of other factors have influenced switching intention in mobile telecommunications specifically. Of particular interest are calling plans and mobile handset usage characteristics, which are discussed below.

i) Calling plan

The type of calling plan and the suitability of the calling plan also influence switching. Calling plans include a standard package or tailored packages, for example packages targeted at teens and young adults or week-end discounts (Ahn *et al*., 2006:558). Calling plans tend to be complicated and often vary across markets and also between customers within a market (Bolton, 1998:55). Seo *et al*. (2008:192) found that as the complexity of the calling plan increased, the likelihood of switching decreased.

Wong (2011:41) found that calling plan suitability significantly influenced switching behaviour and that customers with optimal calling plans were less likely to switch than those with non-optimal calling plans. Wong (2011:40-41) also found that customers were less likely to switch if their calling plan was recently adjusted and that as the frequency of changing calling plans increases, the likelihood to switch decreases. Interestingly, Srinuan *et al*. (2012:455) found that customers remained with their MNO, but switched between various calling plans offered by the MNO.

ii) Mobile handset usage characteristics

An issue particularly prevalent in the mobile telecommunications industry is the type of handset offered by the service provider. If a unique handset is offered by a specific MNO, that service provider may become an attractive alternative. Customers are willing to switch for handsets that offer more advanced features or are more aesthetically pleasing. Most customers consider the handset's capability before purchasing a new handset (Ahn *et al*., 2006:564), which could lead to churn if the current MNO does not offer the desired handset, or if certain handsets are only compatible with certain service providers. Often service providers form strategic alliances with handset manufacturers, enabling them to offer the latest handset with a special contract package, and in-so-doing attract customers (Chuang, 2011:132). Nevertheless, the benefits of switching MNOs for a new handset are short-lived, since all MNOs constantly strive to find the newest and best handsets (Kim & Yoon, 2004:762).

Kim and Yoon (2004:762) found that the duration of mobile handset use is a significant switching determinant. The results show that the longer a customer uses their present mobile handset, the higher the likelihood that the handset is outdated, in turn increasing the customer's intention to switch. Ahn *et al*. (2006:565) found that customers that own old handsets with low functional capability are more likely to switch, in order to get a newer handset with better functionality. Customers will also switch to an alternative service provider that offers a newer and more aesthetically pleasing mobile handset (Ahn *et al*., 2006:564). Obtaining a new handset allows customers access to the latest technology and handset features (Ahn *et al*., 2006:564). Thus, the more sophisticated the handset, the lower the propensity to switch (Seo *et al*., 2008:192). Similarly, Wong (2011:41) found that customers had a lower tendency to switch if their mobile handset was recently upgraded, possibly because the customer had a relatively new handset.

Taking into consideration the strategies that influence switching in the mobile telecommunications industry, the next section discusses repurchase intention and whether the intention is a favourable or unfavourable outcome.

3.3 SWITCHING INTENTION IN PERSPECTIVE

Once the purchase has been made and post-purchase evaluation is complete, the customer decides whether or not to purchase from the same organisation in future. An explanation of repurchase intention precedes the discussion of favourable and unfavourable post-purchase outcomes.

3.3.1 Repurchase intention

Repurchase intention is an individual's judgement regarding purchasing a certain service from the same company in future, while also considering the current purchase situation (Hellier, Geursen, Carr & Rickard, 2003:1764). The customer's intention to repurchase is established after the post-purchase evaluation. The favourable or unfavourable purchase outcomes will determine whether or not the repurchase cycle continues or whether customers switch (Kuo *et al*., 2009:889). Service offerings vary with regard to the length of the repurchase cycle. Some products have a regular and fairly short purchase cycle, for example, dry cleaning, hairstyling and restaurants. Other products have a long and comparatively irregular purchase cycle, such as life insurance, Internet service providers, airlines and MNOs (Pan, Sheng & Xie, 2012:153). Each time a purchase cycle comes to an end, the customer becomes a new prospect for the organisation, there is no guarantee that the customer will definitely repurchase from the current service provider (Pan *et al*., 2012:153). Therefore, strategies need to be implemented to encourage present customers to repurchase from their current service provider.

During the repurchase cycle, the organisation interacts with an experienced customer, because the service offering has been used previously and the customer likely interacted with the organisation and some employees (Patterson & Spreng, 1997:417). Experienced customers are less sensitive to the odd negative service encounter, as they usually weigh up the accumulation of previous encounters (Bolton, 1998:45). Thus the customer's repurchase intention decision varies greatly to the original purchase decision. Experienced customers often skip the pre-purchase phase and move directly into the decision-making phase. During the repurchase decision-making phase, the customer will decide whether to remain with the current service provider (loyalty), or whether to switch (Antón *et al*., 2007a:523). Clearly a favourable outcome is desirable for both the customer and the service provider.

3.3.2 Favourable outcomes – Loyalty

Loyalty is a priority for organisations, hence repeat business exchanges are necessary for the profitability and ultimate survival of any organisation (Gonçalves & Sampaio, 2012:1509). Research has shown that loyal customers generate more profit than non-loyal customers (Hsu & Chang, 2003:322) and that the cost of recruiting new customers is greater than the cost of retaining loyal customers (Negi, 2009:33; Oliver, 1999:33). Consequently loyalty is closely linked to the organisation's profitability (Bodet, 2008:157;

Ganesh *et al*., 2000:66; Min & Wan, 2009:107; Mittal & Lassar, 1998:177; Oliver, 1999:33) and encouraging loyalty should be a primary goal for organisations.

Loyalty research has enjoyed much attention in service marketing literature, since a consistent base of loyal customers ensures continuous business exchange (Chiao, Chiu & Guan, 2008:649). Oliver (1999:34) defined loyalty as "a deeply held commitment to rebuy or re-patronize a preferred product or service consistently in the future, thereby causing repetitive same-brand or same brand-set purchasing, despite situational influences and marketing efforts having the potential to cause switching behaviour".

Satisfaction has been proven to be a strong antecedent of loyalty and several researchers have found a significant positive relationship between satisfaction and loyalty (Aydin & Özer, 2005:150; Aydin *et al*., 2005:97; Chen & Cheng, 2012:815; Deng, Lu, Wei & Zhang, 2010:295; Gerpott *et al*., 2001:264; Kim *et al*., 2004:155; Kuusik & Varblane, 2009:74; Lee, 2010:9; Lim *et al*., 2006:214; Liu *et al*., 2011:75; McDougall & Levesque, 2000:403; Min & Wan, 2009:115; Pan *et al*., 2012:155; Shukla, 2010:477). Notably, O'Malley (1998:48) cautions that assuming that dissatisfied customers will defect and that satisfied customers will remain loyal is a narrow and simplistic view.

Several researchers have concluded that switching is distinct from and possibly directly opposite to customer loyalty and retention (Antón *et al.*, 2007b:137; Bansal & Taylor, 1999b:200; Shukla, 2010:472). Keaveney (1995:72) concurs with this perspective and argues that factors which lead to positive outcomes, such as, loyalty and retention, may be asymmetrical to factors that lead to negative outcomes, such as switching.

3.3.3 Unfavourable outcomes – Switching intention

Even though there is a tendency to focus on positive post-purchase outcomes, an appreciation of the negative post-purchase outcomes is also important. Determining the causes of negative behavioural outcomes could assist the service provider to change strategies, implement service recovery programmes, improve service offerings and attract new customers (Lindquist & Sirgy, 2006:114) but most importantly, to prevent switching.

3.3.3.1. Switching

Switching is a negative response to dissatisfaction due to a variety of causes. Switching means that the customer ends their relationship with their current service provider and in all likelihood starts afresh with an alternate service provider (Huang & Hsieh, 2012:219; Nikbin *et al*., 2012:313; Shin & Kim, 2008:857; Tähtinen & Halinen, 2002:174). Switching can also be described as customer exit, defection or churn (Ahn *et al*., 2006; Dass & Jain, 2011; Hughes, 2008; Keramati & Ardabili, 2011; Kim & Yoon, 2004; Madden *et al*., 1999; Nikbin *et al*., 2012; Wong, 2011). Switching has a negative impact on the organisation's bottom-line profitability, which is in turn damaging to the organisation's long-term survival prospects (Nikbin *et al*., 2012:313; Reicheld, 1996:57). Researchers have noted that many Chief Executive Officers (CEOs) have little or no insight as to the causes of switching (Nikbin *et al*., 2012:313; Reicheld, 1996:56; Scanlan & McPhail, 2000:492). For this reason, organisations are becoming more aware of seeking a means to identify the root causes of switching, so as to prevent the aforementioned behaviour (Nikbin *et al*., 2012:313; Reicheld, 1996:56).

Various levels of switching could take place. In the case of a complete switch, the customer's business has been lost altogether (total defection), whereas only a portion of the customer's business has been lost if a partial switch takes place (partial defection) (Huang & Hsieh, 2012:219; Kaur *et al*., 2012:281). East *et al*. (2008:97) noted that partial defection could be the result of a change in the life-stage of the customer, necessitating a different version of the product, possibly resulting in upgrades or downgrades of the product, but not total defection. Antón *et al*. (2007b:136) suggest that factors relating to the customer, namely switching costs, knowledge of better alternatives and customer involvement also influence customer switching behaviour. Switching does not necessary occur as a result of dissatisfaction, but could be involuntary (Keaveney, 1995:78). Factors beyond the control of the customer and/or the service provider may result in involuntary switching, for instance, either the service provider or the customer may change location, or a change in the service provider's alliances may have a conflict of interest for the customer.

In an attempt to identify whether customer-related factors could determine which customers may or may not switch, Keaveney and Parthasarathy (2001) and Ganesh *et al.* (2000) classified customers as either “switchers” or “stayers”. Customers that were new to the service provider and the service offering, that is, first-time adopters, were called stayers, whereas the term “switchers” described customers that had switched from a previous service provider (Ganesh *et al.*, 2000:65; Shah & Schaefer, 2006:75). Ganesh *et al.* (2000:65) further classified switchers as dissatisfied switchers and satisfied switchers. Satisfied switchers switched for various reasons other than dissatisfaction, for example, moving to another area, changing jobs, entering a different life-cycle phase or a change in family circumstances (Roos & Gustafsson, 2007:94). Dissatisfied switchers may have received a better offer from competing organisations (Roos & Gustafsson, 2007:94) or possibly experienced one or more negative service encounters. Another classification of switchers by Roos and Gustafsson (2007:94) considers passive and active switchers. Passive switchers may switch when contacted by a competitor, even though they did not plan to switch or were not searching for another service provider, whereas active switchers actively search for a new service provider.

3.3.3.2. Switching intention

Switching intention describes the possibility that the customer may switch to another service provider (Chuang, 2011:130) and gives organisations an indication of whether the customer plans to remain with the organisation or defect (Zeithaml *et al.*, 1996:33). Switching intention differs from switching behaviour (Shah & Schaefer, 2006:76) in that switching intention is a possible outcome behaviour and switching is the actual act of changing to another service provider.

Organisations should be proactive in detecting switching intention (Kruger & Mostert, 2012:47; Shah & Schaefer, 2006:87). If customers have entered into a contractual agreement with the organisation, anticipation of switching intention is easier, since the service provider could contact the customer and enquire about their repurchase intention when the contract is due for renewal. Services such as mobile telecommunications, that are provided continuously, usually require the service provider and customer to enter into a formal relationship in the form of a contractual agreement (Bolton & Lemon, 1999:172). Contracts imply that customers are bound to a particular service provider for a specified amount of time. Throughout the duration of the contract, customers interact with the service provider and may experience positive or negative service encounters. Unlike transaction-based purchases where the customer can switch straight after a negative service encounter, they are obliged to remain with the service provider until the contract terminates before they can switch, regardless of whether or not they are satisfied, (Bolton & Lemon, 1999:172).

In order to understand the result of a behaviour, considering the cause of the behaviour is necessary (Lindquist & Sirgy, 2006:18). Therefore, should an organisation wish to know what caused customers to switch to another service provider, the factors (antecedents) that lead to switching should be considered.

3.4 ANTECEDENTS OF SWITCHING INTENTION

With regard to switching, factors that have a direct effect on the dependent variable, switching intention, can be described as factors which either predispose or precipitate the dependent variable. Predisposing factors gradually cause customers to decide to switch, whereas precipitating factors cause a sudden decision to switch. Both predisposing and precipitating factors pertain to either the lack of fulfilment of tasks inherent to the relationship, or to the dyadic relationship itself. Tasks inherent to the relationship include service encounter failures or a sudden unexpected price increase, whereas the dyadic relationship refers to a lack of commitment and trust demonstrated by the organisation, or negative relationship interaction experiences (Antón *et al.*, 2007b:137).

Abundant research has been conducted in an attempt to ascertain what exactly causes customers to switch from one service provider to another (Bansal & Taylor, 1999b; Hu & Hwang, 2006; Keaveney, 1995; Keaveney & Parthasarathy, 2001; Madden *et al*., 1999; Mittal & Lassar, 1998; Xavier & Ypsilanti, 2008; Wong, 2011). However, no consensus has been reached regarding a set of reasons for switching nor which specific antecedents influence switching. A wide variety of switching antecedents have been investigated.

Table 3.1 provides a summary of switching antecedent and researchers that have investigated those antecedents.

Table 3.1: Measurement scale sources

Antecedent	Researchers
Satisfaction	Bansal & Taylor, 1999a; Bansal & Taylor, 1999b; Eshghi *et al*., 2006; Ganesh *et al*., 2000:68; Kaur *et al.*, 2012; Shah & Shaefer, 2006
Service quality	Bansal & Taylor, 1999a; Bansal & Taylor, 1999b; Eshghi *et al*., 2006; Kaur *et al.*, 2012; Shah & Shaefer, 2006
Switching costs	Antón *et al.*, 2007b; Bansal & Taylor, 1999a; Bansal & Taylor, 1999b
Pricing	Keaveney, 1995
Price unfairness	Antón *et al.*, 2007b
Perceived value	Bansal & Taylor, 1999a; Eshghi *et al*., 2006
Commitment	Antón *et al.*, 2007b; Kaur *et al.*, 2012
Trust	Kaur *et al.*, 2012
Alternative attractiveness	Bansal & Taylor, 1999a; Keaveney, 1995
Propensity for variety seeking	Bansal & Taylor, 1999a

Understandably, due to the wide variety of possible variables, no consensus has been reached in the literature regarding switching intention antecedents or a combination of antecedents that influence switching. Cognition should also be taken that a large number of antecedents have a simultaneous effect (Antón *et al*., 2007a:514) and that antecedents also interact with one another, which complicates the identification of specific antecedents and combinations of antecedents. Disagreement and a lack of conclusive results is confirmation that further investigation of switching antecedents is necessary.

Furthermore, switching intention antecedents have been investigated in a wide variety of service industries, such as Internet service providers (Keaveney & Parthasarathy, 2001; Madden *et al*., 1999), the banking industry (Bansal & Taylor, 1999b; Ganesh *et al*., 2000:68; Kaur *et al*., 2012), fixed line telephony (Eshghi *et al*., 2006; Lopez *et al*., 2006), motor car insurance (Antón *et al.*, 2007b), dry cleaning and hairstyling (Bansal & Taylor, 1999a), public transport (Chen & Chao, 2011) and education (Shah & Shaefer, 2006). In addition, extensive research regarding switching intention, switching behaviour and churn determinants has been conducted in the mobile telecommunications industry (Ahn *et al*., 2006; Chuang, 2011; Hu & Hwang, 2006; Malhotra & Malhotra, 2013; Min & Wan, 2009; Ranganathan *et al*., 2006; Shin & Kim, 2008; Shukla, 2010; Wong, 2011).

Taking into consideration all of the switching antecedents mentioned and the diverse service industries that have served as a platform for switching studies, various switching intention antecedents that have been researched in the mobile telecommunications context include, but are not limited to, customer satisfaction (Chuang, 2011; Kim & Yoon, 2004; Lee *et al*., 2006b; Shin & Kim, 2008; Shukla, 2010), service quality (Shin & Kim, 2008; Shukla, 2010), switching costs (Ahn *et al*., 2006; Chuang, 2011; Hu & Hwang, 2006; Shin & Kim, 2008) and trust (Deng *et al*., 2010). Factors that are unique to the mobile telecommunications industry include network coverage and call quality (Chuang, 2011; Kim & Yoon, 2004), call service usage level (Ahn *et al.*, 2006) and handset usage (Ahn *et al.*, 2006; Kim & Yoon, 2004).

Deduced from the above discussion, a wide variety of switching intention antecedents exist which apply to the services industry in general, and the mobile telecommunications industry in particular. The following discussion briefly explains why certain switching intention constructs, notably satisfaction, service quality and trust, were not considered for the current study.

3.4.1 Satisfaction

Customer satisfaction is an important consideration for service organisations, since satisfaction leads to profitability (Choi, Cho, Lee, Lee & Kim, 2004:914; Fornell, 1992:8; Eshghi *et al*., 2006:180; Lee *et al*., 2001:37; McDougall & Levesque, 2000:395; Negi, 2009:33; Rust & Zahorik, 1993:209). Apart from profitability, satisfaction is also known to increase loyalty, prevent switching and reduce customer price sensitivity (Kim *et al*., 2004:148). Other advantages of customer satisfaction are that satisfied users have higher usage levels than unsatisfied users, satisfied users are more likely to recommend the service provider, and satisfied users intend to continue to use the service provider in the future (Deng *et al*., 2010:290). Ample previous research has concluded that satisfaction has a significant negative direct relationship with switching intention (Bansal & Taylor, 1999b:212; Chuang, 2011:135; Eshghi *et al*., 2006:185; Gustafsson, Johnson & Roos, 2005:216; McDougall & Levesque, 2000:402; Shin & Kim, 2008:862). Thus alternate constructs which received less attention in previous research studies, were chosen for the current study.

3.4.2 Service quality

Similar to satisfaction, service quality is also linked to the profitability of an organisation. Research has shown that organisations that deliver a high quality service are more profitable and competitive (Lee, 2010:3; Shah & Shaefer, 2006:77). Debate exists as to whether service quality should be measured as overall service quality, or whether service quality dimensions should be measured. Several conceptualisations for service quality have been proposed in the literature and considerable debate exists as to the basic service quality dimensions (Lee, 2010:3; McDougall & Levesque, 2000:393; Zins, 2001:274). The most well-known service quality conceptualisation is that of Parasuraman, Zeithaml and Berry (1985, 1988). Parasuraman *et al.*'s (1988) SERVQUAL model became the most extensively used scale to measure service quality (Choi *et al*., 2004:914; Gould-Williams, 1999:102).

McDougall and Levesque (2000:394) regard overall service quality to have two sub-dimensions, namely core quality and relational quality. Chen and Cheng (2012:809) expanded upon McDougall and Levesque's (2000) perspective and conceptualised service quality in the mobile telecommunications context as a combination of two constructs, namely core service quality (network quality, clarity of voice reproduction, no connection break-downs, price schedules and quality of value-added services) and interactive quality (customer care). Other researchers in mobile telecommunications have proposed that service quality sub-dimensions should be considered, including network quality, call quality, call drop rate, call failure rate, number of complaints, pricing structure, mobile handset quality, value-added services, convenience in procedures, brand image and customer service (Ahn *et al*., 2006:555; Gerpott *et al*., 2001:258; Lee *et al*., 2001:39; Kim & Yoon, 2004:758-759; Kim *et al*., 2004:149; Vlachos & Vrechopoulos, 2008:281; Woo & Fock, 1999:170).

Research in the mobile telecommunications context found that call drop rates and number of complaints significantly influenced intention to switch (Ahn *et al*., 2006:560). Kim and Yoon (2004:761) showed that call quality significantly influenced switching intention, as well as tariff levels, handsets and brand image. Gerpott *et al*. (2001:262) determined that assessment of price and network quality significantly influenced switching intention, whereas Bolton (1998:58) found that dissatisfaction experienced with billing transactions or service equipment, resulted in switching. Since much attention has been paid to the service quality construct in marketing literature (Cronin *et al.,* 2000:193), thus for the purpose of the current study, constructs that have not yet been researched as extensively were investigated.

3.4.3 Trust

There is no doubt that trust and commitment are central concepts in relationship marketing (Ballantyne *et al*., 2003:160; Möller & Halinen, 2000:41; Morgan & Hunt, 1994:34). Relationship marketing and social exchange theory consider trust to be an essential business ingredient (Luo, 2002:111). Several research studies have shown that trust leads to customer retention (Aydin & Özer, 2005:151; Aydin *et al*., 2005:97; Deng *et al*., 2010:295; Jahanzeb, Fatima & Khan, 2011:13; Liu *et al*., 2011:75). Studies have found trust to be the most important customer loyalty predictor (Pan *et al*., 2012:156). Fundamentally trust almost certainly leads to loyalty, the likelihood exists that a lack of trust will lead to switching, since switching is the opposite of loyalty (Wieringa & Verhoef, 2007:175). Thus, although the influence of trust on switching intention in the context of mobile telecommunications is yet to be explored, the current study presupposes that trust is important and therefore explores other variables for which less certainty exist.

3.4.4 Antecedents to be investigated

Considering the aforementioned, satisfaction, service quality and trust were omitted from the current research and the focus shifted instead to investigate relational switching costs, perceived value and alternative attractiveness in the current study. Bansal *et al*. (2005:108) found that variables traditionally thought to have a significant effect on switching intention, namely, satisfaction, quality and trust, in fact had the weakest effect on switching intention and therefore suggested that further investigation of more significant variables such as switching costs and alternative attractiveness was necessary. In their 1999 study, Bansal and Taylor (1999a:77) found that alternative attractiveness, switching costs and perceived value were significant predictors of switching intention in dry cleaning services, hair styling services and long distance telephone services, all of which are services-related industries. Thus the possibility exists that the same three precursors could be significant in the mobile telecommunications industry and further investigation was pursued in the current study. In addition, Bansal and Taylor (1999b:215) encourage testing a variety of service settings to more deeply understand the customer switching phenomenon. Furthermore, Bansal and Taylor (1999b:215) suggest that 'relationship with the service provider' and 'alternative attractiveness' are variables that require future exploration. Moreover, Lu, Tu and Jen (2011:1085) also suggest that perceived value, alternative attractiveness and switching costs are important to deter switching. Whitten and Wakefield (2006:220) are of the opinion that there is a lack of information in the literature regarding relational switching costs, specifically in the context of contractual service relationships. In their 2007 study, Wieringa & Verhoef (2007:182) found that switching costs and alternative attractiveness were significant determinants of switching intention.

Thus the antecedents chosen for the research were relational switching costs, perceived value and alternative attractiveness. Each antecedent is discussed in the paragraphs to follow, commencing with switching costs.

3.4.5 Switching costs

Due to the pertinence of switching costs in relationship marketing, the literature has focussed considerable attention on the topic (De Matos, Henrique & de Rosa, 2009:518; Whitten & Wakefield, 2006:220). Switching costs have also been investigated in several studies in the telecommunications industry (Nakamura, 2010:737). The central role of switching costs in customer retention has been proven, particularly in service industries (Burnham *et al*., 2003:110; Jones, Mothersbaugh & Beatty, 2002:441; Polo & Sesé, 2009:119). Should switching costs be an important consideration for retention strategies, by inference, switching costs should also be considered when investigating customer switching behaviour. As previously mentioned, switching is considered to be not only the opposite behavioural outcome of loyalty, but also of retention (Antón *et al.*, 2007b:137; Bansal & Taylor, 1999b:200; Shukla, 2010:472; Wieringa & Verhoef, 2007:175).

Switching costs act as barriers that deter customers from switching to an alternative service provider (Aydin & Özer, 2005:142; Büschken, 2004:5; Chuang, 2011:133; Deng *et al*., 2010:292; Edward *et al*., 2010:155; Fornell, 1992:10; Jones, Mothersbaugh & Beatty, 2000:261; Klemperer 1987a:138; Lee *et al*., 2001:36; Liu *et al*., 2011:72; Patterson, 2004:1305; Shin & Kim, 2008:858; Yang & Peterson, 2004:805). Switching costs are defined as the degree to which a customer perceives being locked in to a relationship due to additional costs (whether economic, social or psychological) which will be incurred, should the customer wish to leave the current service provider to pursue a relationship with an alternative service provider (Patterson & Smith, 2003:108; Vasudevan *et al*., 2006:346; Wang, 2009:1233). The magnitude of the barrier will determine the strength of the intention to switch (Shin & Kim, 2008:857). In other words, the strength of the impact that switching costs have on the customer will determine whether or not a switch will take place. Thus, as the level of difficulty to switch increases, the switching costs increase and the propensity to switch decreases (Burnham *et al*., 2003:110; Heide & Weiss, 1995:33; Shi *et al.*, 2006:27). In contrast, switching is much easier when switching costs are low.

Switching costs also indicate how important maintaining the service provider-customer relationship is to the customer, that is, how dependent the customer is on that specific service provider (Wang & Wu, 2012:63). A customer who is bound to a service provider due to high switching costs will remain with the service provider despite low levels of quality and satisfaction (Bansal *et al*., 2005:110; Sharma & Patterson, 2000:474). Previous studies found that customers will not switch, even though they are not satisfied, if the switching costs are too high (Vasudevan *et al*., 2006:343). However, customers more readily switched if the service quality was poor, regardless of the switching costs (Keramati & Ardabili, 2011:349).

De Ruyter, Wetzels and Bloemer (1998:439) noted that the switching costs of physical goods are lower than switching costs for intangible service providers. Since services are intangible and customers cannot evaluate the service prior to purchase, customers face high risk should they switch from one service provider to another (Sharma & Patterson, 2000:474). MNOs offer a service that is partly tangible (the mobile handset received when the contract is signed) and partly intangible (network coverage), thus there is a risk involved in switching to a new MNO. In addition, services are often customised and personalised (Jones *et al*., 2000:261), therefore switching to a new service provider would mean that both the customer and service provider would have to re-customise and re-personalise the service. The uncertainty experienced by the customer not knowing whether the new service provider would succeed in personalising and customising the service to the same degree as the previous service provider may prevent consumers from switching.

Research has shown that repurchase intention is significantly influenced by switching costs (Burnham *et al*., 2003:110; Vasudevan *et al*., 2006:346; Whitten & Wakefield, 2006:220). According to Klemperer's (1987a) two-period switching cost model, the original purchase (first period sale) will determine the aftermarket (second period) switching costs (Shin, 2007:2; Shin & Kim, 2008:857). In other words, the magnitude of the switching costs accumulated after the original purchase will determine the likelihood that the customer will switch or stay with the service provider when the repurchase decision is made. Thus, if high second period switching costs exist, switching intention will decrease.

Many different conceptualisations have been developed for switching costs, as can be deduced from the wide variety of variables that have been used to describe the switching cost construct (Edward & Sahadev, 2011:329). Although some authors have suggested that the variables are exclusively economic in nature, others contend that switching costs are a complicated matter, and consist of a wide variety of factors (Sharma & Patterson, 2000:474). Besides the most common switching cost – financial loss – other forms of switching costs include social, psychological, performance-related, safety-related or time costs (Dick & Basu, 1994:105; Fornell, 1992:10; Kim *et al*., 2004:149; Shin, 2007:2). Antón *et al*. (2007b:141) include emotional costs, cognitive effort and a number of risks, while other researchers include uncertainty costs, learning costs, search costs and transaction costs (Burnham *et al*., 2003:111; Klemperer, 1995:517; Liu *et al*., 2011:72). Some researchers consider the customer's relationship with the service provider and the customer's emotions to be a switching cost. For example, Sharma (2003:255) includes stress, relationship investment and loss of confidentiality as switching costs. Additionally, a loss of benefits or loyal customer discounts and the loss of established habits and relationships are also considered as forms of switching costs (Liu *et al*., 2011:72).

Recent conceptualisations differentiate between positive and negative switching costs (Jones *et al*., 2007:337) or loss and gain costs (Seo *et al*., 2008:185). Negative switching costs or losses result from negative sources of constraint, such as procedural switching costs, while positive switching costs (gains) are associated with loss of social bonds or other benefits, which are considered positive sources of constraint (Jones *et al*., 2007:337; Seo *et al*., 2008:185).

Due to the wide variety of switching cost variables, researchers presently recognise switching costs as a multidimensional construct which has both monetary and non-monetary components (Han *et al*., 2011:621). Jones *et al*. (2002) were the first to conceptualise switching costs as a multidimensional construct (Woisetschläger, Lentz & Evanshitzky, 2011:801), closely followed by Burnham *et al*. (2003). Even though researchers are in agreement regarding the complexity of the switching cost construct, no consensus has been reached as to which switching costs facilitate or inhibit switching, nor the definition and components of switching costs (Hu & Hwang, 2006:77; Huang & Hsieh, 2012:219).

3.4.5.1 Switching cost typologies

Disagreement regarding the aforementioned is reflected in the numerous switching cost models that have been developed which have similar components, but no two are the same (Hu & Hwang, 2006:77). A few of the most cited models include those developed by Porter (1980), Jackson (1985), Guiltinan (1989), Klemperer (1995), Jones *et al*. (2002) and Burnham *et al*. (2003) (De Ruyter *et al*., 1998:439; Edward *et al*., 2010:155; Edward & Sahadev, 2011:329; Huang & Hsieh, 2012:219; Patterson, 2004:1305; Patterson & Smith, 2003:108). Possibly the most widely used switching cost typology is that of Burnham *et al*. (2003), who grouped switching costs into procedural, financial and relational switching costs. Due the extensive use of the Burnham *et al*.'s (2003) typology, a brief explanation of the three switching cost categories follows.

I) Procedural switching costs

The lost time and extra effort associated with switching from one service provider to another are categorised as procedural switching costs (Babin & Harris, 2013:308; Burnham *et al*., 2003:112; Chuang, 2011:133; Jones *et al*., 2007:336). Procedural switching costs include search or evaluation costs (Burnham *et al*., 2003:111), which include, "the effort, inconvenience and money involved in searching for an acceptable, alternative service provider" (Patterson, 2004:1306). Learning costs and setup costs are also regarded as procedural switching costs (Burnham *et al*., 2003:111). Initiating the relationship with the service provider often requires time and effort (setup costs) and often the customer has to learn skills and processes which are service provider-specific (learning costs).

Chuang (2011:135) and Hu and Hwang (2006:83) found a significant negative relationship between procedural switching costs and switching intention. However, even though customers with procedural switching costs remain with the service provider, often the relationship is forced and customers have no other alternative but to remain with the service provider. Jones *et al*. (2007:350) suggest that service organisations should be prudent when implementing retention strategies using procedural switching costs. Negative word-of-mouth and negative emotions are likely outcomes of negative sources of constraint, arising from procedural switching costs.

II) Financial switching costs

Financial switching costs involve the loss of financial resources when switching from one service provider to another (Burnham *et al*., 2003:112; Chuang, 2011:133) and include early termination fees and loss of discounts and benefits (Chuang, 2011:131; Jones *et al*., 2007:337). Patterson (2004:1306) suggests that the loss of special privileges could increase switching costs, since regular customers are often given special prices or are accommodated at short notice.

The literature indicates that high financial switching costs decrease switching intention, as predicted by economic theory (Burnham *et al*., 2003). Chuang's (2011:135) findings that financial switching costs have a significant negative relationship with switching intention are thus widely supported. However, Hu and Hwang (2006:79) propose that the more similar the prices are between competing service providers in an industry, the less significant the effect of financial switching costs will be on switching intention. Their (Hu & Hwang, 2006:83) viewpoint is reflected in their findings which indicated no significant relationship between financial switching costs and switching intention. Hu and Hwang's (2006:83) finding is relevant to the mobile telecommunications industry in South Africa, since this industry is an oligopoly (Lamb *et al*., 2010:120) and competing MNOs have very similar pricing strategies which nullify one another due to their similarity. Competitors frequently introduce incentives to enable customers to overcome switching costs and thereby facilitate switching (Nikbin *et al*., 2012:319; Yang & Peterson, 2004:806). Nonetheless, Shin (2007:3) observed that, should the current service provider's price increase be more than the cost of switching to another service provider, some customers are likely to switch.

Unlike financial incentives, emotional ties between the customer and service provider are not easily replicated (Hu & Hwang, 2006:80). As a result, relationships are thought to be a greater switching barrier than financial switching costs. Babin and Harris (2013:309) mention that even though procedural and financial costs may prevent switching, research has shown that relational barriers are more difficult for competitors to copy and are therefore the most resistant to competitor's influence. Therefore the need exists to create a relational switching cost that cannot easily be duplicated.

III) Relational switching costs

Relational switching costs are mostly present in service-based organisations (Vasudevan *et al*., 2006:343). Relational switching costs refer to the customer suffering emotional or psychological discomfort, brand relationship loss and/or loss of social bonds, following the termination of the service provider relationship (Antón *et al.*, 2007b:141; Babin & Harris, 2013:309; Burnham *et al*., 2003:112; Chuang, 2011:131; Edward & Sahadev, 2011:330; Hu & Hwang, 2006:80; Jones *et al*., 2007:337; Steyn, Mostert & De Jager, 2008:145; Vasudevan *et al*., 2006:343). Close personal relationships and social bonds are built after the service provider and the customer have interacted on several occasions (Kruger & Mostert, 2012:43; Polo & Sesé, 2009:120). Repeated interactions can strengthen bonds and lead to long-term relationships. The development of a strong relationship with the customer has been suggested as a strategy to prevent switching (Shah & Schaefer, 2006:76).

If a customer is recognised by service personnel and treated as more than "just another customer", the bond with the service provider strengthens (Kruger & Mostert, 2012:43; Patterson, "A" & Smith, 2001:6; Vasudevan *et al*., 2006:346). Due to these social bonds, psychological and social costs would be high if the interpersonal relationship were to be terminated (Patterson, 2004:1306). Once social bonds are established, the relationship becomes a high switching barrier and decreases the customer's desire to exit the relationship (Colgate & Lang, 2001:333; Patterson *et al*., 2001:7; Kruger & Mostert, 2012:43; Vasudevan *et al*., 2006:343). Since ending such a relationship may cause stress, switching costs are increased, thereby decreasing switching intention. As a result, Shah and Schaefer (2006:87) encourage organisations to build strong interpersonal relationships between service employees and customers, which act as a barrier to switching.

Customers also seek relationships that provide value and convenience (Gwinner, Gremler & Bitner, 1998:102). Therefore, the more benefits gained from the relationship between the customer and the service provider (Woisetschläger *et al*., 2011:800), the more difficult relationship termination becomes, resulting in high relational switching costs.

Even though switching costs in mobile telecommunications have been well-researched (Ahn *et al*., 2006; Aydin *et al*., 2005; Edward & Sahadev, 2011; Keramati & Ardabili; 2011; Lee *et al*., 2001; Maicas, Polo & Sesé, 2009b; Shin & Kim, 2008), few researchers have investigated individual switching cost components. Researchers that indeed investigated all three individual switching cost components in the same study are Chuang (2011) in the mobile telecommunications context and Hu and Hwang (2006) in terms of e-book readers. Whitten and Wakefield (2006:220) and Maicas *et al*. (2009b:553) encourage the investigation of the categories separately to gain insight regarding the impact of each switching cost component.

Therefore, using a similar approach to Vasudevan *et al*.'s (2006:342) study, only the relational switching costs sub-category of Burnham *et al*.'s (2003) switching cost classification is investigated in the current study. The reason being that the current study follows a relationship marketing approach and thus investigates switching intention from a relationship marketing perspective. A study by Hu and Hwang (2006) suggested that the relational switching costs scale has two dimensions. However, for the purpose of this study, the relational switching costs scale was treated as unidimensional, which is in line with the study conducted by Vasudevan *et al*. (2006).

Adequate research has been conducted concerning the relationship between switching costs and loyalty (Aydin & Özer, 2005; Aydin *et al*., 2005; Deng *et al*., 2010; Lee *et al*., 2001; Liu *et al*., 2011; Min & Wan, 2009; Wang & Wu, 2012; Woisetschläger *et al*., 2010). Surprisingly, fewer studies have examined the relationship between switching costs and switching intention. One study that investigated the direct relationship between switching costs and switching intention found that switching costs significantly influence switching intention (Kaur *et al.*, 2012:291).

Regarding research that considered individual switching cost categories, Chuang (2011:135) found that relational switching costs did not have a significant influence on switching intention. However, Burnham *et al*. (2003:118) and Hu and Hwang (2006:83) found a highly significant negative relationship between relational switching costs and switching intention. From these findings, the following hypotheses are proposed:

H_{1a}: There is a negative relationship between relational switching costs and switching intention.
H_{1b}: There is a negative relationship between relational switching costs and switching behaviour.

Apart from considering the development of relationships with customers, organisations also need to ensure that the service offering is of value to the customer, in order to maintain a meaningful and sustainable relationship. As Bagozzi (1975:36) mentioned, in marketing, exchange can be regarded as a mixed exchange, since both relational and economic exchange take place during service encounters. This, situation raises the issue of the importance of the customers' perception of the value that is derived from the exchange relationship.

3.4.6 Perceived value

For organisations to remain competitive, understanding the value that customers derive from an exchange has become important (Sweeney & Soutar, 2001:204). During the exchange transaction, both the buyer and the seller must receive something of value, otherwise the exchange may not take place (Lamb *et al*., 2010:10; Lovelock, 1996:460). To deliver value, organisations have to identify the benefits that customers seek and determine the costs that customers are willing to incur to obtain the benefits (Lovelock, 1996:461; Pride & Ferrell, 2010:16). Thus value is often described as the trade-off between benefits received and sacrifices made (Bansal & Taylor, 1999a:76; Bolton & Drew, 1991:376; Choi *et al*., 2004:915; Edward *et al*., 2010:154; Gould-Williams, 1999:103; McDougall & Levesque, 2000:394; Patterson & Spreng, 1997:416; Turel *et al*., 2007:65; Yang & Peterson, 2004:803).

Benefits, also known as 'get' components (Zeithaml, 1988:14), are "anything a buyer receives in an exchange" (Pride & Ferrell, 2010:15). These benefits could either be tangible or functional purchase outcomes, such as volume or quality, or intangible psychosocial outcomes, such as convenience received and prestige (Choi *et al.*, 2004:915; Edward *et al*., 2010:155; Kardes *et al*., 2011:279; Kotler & Keller, 2006:25; Zeithaml, 1988:14). On the contrary, sacrifices are "anything a buyer must give up to obtain the benefits the product provides" (Pride & Ferrell, 2010:16). Zeithaml (1988:14) describes sacrifices as 'give' components. Sacrifices can be tangible monetary costs, or intangible non-monetary costs (Choi *et al*., 2004:915; Kotler & Kelller, 2006:25; Yang & Peterson, 2004:802). The actual monetary price paid for the service offering is a tangible monetary cost (Horovitz, 2000:26; Kotler & Kelller, 2006:25). However, a wide variety of intangible costs exist, such as the customer's time, mental effort, physical stress experienced and risk involved in finding and purchasing the desired service offering (Choi *et al.*, 2004:915; Kotler & Keller, 2006:25; Pride & Ferrell, 2010:16; Yang & Peterson, 2004:802; Zeithaml, 1988:14). The stress and effort of understanding a purchase contract is another form of non-monetary sacrifice (Horovitz, 2000:26).

3.4.6.1 The relationship between perceived value, perceived price and quality

The trade-off between benefits received and sacrifices made has also been described as the ratio between quality and price (Sweeney & Soutar, 2001:204). Zeithaml (1988:10) describes price as a 'give' component (sacrifice), and quality as a 'get' component (benefit). The literature has suggested that a relationship exists between perceived price, perceived quality and perceived value (Chang & Wildt, 1994:17; Zeithaml, 1988:3).

Customers often use price as a quality indicator (Lamb *et al*., 2010:423), especially when the purchase decision involves high levels of risk and uncertainty, lacks tangible cues (Zeithaml, 1988:10), or when little alternative information is available (Erickson & Johansson, 1985:196). Since services are inherently intangible and offer few tangible cues to indicate high quality, customer attention to price is greater for services than goods, which causes customers to rely on extrinsic cues when making purchase decisions (Gould-Williams, 1999:99; Zeithaml, 1988:11). A high price indicates high quality and a low price often indicates value-for-money. Therefore, price acts as a quality indicator and influences quality perceptions (Chang & Wildt, 1994:18; Zeithaml, 1988:10).

3.4.6.2 Customer value perceptions

The literature has suggested that price and quality are important contributors to the formation of customer value perceptions (Chang & Wildt, 1994:17). Unlike economics, which defines value from a utility theory perspective, marketing literature defines value from a customer perspective (Patterson & Spreng, 1997:416). Thus, perceived value instead of utility value is more appropriate in marketing. The customer perspective viewpoint is reflected in Zeithaml's (1988:14) definition of perceived value, aptly described as "…the consumer's overall assessment of the utility of a product [or service] based on perceptions of what is received [benefits] and what is given [sacrifices]".

Perceived value is considered to be very personal, idiosyncratic and subjective (Bolton & Drew, 1991:383; Edward *et al*., 2010:155; Lovelock, 1996:461; Pride & Ferrell, 2010:15; Zeithaml, 1988:13). Since customer perceptions differ regarding the comparison of sacrifices and benefits (Gould-Williams, 1999:103; Yang & Peterson, 2004:803), what may be valuable to one customer, may not be valuable to another (Kardes *et al.*, 2011:280). Customers determine whether or not a service offering delivers value according to expectations and previous experience, the customer's frame of reference, monetary and non-monetary costs, customer tastes and characteristics, and the purchase context (Bolton & Drew, 1991:377; Chang & Wildt, 1994:18; Patterson & Spreng, 1997:416; Pride & Ferrell, 2010:16; Zeithaml, 1988:13). On certain occasions customers may regard the lowest price, speed of delivery or convenience as valuable (Pride & Ferrell, 2010:16-17), whereas in other situations, high volumes, high quality or a limited time and effort to obtain the product may be valuable (Gould-Williams, 1999:103). Service providers should therefore offer flexible services to satisfy different customer tastes, needs and expectations (Bolton & Drew, 1991:383-384; Pride & Ferrell, 2010:17).

Customers may be willing to make trade-offs, for example, pay a higher price to obtain more benefits (Lovelock, 1996:461). The greater the difference between the benefits derived and the costs incurred, the higher the perceived value (Horovitz, 2000:19; Lovelock, 1996:363). In other words, perceived value increases when the benefits received are high and the costs incurred are low. Research has shown that high perceived value leads to a willingness to buy (Dodds, Monroe & Grewal, 1991:315). Customers are willing to pay for a service when the benefits of the exchange exceed the sacrifices and if the service offering has superior value when compared to alternative service providers (Dodds *et al*., 1991:308). If customers are of the opinion that the ratio of their benefit to sacrifice is comparable to the service provider's benefit-sacrifice ratio, the customer will feel that they have been treated equitably (Yang & Peterson, 2004:803) and will most likely continue the relationship.

3.4.6.3 Changing customer value perceptions

Perceived value may be increased by either lowering the monetary price of the service offering and maintaining the benefits offered, or adding new benefits while maintaining or decreasing costs associated with the service offering (Lovelock, 1996:461). A service provider can offer better value if unique benefits are offered, or if the service offering's benefits exceed those of the competitor, and the sacrifice is the same or less than that of competing service providers (Horovitz, 2000:20; Kardes *et al.*, 2011:46). Conversely, if the service offering is not very different from the competitors', value is perceived as low (Kardes *et al.*, 2011:46). Superior value is offered when benefits are significantly better than those offered by competitors, while being offered at the same cost of competitors (Horovitz, 2000:20). Superior value enables the organisation to create a competitive advantage and may lead to increased profits (Choi *et al*., 2004:915; Walters & Lancaster, 1999:698). Customers will remain with the service provider as long as they perceive that they are receiving superior value (Wang & Wu, 2012:59). Thus, providing superior value increases customer exit barriers (switching costs) (Wang & Wu, 2012:60) and is essential for the successful development of sustainable long-term relationships (Steyn *et al*., 2008:140).

Customer value judgements change over time (Wang & Wu, 2012:60), thus what customers consider to be valuable at present, may change in the future. Also, due to abundant competition in the marketplace, competitors continuously try to improve their value proposition to encourage customers to switch (Kardes *et al.*, 2011:48; Kotler & Keller, 2006:143). Since value changes constantly, organisations need to re-evaluate their value proposition regularly to ensure that the latest customer needs and wants are satisfied (Kotler & Keller, 2006:41). By monitoring customers, organisations are able to detect when customer needs and wants change, thereby enabling the organisation to speedily respond by adjusting the value proposition accordingly (Kotler & Keller, 2006:41).

3.4.6.4 Conceptualisation of perceived value

Even though the price/quality trade-off approach has been widely used to describe perceived value, Sweeney and Soutar (2001:204) caution that only incorporating price and quality is an overly simplistic view, since customers play a large role in determining perceived value. Patterson and Spreng (1997:416) are of the opinion that the functional approach to measuring perceived value, that is, considering value in terms of price and performance quality, is applicable in an industrial and business-to-business (B2B) context. However, they (Patterson & Spreng, 1997:424) suggest that social and emotional components are more relevant to customer purchases. Accordingly, researchers have included emotional, social and performance dimensions over and above monetary value, in an attempt to measure perceived value more accurately (Pihlström & Brush, 2008:734; Sweeney & Soutar, 2001:211; Turel *et al*., 2007:64). Unfortunately, the wide variety of customer-based value definitions contributes to the complexity of measuring perceived value (Gould-Williams, 1999:103).

Due to the difficulty in defining the perceived value construct, marketing literature has mostly measured the effect of overall perceived value on various behavioural constructs using a single-item scale (Bolton & Drew, 1991:382; Gould-Williams, 1999:107-108; McDougall & Levesque, 2000:397; Patterson & Spreng, 1997:424; Pihlström & Brush, 2008:733). Other researchers have proposed that perceived value is a multidimensional construct. In some studies, multi-item scales were used, which emphasised questions regarding price perceptions (Wang & Wu, 2012:60). Sheth, Newman and Gross (1991) devised five consumption value dimensions, namely, functional, emotional, social, epistemic and conditional value (Pihlström & Brush, 2008:734; Sweeney & Soutar, 2001:205). Building upon Sheth *et al*.'s (1991) research, Sweeney and Soutar (2001) developed the PERVAL model and simplified the perceived value construct into four dimensions, namely, 'performance/quality' functional value, 'value-for-money' functional value, emotional value and social value (Turel *et al.*, 2007:65). Researchers such as Pihlström and Brush (2008) and Turel *et al.* (2007) recognised Sweeney and Soutar's (2001) broader view of perceived value and used multiple dimensions to measure the perceived value construct. Cognisance was taken of the multidimensionality of the perceived value construct. However, for the purposes of the current study, a similar approach to Wang and Wu (2012) was followed in that a single multi-item scale which concentrated on monetary perceived value was used. Thus, perceived value is treated as a unidimensional construct in the study.

Perceived value is widely regarded as an antecedent for customer satisfaction (Soureli, Lewis & Karantinou, 2008:10; Wang & Wu, 2012:60) and has been shown to have a strong, significant impact on satisfaction (Patterson & Spreng, 1997:427). Perceived value is also positively correlated to loyalty, repurchase intention and behavioural intention (Chang & Wildt, 1994:23; Chen & Cheng, 2012:815; Choi *et al*., 2004:918; Johnson, Hermann & Huber, 2006:129; Kuo *et al*., 2009:893; Pan *et al*., 2012:155; Vlachos & Vrechopoulos, 2008:286; Wang & Wu, 2012:66; Yang & Peterson, 2004:812). Chen and Cheng (2012:815) consider the role that perceived value plays in forming customer loyalty so important that the suggestion was put forward that perceived value should always be included in customer loyalty models.

Much less research, however, has investigated the relationship between perceived value and switching intention. As expected, Turel *et al*. (2007:69) found that, as perceived value increased, the propensity to switch decreased. Similarly, Bansal and Taylor (1999a:78) found a significant negative relationship between perceived value and switching intention. On the other hand, Shukla (2010:477) found that perceived value has a positive, but weak effect on customer switching. Due to inconsistent results, further investigation into the effect of perceived value on switching intention is needed. Based on the aforementioned discussion, the findings of Turel *et al*. (2007:69) and Bansal and Taylor (1999a:78) were considered during hypothesis formulation. Thus it was hypothesised that:

H_{2a}: There is a negative relationship between perceived value and switching intention.
H_{2b}: There is a negative relationship between perceived value and switching behaviour.

Even though customers may receive value-for-money from the present service provider, competition in the mobile telecommunications industry is intense and many competitors exist in this saturated industry. Consequently, competitors often attempt to influence customers to switch by offering enticing deals. Therefore, an important consideration in the mobile telecommunications industry is alternative attractiveness, which is discussed below as yet another antecedent of switching intention.

3.4.7 Alternative attractiveness

It appears that customers are much more demanding today than in the past. Many customers have become intolerant of inconsistent or mediocre service (Antón *et al.*, 2007b:136). Thanks to easy access of abundant information, customers are able to make more informed decisions regarding the products they choose to purchase (Antón *et al*., 2007a:512; Baron *et al*., 2010:94; Eshghi *et al*., 2006:179) and the service providers from which they purchase. Due to a wide variety of choices, customers can change to an alternative service provider should they feel that the current service provider does not offer what they desire. Taking into consideration that relationship marketing strategies strive toward customer retention (Antón *et al*., 2007a:512), preventing customers from switching is imperative. As such, alternative attractiveness is important to understand switching intention (Bansal & Taylor, 1999a:78). Considering the attractiveness of alternative service providers and their service offerings will allow the organisation to adapt to competitive requirements and adjust strategies accordingly.

Alternative attractiveness can be described as “a force that pulls subscribers toward competitors” (Chuang, 2011:135) or “the client’s estimate of the likely satisfaction available in an alternative relationship” (Sharma & Patterson, 2000:475). Meaning that, should a customer believe that the service offering of a competing service provider is more desirable than that of the current service provider, the customer will consider switching to the competitor (Chuang, 2011:133; Jones *et al.*, 2000:262).

The degree of attractiveness of alternative service providers is the result of a variety of factors. Alternative attractiveness may be due to better service, a fuller range of services, lower charges, the potential of higher financial returns, or proximity to the customer (Sharma & Patterson, 2000:475). Keaveney (1995:77) posits that customers are attracted to competitors if a more personal service is provided and if a more reliable or higher quality service is provided. A better reputation and/or image, more value-added services and more attractive marketing by the alternative service provider are also factors which influence alternative attractiveness (Chuang, 2011:131-132).

The mere availability of an alternative service provider is reason enough for customers to switch. Convenience at a specific point in time (Dowling & Uncles, 1997:74) or variety-seeking may trigger the desire to switch (Antón *et al*., 2007b:142; Bansal *et al*., 2005:108; Dowling & Uncles, 1997:74). In contrast, customers may choose to switch to a better service provider, instead of switching from an unsatisfactory service provider (Keaveney, 1995:77). Even if customers are satisfied with the current service provider, they may desire better services and are prepared to pay higher prices for a better service (Chuang, 2011:131; Keaveney, 1995:77).

In contrast, customers may continue with their current service provider due to a lack of superior competition (Colgate & Lang, 2001:334). That is, even though customers are not satisfied with the current service provider, if no better alternatives exist, the customer will not consider switching. Sometimes customers have the perception that no alternatives are available, either due to the structure of the industry, due to a limited number of service providers in the industry, or due to a lack of knowledge of the variety that exists (Colgate & Lang, 2001:334; Jones *et al*., 2000:263; Theron, Terblanche & Boshoff, 2008:1000; Wang, 2009:1234). Organisations should take cognisance of the fact that repeat purchases are not necessarily an indication of customer loyalty. Instead, the repeat purchase could be due to the customers' perception that no differences exist between available alternatives

(Colgate & Lang, 2001:334). Conversely, research has indicated that switching intention is increased in individuals that have more knowledge about alternative service offerings or service providers (Antón *et al*., 2007b:148; Bansal *et al*., 2005:108).

Due to intense competition prevalent in the telecommunications industry, organisations often offer attractive deals to competitor's existing customers to encourage switching (Malhotra & Malhotra, 2013:14). However, even if more attractive alternatives are available, if a customer feels 'tied' to a service provider, switching is unlikely (Bansal *et al*., 2005:110). Nonetheless, research has shown that if the strength of the attractiveness of the alternative is greater than the cost of switching, the possibility of switching increases (Min & Wan, 2009:117). In other words, should the alternatives seem much more attractive, the lock-in effect of switching costs will decrease, and thereby increase switching propensity (Bansal, Irving & Taylor, 2004:238). As a result, even though MNOs build in switching costs to retain customers, competing MNOs attempt to offer attractive alternatives to nullify the switching costs, making it easier for the customer to switch (Min & Wan, 2009:110; Polo & Sesé, 2009:122). Especially in situations where the competitor's price is lower than the current service provider's price, the likelihood of switching is high (Polo & Sesé, 2009:128).

3.4.7.1 Conceptualisation of alternative attractiveness

Conceptualisations of the alternative attractiveness construct vary between researchers. Kim *et al*. (2004:149) suggest that alternative attractiveness consists of reputation, image and overall service quality of the service provider. Similarly, Min and Wan (2009:112) measured alternative attractiveness using image, price and service quality attractiveness. Chuang (2011:133) used a different approach and explored the competing service provider's service offering, products and promotion to determine alternative attractiveness. Wu (2011:313) suggests four dimensions, namely: the number of available alternatives, the degree of differences between the alternatives, the difficulty in understanding the alternatives and the degree of difficulty in comparing the alternatives.

Authors in the mobile telecommunications industry seem to agree that the image of the competing service provider is an important aspect of alternative attractiveness (Chuang, 2011:131, Kim *et al*., 2004:149, Min & Wan, 2009:110). Gerpott *et al*. (2001:265) found that, if customers have a more positive image of the MNOs competitors, the lower the customer's loyalty, which by implication would mean that switching propensity increases when the image of the competitors is more positive than the image of the current MNO.

Bansal and Taylor (1999a:77) found that alternative attractiveness is a significant predictor of switching intention. Bansal *et al*. (2005:105) found that the higher the attractiveness of an alternative service provider, the greater customers' switching intention. Similarly, Chuang (2011:135) found that alternative attractiveness has a significant positive influence on customer switching intention, confirming that if competing alternatives have greater attractiveness, switching intention will increase. Thus, the following hypotheses are proposed:

H_{3a}: There is a positive relationship between alternative attractiveness and switching intention.
H_{3b}: There is a positive relationship between alternative attractiveness and switching behaviour.

Considering the conceptualisation of each construct and the hypotheses that were stated in the above section, the ensuing section explores the conceptual switching intention model which comprises the aforementioned constructs, and also investigates the interrelationships between the antecedents.

3.5 TOWARD A MODEL OF SWITCHING INTENTION

Researchers have commented that, to date, the purpose of most switching intention studies has been to identify specific variables that directly influence switching intention (Ahn *et al*., 2006:553; Bansal *et al*., 2005:103; Keramati & Ardabili, 2011:346). For example, Keaveney's (1995) model proposed eight main causal variables that directly influence customer switching behaviour in the service industry. However, research has neglected the examination of comprehensive models that encompass relationships between constructs (Ahn *et al*., 2006:553; Bansal *et al*., 2005:103; Keramati & Ardabili, 2011:346). Nonetheless, some attempts to develop switching models have been made after Keaveney's (1995:81) call for further investigation. For instance, Bansal & Taylor (1999b) proposed the service provider switching model (SPSM) and later Bansal *et al*. (2005) proposed the Push, Pull, Moorings (PPM) migration model of service switching. Since researchers have been encouraged to gain an understanding of constructs, their interrelationships and their consequences so as to build better conceptual models and assist industry practitioners (Fullerton & Taylor, 2002:124), the development of a switching intention model was pursued in this study.

As discussed in the preceding section, previous research found a direct relationship between switching intention and the three predictors discussed, namely, relational switching costs (Burnham *et al*., 2003:117; Hu & Hwang, 2006:83), perceived value (Bansal and Taylor, 1999a:77) and alternative attractiveness (Bansal & Taylor, 1999a:77). In a model, a distinction is necessary between the antecedent and the dependent variable, in order to show which variable has an influence on the other (Baron & Kenny, 1986:1178; Holmbeck, 1997:602). Thus a brief digression is necessary to clarify certain terms to be used in the ensuing paragraphs.

Many alternate terms are used to describe a single variable. For instance, an alternative term commonly used for the dependent variable is the criterion variable or outcome variable (Baron & Kenny, 1986:1174; Holmbeck, 1997:600; Hopwood, 2007:263). Similarly, various terms are used to describe the independent variable, for instance: predictor variable, antecedent or explanatory variable (Baron & Kenny, 1986:1173; Holmbeck, 1997:599; Patterson, 2004:1307). For the purpose of this study, the terms 'antecedent' and 'dependent variable' are adopted. The dependent variable is switching intention, and the antecedents are relational switching costs, perceived value and alternative attractiveness. Interrelationships between the antecedents are discussed in the following section.

3.5.1 Interrelationships between the antecedent variables

Limited research is available regarding the interrelationships among the antecedent variables. In the section to follow, research results, if any, concerning the interrelationships are discussed, followed by the proposed hypotheses for each relationship.

3.5.1.1 Relational switching costs and perceived value

Scant research was found regarding relational switching costs and perceived value. Studies were found where switching costs (not relational switching costs specifically) were tested as a moderator between perceived value and customer loyalty (Yang & Peterson, 2004; Wang, 2010). Another investigated switching costs as a moderator between service quality and perceived value (Edward *et al*., 2010).

One study found that perceived value had a positive influence on switching costs, but the influence was not significant (Edward & Shadev, 2011:338). Due to the lack of previous research, the following non-directional hypothesis was proposed:

H_{4a}: There is a relationship between relational switching costs and perceived value in a switching intention context.
H_{4b}: There is a relationship between relational switching costs and perceived value in a switching behaviour context.

3.5.1.2 Relational switching costs and alternative attractiveness

No research could be found suggesting a relationship between relational switching costs and alternative attractiveness. A study was found that used both switching costs and alternative attractiveness as moderators between trust and relationship commitment and as moderators between service satisfaction and relationship commitment (Sharma & Patterson, 2000), but no studies where their interrelationship was investigated.

Similarly, both switching costs and alternative attractiveness were used as moderators in the customer satisfaction–customer loyalty relationship in the same study, but their inter-relationship was not investigated (Min & Wan, 2009). Other studies used both relational switching costs and alternative attractiveness as constructs in the study, but did not investigate their interrelationships (Chuang, 2010). Due to the lack of information in the literature, the following non-directional hypothesis was proposed:

H_{5a}: There is a relationship between relational switching costs and alternative attractiveness in a switching intention context.
H_{5b}: There is a relationship between relational switching costs and alternative attractiveness in a switching behaviour context.

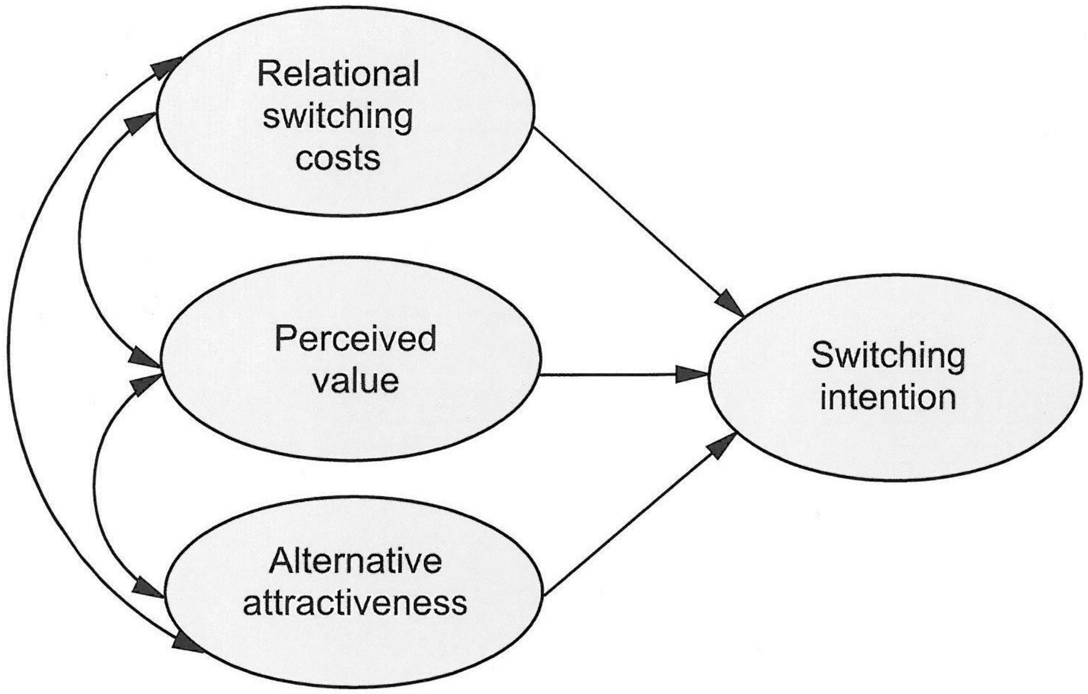
3.5.1.3 Perceived value and alternative attractiveness

No studies could be found testing the direct relationship between perceived value and alternative attractiveness. However, relational switching costs and perceived value were investigated in the same study (Edward & Shadev, 2011:338). Also, even though their interrelationships were not investigated, relational switching costs and alternative attractiveness were constructs used in the same study (Chuang, 2010). Thus it follows that, perceived value and alternative attractiveness may be correlated in some way. Therefore the following non-directional hypothesis is proposed:

H_{6a}: There is a relationship between perceived value and alternative attractiveness in a switching intention context.
H_{6b}: There is a relationship between perceived value and alternative attractiveness in a switching behaviour context.

Taking into consideration the antecedents of switching intention and the proposed interrelationships between the antecedent variables, the conceptual switching intention model is presented in Figure 3.2 below.

Figure 3.2: Interrelationships between the switching intention antecedents



Apart from the model, the correlation between switching intention and relationship characteristics was also investigated. Relationship characteristics, namely relationship length, depth and breadth, are not considered to be theoretical constructs. Instead, relationship characteristics are regarded as characteristics of time, frequency and added purchases, and give insight as to the nature and extent of the service provider–customer relationship (Homburg, Giering & Menon, 2003:39). For this reason, although relationship characteristics are possible antecedents of switching, they reflect the context in which the customer operates and therefore these characteristics were not included in the switching intention model. All three relationship characteristics are discussed in more detail in the section to follow.

3.6 RELATIONSHIP CHARACTERISTICS

Researchers regard relationship characteristics as an indication of loyalty behaviour (Liang & Chen, 2009:223; Lopez *et al*., 2006:560). Consequently, monitoring relationship characteristics could assist service providers in the identification and possible prevention of switching. Relationship characteristics include the duration of the customer-service provider relationship (length), service usage (depth) and service bundling/cross-buying (breadth) (Bolton *et al*., 2004:272; Lopez *et al*., 2006:556; Polo & Sesé, 2009:121; Ranganathan *et al*., 2006:271).

The three relationship characteristics are interlinked and influence one another. Fahy and Jobber (2012:184) state that, as the length of the relationship increases, the possibility exists that the relationship depth and breadth will also increase. Customers are likely to spend more money with the organisation and use a wider variety of services on offer the longer they remain with the service provider. However, Bolton *et al*. (2004:275) suggest that relationship length does not influence relationship depth nor breadth, but that relationship depth may influence both relationship length and breadth.

Past research found a direct relationship between switching intention and relationship length, depth and breadth (Ahn *et al*., 2006:564; Keaveney & Parthasarathy, 2001:378; Keramati & Ardabili, 2011:352; Lee *et al*., 2001:42; Lopez *et al*., 2006:564; Madden *et al*., 1999:205; Maicas *et al*., 2009a:168; Ranganathan *et al*., 2006:274). The influence of relationship length, depth and breadth on switching intention is discussed.

Some studies that have investigated relationship characteristics, have included all three components, namely, relationship length, depth and breadth in a single study (Bolton *et al*., 2004, Liang & Chen, 2009; Lopez *et al*., 2006; Polo & Sesé, 2009, Ranganathan *et al*., 2006). However, the majority of studies focus only on relationship length (Bolton, 1998; Chiao *et al*., 2008; Coulter & Coulter, 2002; Doney & Cannon, 1997; Gonçalves & Sampaio, 2012; Seo *et al*., 2008), while a few exclusively considered relationship depth (Bolton & Lemon, 1999; Keaveney & Parthsarathy, 2001). The minority studies focus on relationship breadth (Soureli *et al*., 2008).

Interestingly, Ranganathan *et al*.'s (2006) study revealed that relationship depth was the strongest switching antecedent, followed by relationship breadth and lastly, relationship length (Ranganathan *et al*., 2006:274). As previously mentioned, most studies have been conducted on relationship length, but since Ranganathan *et al*. (2006:274) found that relationship depth emerged as the strongest switching antecedent, further investigation into relationship depth and breadth could be beneficial.

Most previous studies have concentrated on the effect of relationship characteristics on relational constructs such as satisfaction, trust and perceived quality. Yet scant attention has been paid to the effect of relationship characteristics on switching intention (Lopez *et al.*, 2006:557). Studies that indeed investigated the aforementioned relationship were conducted by Ranganathan *et al*. (2006) and Lopez *et al.* (2006). Findings indicated that all three components of relationship characteristics had a direct negative effect on switching intention (Lopez *et al.*, 2006:568; Ranganathan *et al*., 2006:274).

3.6.1 Relationship length

Relationship length, also referred to as subscription duration or customer tenure, represents the period of time during which a relationship exists between the customer and the service provider (Bolton *et al*., 2004:273; Polo & Sesé, 2009:123; Ranganathan *et al*., 2006:271). A study conducted in the United States found that the average relationship duration to be 33 months (Ranganathan *et al*., 2006:273). In a South African study, the majority of respondents had a relationship with their MNO for between three and ten years (Kruger & Mostert, 2012:47).

Relationship length has been researched more extensively than relationship depth and breadth (Bolton *et al*., 2004:284). A possible explanation for the tendency to focus on relationship length may be due to findings which indicate that profitability is directly proportional to the period of time that a customer purchases service offerings from the service provider (Kruger & Mostert, 2012:41; Ultsch, 2002:315). In other words, the longer the customer remains with the service provider, the higher the service provider's profitability. For this reason organisations are concerned with predicting relationship duration to aid in predicting future revenue (Bolton, 1998:45). Research has shown, however, that the age of the relationship does not guarantee loyalty (Homburg *et al*., 2003:50). Customers do not necessarily become more loyal with time, but are more tolerant of service failures (Bolton, 1998:45; Homburg *et al*., 2003:39). Instead, loyalty is said to depend on trust in the service provider (Chiao *et al*., 2008:663; Homburg *et al*., 2003:50).

During the early stages of the service provider-customer relationship, the customer has little experience with the organisation and thus high uncertainty (Polo & Sesé, 2009:123), especially within a services context. Interdependence as well as monetary and relational investments are low (Polo & Sesé, 2009:123). Thus the significant propensity for customers that recently purchased a service to switch (Lopez *et al*., 2006:564). Consequently, the early stages of the relationship are critical in determining whether the relationship will continue (Lopez *et al*., 2006:560). Therefore it is imperative for organisations to place a strong focus on customer satisfaction and perceived value during the early stages of relationship establishment (Chiao *et al*., 2008:663; Johnson *et al*., 2006:127).

Relational exchanges evolve over time. As the number of interactions increase, relationships are developed. The relationships, in turn, form bonds (Homburg *et al*., 2003:44). As relationship duration increases, increased trust has been found to be a more effective retention tool than satisfaction (Chiao *et al*., 2008:663). Interdependence, trust and psychological attachment also grow as the relationship lengthens, resulting in increased switching costs (Doney & Cannon, 1997:40; Dwyer *et al*., 1987:12; Lopez *et al*., 2006:560; Polo & Sesé, 2009:123). Switching costs increase over time, because customers become more familiar with the organisation and gain experience and knowledge regarding the use of the organisation's service offering (Ranganathan *et al*., 2006:271; Seo *et al*., 2008:187). Customers gain a set of knowledge and expertise unique to the service provider (Ranganathan *et al*., 2006:271) and invest time and energy to learn about services that are exclusive to the current service provider. As a result, the customer's switching propensity will depend on their willingness to learn about new systems at the new service provider. Customers anticipate switching costs when entering into a long-term relationship with the service provider. Thus relationship duration gives organisations a good indication of the customer's intention to remain with the service provider (Vasudevan *et al*., 2006:343) and is considered an indicator of customer retention (Bolton *et al*., 2004:274).

Organisations often make economic and social benefits available to long-term customers to encourage retention (Polo & Sesé, 2009:123; Shin & Kim, 2008:857). Should the customer decide to switch, all of the benefits are forfeited. Consequently, benefits also act as switching costs which inadvertently lock customers into the relationship and discourage switching.

Seo *et al*. (2008:192) found that as the customer's association with the service provider increases, customer retention also increases. By inference, Seo *et al*.'s (2008:187) result implies that the propensity to switch will decrease as relationship length increases. Similarly, research in mobile telecommunications has shown that a negative relationship exists between subscription duration and switching intention – that is, the longer the customer has subscribed to a service provider, the lower the switching intention (Kim & Yoon, 2004:762; Malhotra & Malhotra, 2013:19; Ranganathan *et al*., 2006:273). Lopez *et al*. (2006:564) followed a slightly different approach and measured relationship length in terms of the recency of the subscription instead of the amount of time that the customer had subscribed to the mobile network operator (MNO). The results indicated that the more recent the commencement of the subscription, the higher the switching intention. Therefore, the shorter the relationship length, the higher the switching propensity.

Counterintuitively, some researchers found a positive relationship between relationship length and switching intention (Keramati & Ardabili, 2011:352; Maicas *et al*., 2009a:168). The positive relationship implies that the probability that the customer will switch to another service provider increases the longer the customer remains with the service provider. A possible explanation for this surprising phenomenon is that as the length of time that the customer remains with the service provider increases, there is a higher likelihood that the customer will become aware of competitors, alternative pricing structures and industry trends (Ranganathan *et al*., 2006:271) which may induce a propensity to switch, should customers notice a 'better deal'.

The literature provides conflicting, yet valid findings regarding the influence of relationship length on switching intention. Taking the findings of Kim and Yoon (2004:762), Malhotra and Malhotra (2013:19) and Ranganathan *et al*. (2006:273) into consideration, the following hypotheses are proposed:

H_{7a}: There is a negative relationship between relationship length and switching intention.
H_{7b}: There is a negative relationship between relationship length and switching behaviour.

3.6.2 <u>Relationship depth</u>

Relationship depth (also referred to as service usage) comprises usage frequency and intensity (Keaveney & Parthasarathy, 2001:380; Ranganathan *et al*., 2006:271). Frequency is described as the number of times that the service is used (Bolton *et al*., 2004:273; Liang & Chen, 2009:219; Polo & Sesé, 2009:123). While intensity is the extent to which a customer makes use of a service provider's products or services, that is, the depth of involvement (Ranganathan *et al*., 2006:271). For example, the amount of time a service is used on a particular occasion and/or the amount spent with the service provider (Madden *et al*., 1999:205).

Frequent users are likely to develop a positive attitude toward the service provider (Ranganathan *et al*., 2006:271). It is believed that as customer usage increases, their relationship with the organisation is deepened, leading to increased familiarity with the service provider, decreased uncertainty and strengthened social bonds. (Bolton *et al*., 2004:274; Liang & Chen, 2009:223; Lopez *et al*., 2006:560). Furthermore, frequent users have greater tolerance and less sensitivity toward service failures (Lopez *et al*., 2006:560). Service usage frequency may also influence the customer's decision to purchase premium products (upgrade) in the future (Bolton *et al*., 2004:273). Therefore regular service usage is encouraged.

3.6.2.1 Service usage in mobile telecommunications

In the context of mobile telecommunications, customers can be classified as either heavy, medium or light users (Polo & Sesé, 2009:123). Other methods of comparison have considered peak-time usage, off-peak time usage and week-end usage (Ranganathan *et* *al*., 2006:273). The organisation's long-term profitability is impacted by service usage levels (Bolton & Lemon, 1999:171). Certain MNOs only monitor average monthly consumption (Maicas *et al*., 2009b:548), while the other extreme is to monitor the amount of usage hours per day (Lee *et al*., 2001:41). Keramati & Ardabili (2011:353) used a more general approach and monitored service usage factors in terms of minutes used during the month, number of calls and number of text messages sent.

Customer account status (active use, non-use or suspended customers) should also be monitored (Ahn *et al.* 2006:556). Should customers experience financial problems, use of a service may decline or discontinue altogether. Ahn *et al*. (2006:562) suggest that organisations should monitor when the customer account status changes, for example, from active to either non-use or suspended. A change in customer account status was found to significantly influence switching behaviour (Ahn *et al*., 2006:561).

3.6.2.2 Relationship depth and switching

Many researchers are of the opinion that heavy users are less likely to switch (Keaveney & Parthasarathy, 2001:378; Lee *et al*., 2001:42; Lopez *et al.*, 2006:564). Lee *et al*. (2001:42) also found that heavy users were less likely to switch, however, they speculate that the customers were either true loyalists, in other words, the customers were truly satisfied with the service provider, or the customers were economic hostages, because of customer lock-in. On the contrary, some researchers found that the opposite is true – heavy users are more likely to switch (Ahn *et al*., 2006:564; Madden *et al*., 1999:205). Findings also show that the higher the monthly expenditure, the greater the intention to switch (Madden *et al*., 1999:205). A possible explanation for the contradiction is that heavy users are more price-sensitive due to their high expenditures. The findings of both Ahn *et al*. (2006:564) and Madden *et al*. (1999:205) imply that high users want the best value for money (Lee *et al*., 2001:42) and are therefore constantly on the look-out for specials or discounts, which increases switching probability.

Similar to relationship length, the literature regarding relationship depth has divided opinions regarding the influence of relationship depth on switching intention. Taking the contradictory opinions into consideration, the findings of Keaveney and Parthasarathy (2001:378), Lee *et al*. (2001:42) and Lopez *et al.* (2006:564) led to the following hypotheses:

H_{8a}: There is a negative relationship between relationship depth and switching intention.
H_{8b}: There is a negative relationship between relationship depth and switching behaviour.

3.6.3 Relationship breadth

Even though the literature has mostly focussed on relationship length and depth, understanding the customer's motivation to purchase additional services from the same service provider is also important (Soureli *et al*., 2008:6). The purchase of additional services is an indication that a customer would like to pursue a relationship with an organisation (Lopez *et al*., 2006:561). Liang and Chen (2009:227) found that satisfied customers maintain the existing relationship, but that committed customers are more likely to expand their relationship. Furthermore, bundling products to better meet customer needs can lead to a competitive advantage, since customers will perceive unique bundles as a differentiating variable of the service offering (Burnham *et al*., 2003:119).

The breadth of the consumer–organisation relationship refers to additional products or services purchased over time (Bolton *et al*., 2004:273; Liang & Chen, 2009:219; Polo & Sesé, 2009:124). Relationship breadth can be described as the "expansion of the customer relationship" with the organisation (Bolton *et al*., 2004:274) or the purchase of additional service offerings. Alternative terms to describe relationship breadth are "cross-buying" or "add-on buying" (Bolton *et al*., 2004:273). Another facet of relationship breadth entails modification of the service offering that is currently in use (Burnham *et al*., 2003:113), in other words, an "upgrade" to a more suitable service offering (Bolton *et al*., 2004:273).

When customers purchase complimentary services, relationship breadth is deepened, since the core service is enhanced with extra benefits and the service offering will most likely be more tailored to the customer's specific needs (Lopez *et al*., 2006:561). The wider the variety of service offerings purchased from one organisation, the more costly switching becomes for the customer (Polo & Sesé, 2009:124; Vasudevan *et al*., 2006:346). Evaluation of alternatives becomes more complicated, since the customer will have to evaluate a wider variety of competitor service offerings before switching (Burnham *et al*., 2003:114; Polo & Sesé, 2009:124). Lopez *et al.* (2006:568) strongly advise organisations to extend the range of services on offer. Complimentary services have been shown to increase relationship enhancement and maintenance, because switching costs increase as the number of items in the service bundle increase (Klemperer, 1995:534).

Customers' cross-buying approaches differ. Some customers prefer to purchase additional service offerings from a variety of service providers, either because they do not want to be tied to one service provider for a long time, or because they prefer to diversify their risks. Other customers prefer to purchase several different products from one service provider because of the convenience of a "one-stop shopping" experience (Soureli *et al*., 2008:7).

Intuitively, the expectation exists that, as relationship breadth increases, switching propensity would decrease. Lopez *et al.* (2006:564) found that relationship breadth is negatively correlated to switching intention. Similarly, Ranganathan *et al*. (2006:274) found that service bundling and switching intention have a negative relationship. Thus, as the number of items in the service bundle increase, the customer lock-in effect becomes greater (Ranganathan *et al*., 2006:272), implying that switching costs are increased and thereby switching intention is decreased. However, Maicas *et al*. (2009a:169) found a positive relationship between relationship breadth and switching behaviour, implying that customers who purchase additional services from the service provider (that is, services over and above the core service) are more likely to switch. Ahn *et al*. (2006:564) reported similar results, explaining that heavy users with an accumulation of service experiences may explore more advanced services offered by other service providers.

The above findings are similar to the counterintuitive results found for relationship depth (Ahn *et al*., 2006:564; Madden *et al*., 1999:205) and relationship length (Keramati & Ardabili, 2011:352; Maicas *et al*., 2009a:168) which suggest that long relationship duration and high service usage increase switching propensity, because customers with high usage rates and high expenditures seek the best value-for-money (Ahn *et al*., 2006:564).

As with the two previous relationship characteristics, there are opposing results as to whether relationship breadth has a positive or negative influence on switching intention. Despite the conflicting literature, the findings of Lopez *et al.* (2006:564) and Ranganathan *et al*. (2006:274) were considered to formulate the hypotheses for relationship breadth. Thus the following hypotheses are proposed:

H_{9a}: There is a negative relationship between relationship breadth and switching intention.
H_{9b}: There is a negative relationship between relationship breadth and switching behaviour.

3.7 CONCLUSION

The chapter began with a section on the consumer purchase process, and how post-purchase evaluation results in either a favourable or unfavourable outcome, which ultimately influences re-purchase intention. The focus of the chapter was unfavourable post-purchase evaluation, namely, switching intention.

To prevent switching, marketing practitioners often implement switching costs and lock-in strategies to compel customers to remain with their current service provider. The various hard and soft lock-in strategies were discussed. Nonetheless, some customers may still switch, despite the use of lock-in strategies, thus previous research conducted to ascertain causes of customer switching was explored (Bansal & Taylor, 1999b; Hu & Hwang, 2006; Keaveney, 1995; Keaveney & Parthasarathy, 2001; Madden *et al*., 1999; Mittal & Lassar, 1998; Xavier & Ypsilanti, 2008; Wong, 2011). Consensus has not been reached regarding specific antecedents that influence switching, thus various switching antecedents were discussed. The focus of the chapter was the conceptualisation of switching intention and switching predictors to be explored in the study.

Many switching models have been developed to explore switching. The various models were elaborated upon. Furthermore, the reasoning for the conceptual switching intention model was explained and the conceptualised model, including direct relationships between the proposed switching antecedents and switching intention, as well as interrelationships between the switching antecedents was presented.

Past research found a direct relationship between switching intention and relationship characteristics, namely relationship length, depth and breadth (Ahn *et al*., 2006:564; Keramati & Ardabili, 2011:352; Maicas *et al*., 2009a:168; Ranganathan *et al*., 2006:274).

Counterintuitive results have been found regarding the influence of relationship characteristics on switching intention (Ahn *et al*., 2006:564; Keramati & Ardabili, 2011:352; Madden *et al*., 1999:205; Maicas *et al*., 2009a:168). Possible reasons for the inconsistent results were discussed, and hypotheses were proposed.

In the next chapter, the methodology of the empirical study to investigate the above-mentioned issues will be discussed, including a description of the research design and the intended data analysis techniques to be used.

CHAPTER 4

RESEARCH DESIGN AND METHODOLOGY

4.1 INTRODUCTION

As deduced from the literature review, switching is detrimental to the long-term survival of organisations. Chapter 4 describes the research design and methodology used to achieve the objectives of the research. In sum, the purpose of the study was firstly, to develop and empirically test a conceptual switching intention model (RO1). Secondly, to compare the conceptual switching intention model and actual switching behaviour data by fitting the switching behaviour data to the conceptual switching intention model (RO2). Thirdly, to explore the role of relationship characteristics, namely relationship length, depth and breadth, and their influence on both switching intention and switching behaviour (RO3). Secondary objectives include an investigation of the direct influence of switching antecedents on switching intention and on switching behaviour, and an examination of the interrelationships between the constructs in the conceptual switching intention model, as well as the interrelationships between the constructs in the switching behaviour context.

The chapter is structured upon the research process design suggested by Zikmund, Babin, Carr and Griffin (2009:62):

- Phase 1: Research problem and objectives
- Phase 2: Research design strategy
- Phase 3: Sample design
- Phase 4: Measurement instrument design
- Phase 5: Data collection and preparation
- Phase 6: Data analysis

Before elaborating upon the research design strategy (Phase 2), a summary of the problem statement and research objectives discussed in Chapter 1, is provided.

4.2 PHASE 1: RESEARCH PROBLEM AND OBJECTIVES

In an attempt to understand the causes of switching, a plethora of switching models have been developed, investigating a wide variety of switching predictors. However, results have left researchers with conflicting opinions regarding specific switching predictors. Thus researchers have been encouraged to explore and improve current conceptual switching models (Fullerton & Taylor, 2002:124). In addition, minimal switching research has investigated actual switching behaviour (Ahn *et al.*, 2006:553.), which leaves the combination of accurate switching predictors open for debate. Furthermore, contradictory results have been found regarding the influence of relationship characteristics on switching intention, thus necessitating further exploration. This study's primary and secondary research objectives are listed below (also identified in Chapter 1):

The primary research objectives are:

1. to develop and empirically test a conceptual switching intention model (RO1),
2. to compare the conceptual switching intention model and actual switching behaviour data by fitting the switching behaviour data to the conceptual switching intention model (RO2), and
3. to explore the role of relationship characteristics, and their influence on both switching intention and switching behaviour (RO3).

Secondary objectives following from research objective one (RO1) are:
Firstly, to investigate the direct influence of switching antecedents on switching intention, that is:

- to investigate the relationship between relational switching costs and switching intention,
- to investigate the relationship between perceived value and switching intention, and
- to investigate the relationship between alternative attractiveness and switching intention.

Secondly, to investigate the interrelationships between the switching intention antecedents, specifically:

- to investigate the relationship between relational switching costs and perceived value,
- to investigate the relationship between relational switching costs and alternative attractiveness, and
- to investigate the relationship between perceived value and alternative attractiveness.

Secondary objectives following from research objective two (RO2) are:
Firstly, to investigate the direct influence of switching antecedents on switching behaviour, that is:

- to investigate the relationship between relational switching costs and switching behaviour,
- to investigate the relationship between perceived value and switching behaviour, and
- to investigate the relationship between alternative attractiveness and switching behaviour.

Secondly, to investigate the interrelationships between the switching behaviour antecedents, that is:

- to investigate the relationship between relational switching costs and perceived value,
- to investigate the relationship between relational switching costs and alternative attractiveness, and
- to investigate the relationship between perceived value and alternative attractiveness.

Secondary objectives for research objective three (RO3) are:

- to investigate the influence of relationship length on switching intention,
- to investigate the influence of relationship depth on switching intention,
- to investigate the influence of relationship breadth on switching intention, and
- to investigate the influence of relationship length on switching behaviour,

- to investigate the influence of relationship depth on switching behaviour,
- to investigate the influence of relationship breadth on switching behaviour.

The research design strategy acts as a blueprint for data collection, measurement and analysis, in order to answer the research objectives of a study (Cooper & Schindler, 2014:125). Each research design aspect applicable to the study is discussed in the sections to follow and where appropriate, examples applicable to the study are given.

4.3 PHASE 2: RESEARCH DESIGN STRATEGY

Empirical research was the approach used to conduct the study. Conducting empirical research implies designing procedures to collect factual information in order to address problems (Cooper & Schindler, 2014:66). Descriptive research was conducted to examine the relationships and interrelationships between various constructs and variables (Leedy & Ormrod, 2010:182). The study can also be described as cross-sectional, since the research was conducted once, at one specific point in time (Cooper & Schindler, 2014:128). An *ex post facto* research design collects data to investigate conditions that already exist or events that occurred in the past, and to determine whether relationships exist between dependent and independent variables (Leedy & Ormrod, 2010:238-239). Since an investigation was conducted to investigate whether relationships exist between the dependent variable, switching intention, and various independent variables, namely, relational switching costs, perceived value and alternative attractiveness, the study is also considered to have used an *ex post facto* design.

4.3.1 <u>Data sources</u>

Primary data are collected to satisfy specific requirements (Bradley, 2013:112; McDaniel & Gates, 2013:910), whereas secondary data collection concerns data that was "previously collected for any purpose other than the current problem at hand" (Lamb *et al*., 2010:152). Secondary data can be obtained from various sources, for example, online databases, university research bureaus or commercial publications (Lamb *et al*., 2010:153). Secondary data was the source for the literature review in the previous chapters.

Survey research, observation research or experiments can be used to collect primary data (Lamb *et al*., 2010:155; McDaniel & Gates, 2013:910). Experiments alter one or more variables in a controlled environment, after which the effects are observed and recorded (Lamb *et al*., 2010:162). Observation research avoids direct interaction with respondents. Subjects are monitored from a distance, and conclusions are based on the data collected (Cooper & Schindler, 2014:173; Lamb *et al*., 2010:160). Survey research poses a series of questions to respondents, summarises the responses using statistical techniques and then analyses the responses to draw conclusions (Leedy & Ormrod, 2010:186).

Primary data were collected to obtain information pertaining to the specific objectives of the study. An online survey was conducted using Consulta Research's online database in order to obtain the primary data.

4.3.2 Research methodology

Quantitative research uses surveys consisting of a combination of measurement scales to measure psychological behaviour or characteristics (Leedy & Ormrod, 2010:94). All respondents are asked the exact same set of questions, so that answers can be changed into a numeric format and summarised using percentages, averages, or a wide variety of statistical techniques (Lamb *et al*., 2010:162). In contrast, qualitative research collects descriptive data using open-ended questions, to examine the complexities and nuances of a particular phenomenon to gain an in-depth understanding thereof (Cooper & Schindler, 2014:146; Lamb *et al*., 2010:162; Leedy & Ormrod, 2010:94). All respondents are not necessarily asked the same questions.

Quantitative research was used to collect the primary data, because the study intended to collect numeric data which could be statistically analysed. Quantitative research commonly uses the survey method in the form of a structured questionnaire for data collection.

4.3.3 Data collection method

Bradley (2013:191) describes a questionnaire as a structured set of questions used to obtain information from the target population. A structured questionnaire standardises question wording and sequencing (Cooper & Schindler, 2014:219; Mooi & Sarstedt, 2011:70). Thus answers can be compared statistical inferences can be made since respondents are asked the exact same set of questions (Leedy & Ormrod, 2010:188). Questions could enquire about characteristics, opinions, attitudes or previous experience, to gain an understading about the population. Responses are summarised using frequency counts, percentages or other statistical methods, to draws inferences about a population (Leedy & Ormrod, 2010:187).

No research technique is without criticism. Disadvantages of using structured surveys include: the questionnaire can not be long or complex; respondents may answer what they believe to be true, or give a response that they believe the researcher wants; and respondents could intentionally misrepresent the facts (Cooper & Schindler, 2014:225; Leedy & Ormrod, 2010:188).

Despite the abovementioned disadvantages, the survey method was chosen for primary data collection. The choice was attributable to the uniformity of information that is collected via surveys, the ability of survey research to collect large amounts of information which can be quantified, and the fact that the quantified information can be used to make statistical inferences. Primary data were collected using a structured, self-administered questionnaire in the form of an online survey (Bradley, 2013:119). The survey was self-administered, meaning that the respondents completed the survey independently, without the assistance of a field worker. Advantages of self-administered surveys include rapid data collection and wide geographic coverage, however, low response rates are also characteristic of self-administered surveys (Cooper & Schindler, 2014:225).

Online data collection techniques are becoming popular since respondents are more accessible (Bradley, 2013:170). The Survey Workbench programme (an advanced survey design programme) was used to create the web-based survey and to distribute and collect the survey responses. (Vovici Corporation, 2010).

Once the research design strategy is established, the target population and sample elements to be studied should be ascertained. Therefore the sample design is discussed next.

4.4 PHASE 3: SAMPLE DESIGN

In an ideal world, data would be obtained from each and every individual that could assist in solving the research problem. However, obtaining information from each target population element is difficult, generally due to monetary and time constraints (Malhotra, 2009:370; McDaniel & Gates, 2013:380). Instead, researchers use sampling to gather information from a portion of the target population. Sampling is a procedure used to determine how a portion of the target population, known as the sample, can best represent the entire target population. A sample should have the same characteristics as the target population so that conclusions to be drawn regarding the entire target population (Bradley, 2013:149; Cooper & Schindler, 2014:338; Zikmund *et al*., 2009:68).

Selection of the target population, population elements and the sampling procedure are explained below.

4.4.1 <u>Target population and population elements</u>

The target population is all the respondents from whom information is to be gathered to solve the research problem (Berndt & Petzer, 2011:165; Zikmund *et al.*, 2009:69). The target population consists of population elements, that is, the individuals that are measured to solve the research problem (Cooper & Schindler, 2014:338).

All individuals in the target population should meet specific criteria. The current study's target population was required to:

- be adults (persons over the age of 18);
- reside in South Africa;
- have the ability to independently choose the MNO with whom they had a contract. In some organisations, employees receive benefits, such as a mobile phone with a contract. In such cases the employee has to use the MNO that the organisation selected and is not able to independently select their preferred MNO; and
- have an existing contract with a mobile network operator (MNO) at the time the research was conducted.

Thus, the group of adults that met the above criteria formed the target population, and each individual adult that met the criteria were the population elements.

4.4.2 Sampling

To ensure that a representative sample of the target population is measured, an appropriate sampling method should be chosen. Sampling methods vary in relation to whether a probability or nonprobability sample is drawn. Probability sampling is appropriate when every element in the population has a known, nonzero likelihood of selection. In the case of nonprobability sampling, the likelihood of any particular member of the population being chosen is unknown (Zikmund *et al.*, 2009:395).

Various probability and non-probability sampling methods exist. Convenience and judgement sampling are applicable to the current study. When using judgment sampling, the researcher selects the sample based on characteristics required of the sample. Thus researchers select samples that satisfy their specific purposes, even if the sample is not fully representative (Zikmund *et al.*, 2009:396). The Consulta Research online panel members were asked screening questions to ensure that they met the target population criteria mentioned in Section 4.4.1. If all four criteria were met, the respondents could continue answering the survey, inferring the use of judgement sampling. All Consulta Research online panel members were requested, via email, to participate in the survey.

Thus, a further criterion for inclusion in the sample was that the population elements had to have an email address.

Convenience sampling refers to sampling respondents that are conveniently available. Convenience samples are generally used to obtain a large number of completed questionnaires quickly and economically, or when obtaining a sample via other means is impractical (Zikmund *et al.*, 2009:396). Convenience sampling was used in the current study, since Consulta Research granted permission to use their online panel for data collection.

A slight digression is necessary at this point to explain the term 'online panel' in the context of this study. A panel is defined by Cooper and Schindler (2014:662) as "…a group of … participants who have indicated a willingness to participate in research studies". A panel is generally used to collect data from the same respondents over an extended period of time (Bradley, 2013:115; Cooper & Schindler, 2014:128). However, the current study is cross-sectional, and thus the panel were interviewed only once. Therefore, in the context of this study the term 'panel' refers to the 'group of participants' only and not to longitudinal data collection.

4.4.3 <u>Sample</u>

At the time that the research was conducted, the Consulta Research online panel had 55,224 members. A total of 51% of the panel members were female and 49% were male. In terms of cultural groups, the panel comprised 53% White, 28% African, 11% Coloured, 7% Indian and 1% Asian members. Seven of the official South African languages are represented in the panel, the most common language being English (70%). Income groups ranged from panel members that earned a monthly income of less than R2,500 (9%) to members that earned between R25,001 and R40,000 per month (19%). The panel was represented by all age groups, from a minimum of 18 years of age. The largest age group was the 36-45 year group (28%), followed by the 46-55 year group (24%).

Surveys intend to portray a representative cross-section of a particular target population (Zikmund *et al.*, 2009:188). Although care is taken to include all eligible population elements in the sample, errors in survey research may occur. Errors result in inaccurate conclusions about the target population (Zikmund *et al.*, 2009:69). Thus the following errors in survey research should be considered.

4.4.4 Errors in survey research

Although researchers attempt to avoid research shortcomings, completely eliminating errors is not possible (Bradley, 2013:134; Malhotra, 2009:109). However, suitable strategies can be implemented to decrease shortcomings as far as possible. Two main error categories are sampling error and nonsampling error (systematic sampling error) (Berndt & Petzer, 2011:147; Malhotra, 2009:109; Zikmund & Babin, 2013:319).

4.4.4.1 Sampling errors

Sampling errors occur because a sample is "an imperfect representation of the population of interest" (Malhotra, 2009:371). Sampling error is thus the variation between the results obtained from using a sample rather than the total population (Hair, Black, Babin, Anderson & Tatham, 2014:156; Zikmund & Babin, 2013:319). Sampling error is affected by sample size (Schreiber, 2008:86; Zikmund *et al.*, 2009:188). The smaller the sample size, the higher the likelihood of sampling error, since less cases are compared to the total population (Hair *et al*., 2014:189-190). Sampling error can be decreased by increasing the sample size (Hair *et al*., 2014:190; Zikmund *et al.*, 2009:203). In an attempt to reduce sampling error, this study used a large sample – the target population consisted of 55,224 online panel members.

4.4.4.2 Nonsampling errors

Nonsampling errors occur due to researcher or respondent error (Bradley, 2013:322; Malhotra, 2009:109). Nonresponse bias is a common respondent error which occurs because of non-participation in a study. Should a respondent in the sample either not be located, or be unwilling to participate in the survey, nonresponse bias occurs (Bradley, 2013:322; McDaniel & Gates, 2013:156). Researchers attempt to minimise non-participation, since results can not be generalised if respondents and nonrespondents differ (Armstrong & Overton, 1977:396). Since the Consulta Research panel members voluntarily agreed to regularly participate in surveys, the likelihood of nonresponse error was limited. However, although panel members volunteered to be part of the panel, the possibility exists that some panel members do not regularly participate in the surveys.

Even though nonresponse bias can not be totally eliminated, a test for nonresponse bias can be conducted to establish whether nonresponse bias is present in a sample. An assessment of nonresponse bias is discussed in the data preparation section (see Section 4.6.7).

Researcher errors include sample selection bias and measurement errors. If certain sections of the target population are not represented at all, represented to a lesser degree, or duplicated, sample selection bias (sampling frame error) occurs (Bradley, 2013:323; Malhotra, 2009:372; Zikmund *et al*., 2009:194). Consequently the target population's characteristics are not clearly reflected in the sample, resulting in misleading results (Leedy & Ormrod, 2010:215; McDaniel & Gates, 2013:154). Measurement errors are caused by the use of erroneous or inaccurate measurement scales or ambiguous questions (Bradley, 2013:323; McDaniel & Gates, 2013:155). A well-planned measurement instrument can reduce measurement errors (Hair *et al*., 2014:2). Thus existing measurement scales proven reliable in previous studies, were used in an attempt to reduce measurement error. To detect ambiguity, the pre-test respondents were asked for feedback regarding questions in the survey. The pre-test feedback detected no ambiguous questions.

The preceding section described the target population and sample used to collect the data. The next section discusses the development of the measurement instrument used for data collection.

4.5 PHASE 4: MEASUREMENT INSTRUMENT DESIGN

The purpose of business research is to gather data with a view to describe the characteristics of a specific target population (Zikmund *et al.*, 2009:5). The characteristics that are measured are known as constructs (Cooper & Schindler, 2014:52). Constructs cannot be observed directly or indirectly (Babbie, 2010:129), thus an appropriate measurement scale is required for each construct.

A questionnaire (measurement instrument) is used in survey research for data collection (Berndt & Petzer, 2011:32). The measurement instrument consists of a collection of questions. In turn, each question consists of a measurement scale. The purpose of each measurement scale is to measure a different, but specific construct (Babbie, 2010:129). The next section explains how the constructs are measured, and how the measurement scales for each construct were chosen.

In order to decide upon the measurement scales to be included in the measurement instrument, the following steps were considered (Berndt & Petzer, 2011:181; Cooper & Schindler, 2014:271; Zikmund *et al.*, 2009:335):

1. Identify the constructs to be measured
2. Decide whether existing or new measurement scales will be used
3. Measurement scale reliability and validity
4. Decide on the number of items for each measurement scale
5. Decide on the number of scale points for the measurement scales
6. Consider the dimensionality of the measurement scales
7. Identify the level of measurement associated with each measurement scale
8. Decide on the type of measurement scale response
9. Consider the layout of the measurement instrument

Each point is discussed in the paragraphs to follow. Firstly, the constructs must be identified.

4.5.1 Identify the constructs to be measured

The constructs to be measured must be identified and defined (Hair *et al*., 2014:605). Each construct was discussed in detail in the literature review (Chapter 3). To summarise, the constructs for the current study are switching intention, switching behaviour, relational switching costs, perceived value and alternative attractiveness. Relationship characteristics, namely relationship length, depth and breadth, were also investigated.

4.5.2 Existing versus new scales

To measure the constructs, existing scales were chosen from the literature. One of the main research objectives is to test a conceptual model. Therefore, the use of scales that demonstrated reliability and validity in previous research was essential. As per Pihlström and Brush's (2008:740) study, slight modifications were required to adapt the wording of the measurement scales to suit the mobile telecommunications context. Malhotra and Malhotra's (2013) switching intention scale was used to measure switching intention (Question A5) and switching behaviour (Question B6). Burnham, Frels and Mahajan's (2003) relational switching costs scale was used to measure relational switching costs (Questions A6/B7). Perceived value (Questions A7/B8) was measured using Pihlström and Brush's (2008) perceived (monetary) value scale. Bansal, Taylor and St. James' (2005) alternative attractiveness scale was used for Question A8 and Question B9.

Measurement scales were adapted for each of the three components of relationship characteristics, based on scales used by Maicas, Polo & Sesé (2009b) and were adapted to the mobile telecommunications context. Relationship length (Questions A9/B10) was based on contract length. Relationship depth (Questions A10/B11) was based on estimated monthly spend. Relationship breadth (Questions A11/B12) included three typical mobile telecommunications relationship breadth indicators derived from the literature, and made provision for an open-ended response to gather further information.

To screen respondents, Questions A1/B1 (decision-maker) and Questions A2/B2 (contract or pre-paid) were developed to separate the switching intention sample (N_1) from the switching behaviour sample (N_2) respondents. In addition, Questions A3/B3 (main MNO), Questions A4/B4 (switched or not) and Question B5 (MNO switched from) were designed to gather descriptive information.

Age (Questions A12/B13) was the only demographic question included in the questionnaire. In an attempt to shorten the questionnaire and lower possible respondent fatigue, the remainder of the demographic information was obtained from the Consulta Research database. Demographic data available on the Consulta Research database at the time of the survey was matched to each respondent. Upon completion of data collection, it was concluded that it would have been beneficial to collect the demographic information since the Consulta Research database was not current. As a result, limited demographic information is available, which is noted as a limitation to the study. Table 4.1 summarises the scale sources.

Table 4.1: Measurement scale sources

Construct	Measurement scale source
Screening questions	Own design: based on the target population criteria
Categorisation/branching questions	Own design: developed to obtain descriptive information from the respondents, based on the mobile telecommunications industry
Switching intention	Malhotra & Malhotra, 2013
Relational switching costs	Burnham, Frels & Mahajan, 2003
Perceived value	Pihlström & Brush, 2008
Alternative attractiveness	Bansal, Taylor & St. James, 2005
Relationship length	Own design, adapted from Maicas, Polo & Sesé, 2009b

Construct	Measurement scale source
Relationship depth	Own design, adapted from Maicas, Polo & Sesé, 2009b
Relationship breadth	Own design, adapted from Maicas, Polo & Sesé, 2009b
Demographic question	Age – own design

A well-designed measurement scale is vital for successful data collection and analysis. Ideally measurement scales should provide consistent results and measure only the characteristics which the scale claims to measure (Cooper & Schindler, 2014:257). Thus it is necessary to evaluate reliability and validity of the measurement scales (Hair *et al*., 2014:122; Leedy & Ormrod, 2010:91-92).

4.5.3 Measurement scale reliability and validity

Reliability is a necessary condition for validity (Mooi & Sarstedt, 2011:35; Zikmund *et al*., 2009:306), thus reliability is first considered.

4.5.3.1 Reliability assessment

To ensure reliability, the measurement scale must yield consistent results on each occasion that the construct is measured. Reliability indicates how consistent the measurement scale is in achieving a certain result (Boslaugh, 2013:10; Malhotra, 2009:315; Zikmund & Babin, 2013:257). Reliability can be assessed using a variety of methods, such as test-retest reliability, equivalent form reliability, internal consistency reliability, parallel-forms reliability or split-half reliability (Boslaugh, 2013:11; Hair *et al*., 2014:123; Kline, 2011:69; Leedy & Ormrod, 2010:93; Malhotra, 2009:315; McDaniel & Gates, 2013:286; Zikmund & Babin, 2013:257). The most commonly used reliability measure is internal consistency (Hair *et al*., 2014:213; Zikmund *et al*., 2009:303).

Internal consistency demonstrates the extent to which each measurement item in the measurement scale measures a common meaning and produces a similar result (Leedy & Ormrod, 2010:93; Malhotra, 2009:316; Zikmund & Babin, 2013:257). Internal consistency can be measured using inter-item correlation and item-to-total correlation, the Cronbach's alpha (α) reliability coefficient or composite reliability (Hair *et al*., 2014:123). Cronbach's alpha is the most widely used measure for internal consistency (Hair *et al*., 2014:123; Kline, 2011:69; McDaniel & Gates, 2013:289; Zikmund & Babin, 2013:257) and is thus the method which is elaborated upon. Researchers suggest a range for the Cronbach's alpha value. Values above 0.90 indicate excellent reliability; values between 0.71 and 0.89 indicate good reliability; and values below 0.70 indicate poor reliability (Kline, 2011:70; Zikmund & Babin, 2013:257). The generally accepted 0.70 cut-off criterion for Cronbach's alpha (Peterson, 1994:381) was used in the current study.

The scales which measured the core constructs were tested in previous studies and demonstrated acceptable reliability values. Hence the scales used in the current study were expected to be reliable. Table 4.2 summarises the reliability of each measurement scale used to measure the core constructs in the study. The source of each measurement scale and the reliability value obtained for each measurement scale in previous studies are also included in Table 4.2.

Table 4.2: Measurement scale reliability

Key construct	Measurement scale source	Reliability (Cronbach's alpha)
Switching intention	Malhotra & Malhotra, 2013	α = 0.91
Relational switching costs	Burnham, Frels & Mahajan, 2003	α = 0.87
Perceived value	Pihlström & Brush, 2008	α = 0.86
Alternative attractiveness	Bansal, Taylor & St. James, 2005	α = 0.92

Once reliability is confirmed, the validity assessment can commence.

4.5.3.2 Validity assessment

Validity indicates the ability of the measurement scale to measure the construct that was intended to be measured (Boslaugh, 2013:12; Hair *et al*., 2014:124; Leedy & Ormrod, 2010:28; Mooi & Sarstedt, 2011:34). Zikmund and Babin (2013:258) describe validity as the extent to which a measurement scale “truthfully represents” a construct. False conclusions could be drawn if findings are based on an inaccurate measurement scale (Zikmund & Babin, 2013:258). Thus validity is of great concern to researchers (Zikmund & Babin, 2013:258). To determine measurement scale validity, content validity and construct validity are assessed (Leedy & Ormrod, 2010:92; Malhotra, 2009:316; Zikmund & Babin, 2013:258).

I) Content (face) validity

To determine content validity, the content of each measurement item in the measurement scale should match the definition of the construct being measured (Zikmund & Babin, 2013:258). Content, or face validity, is assessed by experts in the field and confirmed when consensus regarding the match between the measurement scale items and the construct being measured is reached (Hair *et al*., 2014:123; Zikmund & Babin, 2013:258). Content validity must be confirmed prior to data collection (Strasheim, Pitt & Caruana, 2007:109). Thus each measurement item was assessed for content validity to determine whether the measurement item would be applicable not only to the study, but also to the mobile telecommunications industry.

II) Construct validity

Construct validity determines to what extent a measurement scale measures a construct that can not be directly observed, but is thought to exist (Boslaugh, 2013:546; Leedy & Ormrod, 2010:92). Thus construct validity assesses which construct the scale is in actual fact measuring (Malhotra, 2009:317). A construct validity assessment has three main components, namely convergent, discriminant and nomological validity (Hair *et al*., 2014:124; Malhotra, 2009:317; Strasheim *et al*., 2007:105). Each construct validity component is discussed below.

Convergent validity indicates the extent to which measurement items in a measurement scale measure the same construct (Hair *et al*., 2014:124; Kline, 2011:71; Malhotra, 2009:317). High correlations between the measurement items indicate that the measurement scale measures the construct that the scale intended to measure (Hair *et al*., 2014:124; Kline, 2011:71). Convergent validity is dependent on internal consistency (Zikmund & Babin, 2013:260). In turn, internal consistency is assessed through reliability. In the current study, convergent validity was established by considering the Cronbach's alpha reliability coefficient.

Discriminant validity indicates whether constructs are conceptually distinct (Hair *et al*., 2014:124; Malhotra; 2009:317; Zikmund & Babin, 2013:260). Discriminant validity thus assesses correlations between the measurement scales in the measurement instrument, in contrast to convergent validity, which assesses correlations between the measurement items in the measurement scale. Low construct inter-correlations indicate sufficient discriminant validity (Hair *et al*., 2014:124; Kline, 2011:72; Zikmund & Babin, 2013:260). Ideally constructs should be independent from one another, so that each construct measures a specific concept (Hair *et al*., 2014:124; Kline, 2011:72; Zikmund & Babin, 2013:260). In the current study discriminant validity was assessed during the exploratory factor analysis (EFA) (refer to Section 4.7.3.1).

Nomological validity assesses the degree to which the measurement scales correlate to measure constructs that are different, yet related (Hair *et al*., 2014:124; Malhotra, 2009:317). Relationships between the constructs should be justified by theory and previous research, after which the scales in the measurement instrument should be assessed for corresponding relationships (Hair *et al*., 2014:124). The structural part of the SEM is well-suited to assess nomological validity (Anderson & Gerbing, 1988:411; Schumacker & Lomax, 2010:114), because nomological validity essentially assesses relationships between variables as posited by theory, as does SEM (Malhotra, 2009:317). Goodness-of-fit indices are used as indicators of nomological validity, since these indices show how well the collected data fits a hypothesised conceptual model (Mackay, 2012:158). Nomological validity is assessed during the evaluation of model fit.

The measurement scales used to measure the core constructs in the current study were shown to be valid in previous studies (Burnham *et al*., 2003:120), therefore construct validity was expected. However, as is customary, construct validity was assessed. Various methods are used to assess construct validity, for example a multitrait-multimethod (MTMM) matrix analysis or multivariate SEM-based methods such as CFA (Cooper & Schindler, 2014:257; Hair *et al*., 2014:124). As is discussed in Section 4.7.3.2, SEM is a powerful multivariate data analysis technique that is able to examine the validity and reliability of the measurement scales for each construct, while also testing direct and indirect relationships between constructs (Schreiber, 2008:85). SEM has two components, namely a measurement model and a structural model. The measurement part of the SEM is used for the assessment of convergent and discriminant validity and the structural part of the SEM is used to assess nomological validity (Anderson & Gerbing, 1988:411; Schreiber, 2008:91). SEM is thus a “comprehensive confirmatory assessment of construct validity” (Bentler, 1978, in Anderson & Gerbing, 1988:411).

4.5.4 Number of measurement scale items

Due to the anticipated use of structural equation modeling (SEM) as a data analysis technique (see Section 4.7.3.2), all scales had to have a minimum of three measurement items (Hair *et al*., 2014:614; Iacobucci, 2010:92). If one of the measurement items need to be deleted from the measurement scale due to validity and/or reliability issues, unidimensionality can not be determined with only the two remaining measurement items (Hair *et al*., 2014:614; Iacobucci, 2010:92). Thus only scales with three items or more were considered.

4.5.5 Number of scale points

The number of points to use on a rating scale is a popular topic of debate between academics and practitioners alike (Cooper & Schindler, 2014:273). Rating scales typically use either 5-point scales, 7-point scales or more (Cooper & Schindler, 2014:274). The more scale points, the more sensitive and accurate the scale is (Leedy & Ormrod, 2010:27). An 11-point scale was used for the study, numbered from 0 to 10, where 0 = do not agree at all, and 10 = completely agree.

4.5.6 Dimensionality

Items in a measurement scale that represent a single construct and are strongly associated with one another indicate unidimensionality. Unidimensional scales are preferable, since discriminant and convergent validity are more accurately tested when using unidimensional models (Kline, 2011:115). A multidimensional scale consists of a construct with underlying factors (dimensions) which together measure the construct better, but can not measure the construct if each dimension is measured separately (Cooper & Schindler, 2014:272; Hair *et al*., 2014:123; McDaniel & Gates, 2013:305).

It should be noted that the relational switching cost scale is a sub-scale of the multidimensional switching cost scale designed by Burnham, Frels and Mahajan (2003). The original scale measures switching costs using three dimensions, namely procedural, financial and relational switching costs (Burnham *et al*., 2003:112). The researcher was cognisant of the fact that Burnham *et al.* (2003) and Hu and Hwang (2006) indicated that the relational switching costs scale consisted of two dimensions, namely personal relationship loss and brand relationship loss. However, subsequent research used the relational switching cost scale independently as a unidimensional scale (Vasudevan *et al*., 2006). Therefore, given the study's relationship marketing focus, and the fact that the relational switching costs scale has been used as an independent unidimensional scale in previous research, the scale was used autonomously in the current study.

4.5.7 Level of measurement

The four levels of measurement are categorised into nominal, ordinal, interval and ratio data (Leedy & Ormrod, 2010:25; McDaniel & Gates, 2013:280). Each level of measurement possesses certain characteristics. The lowest level, nominal data, possess only classification characteristics. Ordinal data have order and classification characteristics. Interval data have distance, order and classification characteristics. Lastly, ratio data possess all four characteristics (Cooper & Schindler, 2014:250). Each individual level of measurement is discussed in more detail below.

4.5.7.1 Nominal scales

Nominal scales collect categorical data, which groups the information collected into mutually exclusive and collectively exhaustive categories (Cooper & Schindler, 2014:250; McDaniel & Gates, 2013:280). Each category can be assigned a name or label (Hair *et al*., 2014:5; Leedy & Ormrod, 2010:25). Despite being considered statistically weak, nominal data can be used to uncover relationships (Cooper & Schindler, 2014:252). Dichotomous questions, multiple-choice single-response questions and checklists produce nominal data (Cooper & Schindler, 2014:275). Demographic data are typically collected using a nominal scale (Cooper & Schindler, 2014:252).

In the measurement instrument Questions A1/B1 (decision-maker), Questions A2/B2 (contract or pre-paid) and the branching questions – Questions A3/B3 (main MNO), Questions A4/B4 (switched or not) and Question B5 (MNO switched from) – collected nominal data. The relationship characteristic questions, namely relationship length (Questions A9/B10), relationship depth (Questions A10/B11) and relationship breadth (Questions A11/B12) also collected nominal data.

The second level of measurement is ordinal scales.

4.5.7.2 Ordinal scales

In addition to categorising data, ordinal scales also indicate that one category is greater than, less than, or equal to another. Thus variables in ordinal scales can be ranked (Cooper & Schindler, 2014:252; Hair *et al*., 2014:5; Leedy & Ormrod, 2010:26; McDaniel & Gates, 2013:281). Ordinal scales, however, do not provide actual values to indicate how much more or less one category is than the other (Cooper & Schindler, 2014:252). For example, income could be grouped into "low, medium, high", indicating a rank order (Mooi & Sarstedt, 2011:91). But the actual numerical amount by which one category is greater than or less than another can not be indicated. Multiple-choice single-response questions that have some form of ranking collect ordinal data (Cooper & Schindler, 2014:275).

Two of the relationship characteristics questions, that is, relationship length (Questions A9/B10) and relationship depth (Questions A10/B11) collected ordinal data.

The third level of measurement category is interval scales.

4.5.7.3 Interval scales

Interval data have all the characteristics of the aforementioned levels of measurement, and incorporate "equality of intervals" (Cooper & Schindler, 2014:253). Therefore interval scales are said to indicate equi-distant points on a scale. Unlike ratio scales that indicate an absolute zero point (elaborated upon in the next paragraph), interval scales indicate an arbitrary zero point (Hair *et al*., 2014:6). The arbitrary zero point allows inferences to be made about one scale point being more or less than another. However, the magnitude of the difference between the scale points can not be indicated (McDaniel & Gates, 2013:283).

Researchers typically use interval scales to measure attitudes (Cooper & Schindler, 2014:253). Even though rating scales such as Likert-type scales are strictly ordinal in a mathematical sense, marketing research treats Likert-type scales with 5 or more points as interval scales due to the underlying continuum of equi-distant points (Zikmund & Babin, 2013:254). The more points on the Likert-type scale, the more sensitive and accurate the scale is, since the high number of scale points gives a more refined measurement (Leedy & Ormrod, 2010:27). Thus the ordinal data approach the characteristics required for interval measurement (Cooper & Schindler, 2014:252).

The study used 11-point Likert-type scales to measure the four constructs: switching intention (Questions A6/ B7), relational switching costs (Question A7/ B8), perceived value (Question A8/ B9) and alternative attractiveness (Question A9/B10).

4.5.7.4 Ratio scales

Ratio scales incorporate categories (nominal scales), a ranked difference between the categories (ordinal scales), equal measurement units (interval scales) and are able to measure origin (Cooper & Schindler, 2014:253; Leedy & Ormrod, 2010:27; McDaniel & Gates, 2013:283). Thus ratio scales measure actual amounts such as height, weight and distance (Cooper & Schindler, 2014:253). As a result, the magnitudes among ratio-scaled data can be compared (McDaniel & Gates, 2013:283).

The scale used to measure age (Questions A12/B13) uses a ratio level of measurement.

The data generated by each level of measurement dictates which statistical procedures can be used for data analysis (Zikmund *et al.*, 2009:296). Thus the appropriate statistical techniques should be taken into consideration when the measurement instrument is developed, and not once the data has been collected.

Once the existing measurement scale has been identified, the type of measurement scale response is considered.

4.5.8 <u>Measurement scale response type</u>

Depending on the information required, the researcher can make use of ranking (comparative) or rating (non-comparative) scales, or categorical or sorting scales (Cooper

& Schindler, 2014:271). Only rating scales, namely dichotomous questions, multiple-choice single-response questions, multiple-choice multiple-response (checklist) questions and Likert-type scales were used in the study (Cooper & Schindler, 2014:275-279). Section 4.5.8 concludes with Table 4.3 which provides a summary of the variables investigated in both measurement instruments, the type of measurement scale used to measure each variable, the response type and the level of measurement for each variable.

Table 4.3: Measurement scale, response type and corresponding level of measurement

Q A	Q B	Variable	Measurement scale	Response type	Level of measurement
A1	B1	Decision-maker	Dichotomous	Categorical	Nominal
A2	B2	Contract or pre-paid	Dichotomous	Categorical	Nominal
A3	B3	Main MNO	5 item, multiple-choice, single-response	Categorical	Nominal
A4	B4	Switched or not	Dichotomous	Categorical	Nominal
	B5	MNO switched from	5 item, multiple-choice, single-response	Categorical	Nominal
A5	B6	Switching intention/Switching behaviour	5 item, 11 point Likert scale	Rating	Interval
A6	B7	Relational switching costs	7 item, 11 point Likert scale	Rating	Interval
A7	B8	Perceived value	3 item, 11 point Likert scale	Rating	Interval
A8	B9	Alternative attractiveness	4 item, 11 point Likert scale	Rating	Interval
A9	B10	Relationship length	9 item, multiple-choice, single-response	Rank	Ordinal
A10	B11	Relationship depth	16 item, multiple-choice, single-response	Rank	Ordinal

Q A	Q B	Variable	Measurement scale	Response type	Level of measurement
A11	B12	Relationship breadth	Combination: 4 item multiple-choice, single-response; single item open-ended	Categorical	Nominal
A12	B13	Age (in years)	1 item, multiple-choice, single-response	Rank	Ratio

Once the most appropriate and reliable scales are chosen, the layout of the measurement instrument is planned, as explained in the section to follow.

4.5.9 Layout of the measurement instrument

Important points to consider when designing the measurement instrument is that it should provide clear instructions, be as brief as possible and simple to read. The measurement instrument should also use simple, clear and unambiguous language (Bradley, 2013:214; Leedy & Ormrod, 2010:194). A long measurement instrument should collect the most important information first, since respondents may lose concentration or stop answering the survey. Sensitive questions, such as age, income and other demographic questions may cause respondents to stop answering the survey and should therefore be placed at the end of the measurement instrument (Bradley, 2013:214; Cooper & Schindler, 2014:317-320).

Two separate measurement instruments were developed. Questionnaire A was designed to collect the switching intention data and Questionnaire B was designed to collect actual switching behaviour data. The layout of the two measurement instruments is very similar, however, the switching intention questionnaire (Questionnaire A) has 19 questions while the switching behaviour questionnaire (Questionnaire B) has 20 questions. The extra question in the switching behaviour questionnaire (Questionnaire B) measured *from* which MNO the switching behaviour sample (N_2) had switched. The questions are in the same order, and contain the same sub-sections: screening questions; categorisation; branching; construct measurement; and demographics. The complete measurement instruments are included in Appendix B. Each section of the measurement instrument is described below.

Section 1: Screening

Screening questions are used to determine whether the respondent qualifies as part of the target population (Cooper & Schindler, 2014:316). Respondents had to fulfil certain criteria in order to participate in the survey (see Section 4.4.1). All Consulta Research online panel members were adults residing in South Africa, thus the online panel members automatically met the first two criteria. Consequently, the only two criteria that had to be screened were i) whether the respondents were able to independently choose their MNO, and ii) whether or not the respondent had a contract with a MNO at the time of completing the survey. Questions A1/B1 (decision-maker) and A2/B2 (contract or pre-paid) were used as screening questions. Respondents that answered no to either of the two aforementioned questions were thanked for their time and the survey ended.

Section 2: Categorisation

Next the respondents were asked to identify their main MNO. The purpose for asking the question was twofold. Firstly, the possibility exists that respondents have contracts with more than one MNO. Thus the question orientated the respondents to answer the questions exclusively about their main MNO. Secondly, the Survey Workbench programme has an advanced function which is able to include the name of the respondents' main MNO in all the questions that follow. Mentioning the MNOs name in each question enhances the survey experience for the respondent. Questions A3/B3 (main MNO) were used in Section 2.

Section 3: Branching

Branching questions direct respondents to questions that are relevant to them (Bradley, 2013:214). The respondents were asked whether or not they had switched MNOs during the previous six months. Depending on the response, respondents were branched to either the switching intention questionnaire (Questionnaire A) or the switching behaviour questionnaire (Questionnaire B). Questions A4/B4 (switched or not) were the questions used in the branching section.

After separating the two groups, respondents that had switched were also asked *from* which MNO they switched – Question B5 (MNO switched from). The Survey Workbench programme then included the name of the MNO from which the respondent had switched in all relevant questions.

Section 4: Construct measurement

Respondents were asked the same questions regarding each construct, but the question wording of the two measurement instruments differed slightly. The questions for the switching intention respondents (Questionnaire A) remained similar to the original scales, but the wording of the switching behaviour questionnaire (Questionnaire B) were changed into the past tense.

The constructs were measured using Questions A5/B6 (switching intention/switching behaviour), Questions A6/B7 (relational switching costs), Questions A7/B8 (perceived value) and Questions A8/B9 (alternative attractiveness). The relationship characteristics questions were separated into three parts: relationship length (Questions A9/B10), relationship depth (Questions A10/B11) and relationship breadth (Questions A11/B12).

Section 5: Demographics

The measurement instrument concluded with a demographic question for age (Questions Q12/B13).

Table 4.4 provides a summary of the five sections of both measurement instruments and the variables that were measured in each section.

Table 4.4: Five sections of the measurement instruments

MEASUREMENT INSTRUMENT SECTIONS	
Questionnaire A: Switching intention	**Questionnaire B: Switching behaviour**
SECTION 1: SCREENING	
A1: Decision-maker (independently choose network) A2: Contract or pre-paid	B1: Decision-maker (independently choose network) B2:Contract or pre-paid
SECTION 2: CATEGORISATION	
A3: Main mobile network operator with whom have contract	B3: Main mobile network operator with whom have contract

SECTION 3: BRANCHING	
A4: Switched or not	B4: Switched or not B5: Switched from whom
SECTION 4: CONSTRUCT MEASUREMENT	
A5: Switching intention A6: Relational switching costs A7: Perceived value A8: Alternative attractiveness A9: Relationship length A10: Relationship depth A11: Relationship breadth	B6: Switching behaviour B7: Relational switching costs B8: Perceived value B9: Alternative attractiveness B10: Relationship length B11: Relationship depth B12: Relationship breadth
SECTION 5: DEMOGRAPHICS	
A12: Age)in years)	B13: Age in years

Once the measurement layout has been planned, it is useful to verify whether all of the questions included in the measurement instrument will address all of the hypotheses and in turn, the research objectives. As a precautionary measure, such an inspection was performed. Table 4.5 provides a summary of each research objective and the associated hypothesis, as well as the appropriate measurement scale in the measurement instrument is to be used to measure the research objective.

Table 4.5: Research objectives and associated hypothesis

Research objective and associated hypothesis	Questionnaire A: Switching intention	Questionnaire B: Switching behaviour
To investigate the relationship between relational switching costs and switching intention. H_{1a}: There is a negative relationship between relational switching costs and switching intention. To investigate the relationship between relational switching costs and switching behaviour. H_{1b}: There is a negative relationship between relational switching costs and switching behaviour.	A5 & A6	B6 & B7
To investigate the relationship between perceived value and switching intention. H_{2a}: There is a negative relationship between perceived value and switching intention. To investigate the relationship between perceived value and switching behaviour. H_{2b}: There is a negative relationship between perceived value and switching behaviour.	A5 & A7	B6 & B8

Research objective and associated hypothesis	Questionnaire A: Switching intention	Questionnaire B: Switching behaviour
To investigate the relationship between alternative attractiveness and switching intention. H_{3a}: There is a positive relationship between alternative attractiveness and switching intention. To investigate the relationship between alternative attractiveness and switching behaviour. H_{3b}: There is a positive relationship between alternative attractiveness and switching behaviour.	A5 & A8	B6 & B9
To investigate the relationship between relational switching costs and perceived value. H_{4a}: There is a relationship between relational switching costs and perceived value in a switching intention context. To investigate the relationship between relational switching costs and perceived value. H_{4b}: There is a relationship between relational switching costs	A6 & A7	B7 & B8
To investigate the relationship between relational switching costs and alternative attractiveness. H_{5a}: There is a relationship between relational switching costs and alternative attractiveness in a switching intention context. To investigate the relationship between relational switching costs and alternative attractiveness. H_{5b}: There is a relationship between relational switching costs and alternative attractiveness in a switching behaviour context.	A6 & A8	B7 & B9
To investigate the relationship between perceived value and alternative attractiveness. H_{6a}: There is a relationship between perceived value and alternative attractiveness in a switching intention context. To investigate the relationship between perceived value and alternative attractiveness. H_{6b}: There is a relationship between perceived value and alternative attractiveness in a switching behaviour context.	A7 & A8	B8 & B9
To investigate the relationship between relationship length and switching intention. H_{7a}: There is a negative relationship between relationship length and switching intention. To investigate the relationship between relationship length and switching behaviour. H_{7b}: There is a negative relationship between relationship length and switching intention.	A5 & A9	B6 & B10

Research objective and associated hypothesis	Questionnaire A: Switching intention	Questionnaire B: Switching behaviour
To investigate the relationship between relationship depth and switching intention. H_{8a}: There is a negative relationship between relationship depth and switching intention. To investigate the relationship between relationship depth and switching behaviour. H_{8b}: There is a negative relationship between relationship depth and switching behaviour.	A5 & A10	B6 & B11
To investigate the relationship between relationship breadth and switching intention. H_{9a}: There is a negative relationship between relationship breadth and switching intention. To investigate the relationship between relationship breadth and switching behaviour. H_{9b}: There is a negative relationship between relationship breadth and switching behaviour.	A5 & A11	B6 & B12

Once the research objectives to be answered are confirmed, data collection can commence. The next section explains the data collection procedure.

4.6 PHASE 5: DATA COLLECTION AND PREPARATION

Prior to actual data collection, the measurement instrument is pre-tested to check for errors. Adherence to ethical research methods is also an important consideration. Pre-testing and research ethics are discussed in the ensuing paragraphs, followed by a discussion regarding the cover letter sent to all respondents, the time period during which the data were collected and the survey response rate.

4.6.1 Pre-testing

A pre-test is conducted to investigate whether the measurement instrument is understandable, easy to use, and to detect ambiguities (Zikmund *et al.*, 2009:361). A live pre-test was conducted, meaning that the actual online survey, and not a paper-based format online survey, was pre-tested. Pre-testing was conducted in three phases. Phase 1: the researcher completed both the switching intention and switching behaviour surveys to check whether all the questions were uploaded correctly, whether the instructions were clear and easy to follow, whether there were any spelling or grammar errors and whether the branching worked correctly. Phase 2: 43 colleagues, family and friends were asked to complete the survey and to provide feedback, with possible suggestions for improvement. Changes were made to the measurement instrument after both phases. As suggested, a progress indicator was included in the online survey. A progress indicator shows respondents how close they are to completing the survey. Bradley (2013:217) suggests that adding a progress bar to an online survey is good practice. The online pre-test indicated that the survey took approximately 5 minutes to complete. So, as respondents completed the survey, the progress bar indicated what percentage of questions had been completed. Phase 3: the survey was sent to 300 Consulta Research online panel members. None of the online panel members suggested changes.

4.6.2 Research ethics and informed consent

Research ethics are an important consideration when designing a research project. Researchers must ensure that participants are protected from harm, give consent to participate in the study and are informed of the purpose of the study (Leedy & Ormrod, 2010:101-104). The Research Ethics Committee of the Faculty of Economic and Management Sciences at the University of Pretoria granted ethical clearance prior to data collection (see Appendix C).

Ethical procedures require researchers to obtain informed consent from potential participants to indicate that they wish to participate in the survey. Upon registration with the Consulta Research panel, members go through a double opt-in process, thus confirming twice to regularly participate in surveys. ‘Opt-in’ means that permission is given to be solicited for survey participation (Zikmund & Babin, 2013:321). The registration procedure clearly explains that participation in any survey is voluntary and that panel members have the option to withdraw from the panel at any time. Thus, since panel members give ‘overall’ consent to participate in all Consulta Research surveys, by implication, consent had already been received from all panel members. Therefore respondents were not required to complete another consent form for the current survey.

See Appendix D for an example of the Consulta Research online panel registration and consent form. Furthermore, every survey gives panel members the option to unsubscribe from that particular survey or from the entire Consulta Research panel.

4.6.3 Cover letter

Cover letters are essential for self-completion surveys to: introduce the survey topic; describe the purpose of the survey and the type of information required of respondents; provide instructions on how to complete the survey; and to provide the estimated time required to complete the survey (Bradley, 2013:194). Such information was provided in the email invitation (see Appendix E)sent to the Consulta Research online panel members.

4.6.4 Time period and incentives

As suggested by Consulta Research, the data were collected over a period of seven days. The time period is in line with Bradley's (2013:114) suggestion that online fieldwork should be between one and seven days. The survey was sent out on 29 October 2013. After four days, a reminder email was sent to respondents. The survey was closed on 5 November 2013.

Incentives are used to encourage respondents to complete a survey. Examples of incentives are automatic entries into a competition, prize draws, gifts or charity donations on behalf of the respondent, As per the regulations of the Research Ethics Committee of the Faculty of Economic and Management Sciences at the University of Pretoria, no incentives or rewards were offered to respondents, since the possibility exists that an incentive could bring about biased cooperation from the respondent (Bradley, 2013:194).

4.6.5 Response rate

The Consulta Research online panel had 55,224 members at the time of the study. During the live pre-test, the survey was sent to 300 online panel members. The actual survey was sent to the remaining 54,924 online panel members. A total of 1,668 surveys were returned, thus a response rate of 3% was realised. The observations were separated into switching intention observations (N_1 = 1,483) and switching behaviour observations (N_2 = 185). One would expect a high response rate from a panel that has volunteered to regularly complete surveys, however this was not the case. A possible contributing factor toward the low response rate is that no incentives were given. The Consulta Research online panel members are accustomed to receiving incentives and so may have been reluctant to complete a survey that did not offer a potential reward.

Once the data are collected, preparation for data analysis commences. The section to follow explains how the data were edited, coded and captured.

4.6.6 <u>Data preparation</u>

Before data analysis, the data are converted from the responses obtained in the survey, into a format that can be analysed. Quantifying the measurement instrument assists the researcher to convert the words and/or statements in the measurement instrument into numbers that can be analysed statistically. The quantification procedure is described below.

4.6.6.1 Data capturing

Data capturing is used to convert the information collected into a format that can be used for data analysis (Cooper & Schindler, 2014:391). The codes that were assigned to each question are entered into a matrix-type format. The Survey Workbench programme automatically entered responses into a matrix format as soon as each online survey was completed. Once the survey was closed, the researcher received the data extract in MS Excel format, which eliminated traditional data capturing by hand. Automatic data capturing is highly advantageous, since errors in data capturing are avoided and the data are instantaneously available.

4.6.6.2 Data editing

Editing ensures that errors are detected and that answers are accurate and complete (Bradley, 2013:313; Cooper & Schindler, 2014:441). The possibility exists that data were omitted (Bradley, 2013:314). Thus cases were inspected to identify incomplete or unreliable cases, since incomplete cases negatively influence data validity (Bradley, 2013:313). To deal with missing values, the respondent could be contacted to verify the missing information, or case wise or pairwise deletion could be used (Byrne, 2010:355-356). Case wise deletion implies completely deleting all cases that have a missing value for any of the variables in the data. Pairwise deletion excludes missing cases for certain analyses but cases are kept for other analyses (Byrne, 2010:355-356). Both case wise and pairwise deletion were used. Cases with incomplete demographic information were not discarded (pairwise deletion) since the demographic data were not incorporated into the SEM model and were also not the focus of the study. However, cases with missing values for the constructs were deleted (case wise deletion). Once the case wise deletion was complete, a usable sample of switching intention observations (N_1 = 1,025) and switching behaviour observations (N_2 = 163) remained.

4.6.6.3 Data coding

When coding, numbers (or symbols) are assigned to the responses to facilitate grouping the responses into categories (Cooper & Schindler, 2014:379). Generally closed-ended questions are pre-coded (Bradley, 2013:314; Cooper & Schindler 2014:380). Open-ended questions are coded after data collection because researchers do not know what categories may arise from the data (Cooper & Schindler, 2014:382). To code open-ended questions, words or phrases that commonly occur in the answers are identified, after which common elements are assigned the same code to form a new category (Bradley, 2013:314). Researchers should be mindful that the same answer can be given in many different ways, therefore open-ended questions have to be carefully analysed to form mutually exclusive categories and avoid category duplication (Cooper & Schindler, 2014:382).

Only the age question and the Likert-type scale questions generated numeric responses. All other questions had to be coded. To code the open-ended relationship breadth questions (Questions A11/B12), answers with similar content were combined to form categories. Four new categories were created for additional services purchased by respondents, namely: i) additional airtime; ii) BlackBerry Internet Service (BIS) including BBM (BlackBerry Messenger); iii) insurance (mobile phone/sim card); iv) laptop or tablet with data contract.

4.6.6.4 Reverse-scoring

If the value assigned to a scale item is opposite to that of the other items, that value should be changed into the same direction before data analysis, otherwise the average scale value can not be calculated because items with positive values will cancel out items with negative values (Hair *et al*., 2014:91; Zikmund & Babin, 2013:256). Hence the need for reverse scoring – the procedure used to change items into the same direction.

Question A5_1 in the switching intention questionnaire (Questionnaire A) was reverse-scored, while Questions B6_1, B7_2 and B8_3 in the switching behaviour questionnaire (Questionnaire B) were reverse-scored.

4.6.7 Assessment of nonresponse bias

As a final measure of data preparation, a test for nonresponse bias was performed. As mentioned in the sample discussion (see Section 4.3.3), nonresponse bias occurs due to non-participation in a study. If nonresponse bias is present, results can not be generalised, since respondents differ from nonrespondents (Armstrong & Overton, 1977:396). Due to the low response rate (3%) a test for nonresponse bias was deemed necessary.

Since the study was conducted online, the dataset contained the date and precise time of completion for each respondent. Hence respondents could be grouped according to date and time of completion. The data were then placed in to four equal groups (known as quartiles). The first quartile – the first 25% of respondents to complete the survey – were compared to the last quartile of respondents (the last 25% of respondents to complete the survey). The objective was to find no difference between the sample profiles of the first and last quartiles to indicate that the likelihood of nonresponse bias was low or absent. Armstrong and Overton (1977:397) suggest that the last respondents to complete surveys are similar to nonrespondents. Thus, examining the last respondents could assist researchers to predict the composition of the nonrespondent sample. By implication, comparing the last respondents to the first respondents indicates whether a difference exists between the survey respondents and nonrespondents.

A common method used to examine relationships (associations) between two or more categorical variables is the Pearson Chi-square test for independence (Boslaugh, 2013:127). The Pearson Chi-square test for independence tests the null hypothesis that no relationship exists between two variables (Boslaugh, 2013:127). Consequently, the following null hypothesis was formulated to conduct the nonresponse bias test.

$H_{10(null)}$: There is no association between the first and last quartile group of respondents with regard to all the variables of interest.

The decision rule for the hypothesis was that if the Pearson Chi-square test for independence was not significant (p-value > 0.05), there was no difference between the first and last quartile of respondents. Alternatively, should the Pearson Chi-square test for independence be significant (p-value < 0.05), nonresponse bias may be present, thus indicating a possible difference between the first quartile and last quartile of the sample.

Using the Pearson Chi-square test for independence for the contingency tables, the first and last quartile were compared using various variables of interest, for example ‘main MNO’ or demographic variables. The results of the Pearson Chi-square tests for independence are presented in Table 4.6.

Table 4.6: Results for the assessment of nonresponse bias

Independent variables	Chi-square value (χ^2)	*df*	Significance ($p > 0.05$)
Main mobile network operator	2.667	4	0.615
Gender	2.565	1	0.109
Ethnicity	4.576	5	0.470
Preferred language	5.742	5	0.332
Education level	4.987	7	0.662
Employment status	6.023	6	0.421
Personal monthly income	13.46	11	0.264
Monthly household income	13.06	10	0.220

None of the independent variables (variables of interest) were significant. Therefore, the null hypotheses that there is no association between the first and last quartile group of respondents with regard to all the variables of interest, is supported. Thus, the conclusion can be made that nonresponse bias is not present in the current study, since there was no association between the first and last quartile group of respondents with regard to all the variables of interest.

Once data preparation was complete, the data were ready for analysis. The ensuing sections explain the data analysis techniques that are implemented in Chapter 5. Univariate data analysis techniques were used to derive descriptive statistics for the switching intention sample and the switching behaviour sample. Multivariate data analysis techniques were used to test the conceptual switching intention model, to compare the conceptual switching intention model and actual switching behaviour data, to explore the role of relationship characteristics and their influence on both switching intention and switching behaviour, and to conduct hypothesis testing.

4.7 PHASE 6: DATA ANALYSIS

Data are analysed to obtain the information needed to solve the research objectives, and to discover and confirm meaningful relationships (Bradley, 2013:319). Datasets are generally described using univariate, bivariate and multivariate analysis. Univariate analysis investigates only a single variable while bivariate analysis investigates the relationship between two variables. Multivariate statistical analysis techniques are an extension of univariate and bivariate analysis techniques (Hair *et al*., 2014:4). Multivariate analysis investigates relationships between three or more variables with the aid of advanced statistical techniques (Leedy & Ormrod, 2010:282). The next section discusses typical univariate descriptive statistics, followed by an examination of multivariate data analysis techniques. The chapter concludes with an explanation of hypothesis testing.

4.7.1 <u>Phase 6.1: Descriptive statistics</u>

Descriptive statistics are used as preliminary tools to describe a body of data (Cooper & Schindler, 2014:398; Leedy & Ormrod, 2010:265). The paragraphs below discuss the types of descriptive statistics that are used in the results chapter (Chapter 5). Since visual inspection of the data facilitates interpretation of the basic descriptive statistics (Cooper & Schindler, 2014:407), the use of frequency tables, cross-tabulations and graphs is also discussed. Descriptive measures, namely measures of central tendency, measures of spread, and measures of symmetry, are used as preliminary tools to describe the data set (Cooper & Schindler, 2014:398). Each descriptive measure is explained in the section to follow.

4.7.1.1 Measures of central tendency

Measures of central tendency indicate the midpoint of the distribution and thereby establish the central point around which data revolve (Leedy & Ormrod, 2010:265; Malhotra, 2009:484). Three commonly used measures of central tendency are the mode, median and mean (Leedy & Ormrod, 2010:265). The mode indicates the variable that occurs most frequently (not reported in the results). The median is the numerical centre of the data and has exactly the same number of scores above and below it. Medians are typically used to determine the midpoint of financial variables, such as income. The mean represents the average response (Cooper & Schindler, 2014:400). Both the median (*Mdn*) and the mean (*M*) were reported for the Likert scales in this study, and also for the nominal scales that were converted to quantitative numerical scale using midpoints.

4.7.1.2 Measures of spread

Measures of spread (also known as measures of variability or measures of dispersion) measure the variations of scores, and thus “describe how scores cluster or scatter in a distribution” (Boslaugh, 2013:90; Cooper & Schindler, 2014:401). Three measures of spread are the range, standard deviation and variance. The range indicates the spread of the data from the lowest to the highest value (Leedy & Ormrod, 2010:269). The variance indicates the spread around the mean – the greater the spread, the greater the variance (Cooper & Schindler, 2014:401). Variance can be used in addition to, or instead of the standard deviation (Leedy & Ormrod, 2010:270). Neither the range nor the variance were reported in the results.

The standard deviation (*SD*) is a more commonly used measure of variability (Leedy & Ormrod, 2010:270) and was reported during data analysis (see Chapter 5). Standard deviation indicates how much the data varies from the average data (Cooper & Schindler, 2014:401). That is, the standard deviation indicates how clustered or spread the distribution is around the mean (Malhotra, 2009:486). If the values are close to the mean, the standard deviation is small, implying consistency in the data. However, if the values are far from the mean, the high standard deviation indicates inconsistency or variance, meaning that a difference exists between respondents in the sample.

4.7.1.3 Measures of symmetry

Measures of symmetry, also known as assessment of normality, indicate whether a distribution is symmetrical or skewed (Gravetter & Wallnau, 2013:50). When the mean, median and mode are in the same location, the distribution is symmetrical and the curve is said to have normal distribution (Leedy & Ormrod, 2010:263). If the distribution ‘leans’ toward the right or left, the distribution is skewed, or nonnormal (Cooper & Schindler, 2014:402; Gravetter & Wallnau, 2013:50; Leedy & Ormrod, 2010:264). A distribution is positively skewed if the peak of the curve lies to the right of the midpoint, and negatively skewed if the curve’s peak lies to the left of the midpoint (Leedy & Ormrod, 2010:264).

If the skewness of the distribution is less than 2.00, the data falls within acceptable limits of normality (Schreiber, 2008:88).

Apart from considering the symmetry or skewness of the distribution, the peakedness or flatness is also assessed. Kurtosis is a measure of how peaked or flat the distribution curve is (Cooper & Schindler, 2014:402; Kline, 2011:60). An unusually peaked or pointy curve is called a leptokurtic curve and an unusually flat curve is called a platykurtic curve (Kline, 2011:60; Leedy & Ormrod, 2010:264). If the curve is neither too peaked, nor too flat, the curve is described as mesokurtic (Cooper & Schindler, 2014:402). If the kurtosis of the distribution is less than 7.00, the data falls within acceptable limits of normality (Byrne, 2010:103). The skewness and kurtosis are reported and discussed for each construct in the SEM model, and is also reported with each Likert-type scale.

4.7.1.4 Frequency distributions

Frequency distributions are tables used to arrange numerical data into a data array. Frequency tables generally report frequency, percent, valid percent and cumulative percent (Cooper & Schindler, 2014:407; Malhotra, 2009:480). In the current study, the frequency and valid percent were reported for every question in the measurement instrument; however, tables were only included where appropriate.

4.7.1.5 Cross-tabulations

Cross-tabulations are used to compare two or more categorical variables simultaneously (Cooper & Schindler, 2014:419; Malhotra, 2009:493). Cross-tabulations with two variables include every possible combination of the categories of the two variables being compared (Malhotra, 2009:493). Cross-tabulations were not pursued, because the information that would be obtained was not the focus of the study. Possible cross-tabulations could have been switching intention/age; switching intention/level of education; relationship length/age; relationship length/level of education; relationship depth/age; relationship depth/level of education; relationship breadth/age; relationship breadth/level of education and so forth. Such investigations could be pursued in future research.

4.7.1.6 Graphic representation

Apart from tables, data can be presented using various graphs or charts (Zikmund *et al.*, 2009:498). Pie charts, bar charts, histograms and box plots are typical graphical representations of data (Cooper & Schindler, 2014:407-415; Zikmund *et al.*, 2009:498). Where appropriate, bar charts were included in the descriptive statistics section of the results chapter (see Chapter 5).

Once preliminary results are obtained more complex data analysis can be pursued. After the descriptive statistics are analysed, the research objectives can be investigated using hypothesis testing.

4.7.2 Phase 6.2: Hypothesis testing

A hypothesis is a statement which proposes that something may be true (Bradley, 2013:37). In other words, a hypothesis is a "guess … about some characteristic of the population being investigated" (McDaniel & Gates, 2013:472). Prior to data collection, research objectives are converted into statements. Such statements, or propositions, are collectively known as hypotheses (hypothesis in the singular form). Hypothesis testing is conducted to find evidence in the data to determine whether the "guess" was correct (Cooper & Schindler, 2014:430; McDaniel & Gates, 2013:473). Thus the data will either support the hypothesis, or not (Bradley, 2013:37). Note that hypotheses are created at the beginning of the research project, prior to data collection, so that results can be compared against the predictions (Bradley, 2013:37).

The following four aspects of hypothesis testing are discussed in the next section (Cooper & Schindler, 2014:438; Diamantopoulos & Schlegelmilch, 2000:136; Malhotra, 2009:487; McDaniel & Gates, 2013:472):

1. Formulation of the null and alternative hypotheses
2. Specification of the level of significance and the confidence interval
3. Decision to reject or not reject the null hypothesis
4. Drawing conclusions

4.7.2.1 Formulation of the null and alternative hypotheses

Hypotheses are derived from the research objectives and are formulated into a pair of statements (Zikmund & Babin, 2013:372). The first statement – the null hypothesis (H_{null}) – indicates that no difference exists, or that no change has taken place, and is therefore often referred to as the status quo hypothesis (Malhotra, 2009:488; McDaniel & Gates, 2013:473). The second statement, known as the alternative or research hypothesis (H_{alt}), is the logical opposite of the null hypothesis, and postulates that a difference exists or that a change has occurred (Bradley, 2013:37; Cooper & Schindler, 2014:432; Diamantopoulos & Schlegelmilch, 2000:136; McDaniel & Gates, 2013:473). Researchers intend to reject the null hypothesis in order to find support for the alternative hypothesis (Bradley, 2013:37). Note that an alternative hypothesis can never be directly tested, and therefore can not be 'accepted'. Therefore, the purpose of hypothesis testing is to reject the null hypothesis and thereby indirectly obtain support for the alternative hypothesis, as opposed to 'accepting' the alternative hypothesis (Cooper & Schindler, 2014:432; Diamantopoulos & Schlegelmilch, 2000:136; McDaniel & Gates, 2013:478).

A summary of the hypotheses to be tested is given in Table 4.7 below. Both the null and the alternative hypotheses are stated for both the switching intention and switching behaviour samples. Motivations for choosing each hypothesis were provided in Chapter 3 of the literature review.

Table 4.7: Summary of the null and alternative hypotheses

Null and alternative hypotheses
$H_{1a(null)}$: There is no relationship between relational switching costs and switching intention. $H_{1a(alt)}$: There is a negative relationship between relational switching costs and switching intention. $H_{1b(null)}$: There is no relationship between relational switching costs and switching behaviour. $H_{1b(alt)}$: There is a negative relationship between relational switching costs and switching behaviour.
$H_{2a(null)}$: There is no relationship between perceived value and switching intention. $H_{2a(alt)}$: There is a negative relationship between perceived value and switching intention. $H_{2b(null)}$: There is no relationship between perceived value and switching behaviour. $H_{2b(alt)}$: There is a negative relationship between perceived value and switching behaviour.
$H_{3a(null)}$: There is no relationship between alternative attractiveness and switching intention. $H_{3a(alt)}$: There is a positive relationship between alternative attractiveness and switching intention. $H_{3a(null)}$: There is no relationship between alternative attractiveness and switching behaviour. $H_{3b(alt)}$: There is a positive relationship between alternative attractiveness and switching behaviour.
$H_{4a(null)}$: There is no relationship between relational switching costs and perceived value. $H_{4a(alt)}$: There is a relationship between relational switching costs and perceived value in a switching intention context. $H_{4b(null)}$: There is no relationship between relational switching costs and perceived value. $H_{4b(alt)}$: There is a relationship between relational switching costs and perceived value in a switching behaviour context.
$H_{5a(null)}$: There is no relationship between relational switching costs and alternative attractiveness. $H_{5a(alt)}$: There is a relationship between relational switching costs and alternative attractiveness in a switching intention context. $H_{5b(null)}$: There is no relationship between relational switching costs and alternative attractiveness. $H_{5b(alt)}$: There is a relationship between relational switching costs and alternative attractiveness in a switching behaviour context.

Null and alternative hypotheses
$H_{6a(null)}$: There is no relationship between perceived value and alternative attractiveness. $H_{6a(alt)}$: There is a relationship between perceived value and alternative attractiveness in a switching intention context. $H_{6b(null)}$: There is no relationship between perceived value alternative attractiveness. $H_{6b(alt)}$: There is a relationship between perceived value and alternative attractiveness in a switching behaviour context.
$H_{7a(null)}$: There is no relationship between relationship length and switching intention. $H_{7a(alt)}$: There is a negative relationship between relationship length and switching intention. $H_{7b(null)}$: There is no relationship between relationship length and switching behaviour. $H_{7b(alt)}$: There is a negative relationship between relationship length and switching behaviour.
$H_{8a(null)}$: There is no relationship between relationship depth and switching intention. $H_{8a(alt)}$: There is a negative relationship between relationship depth and switching intention. $H_{8b(null)}$: There is no relationship between relationship depth and switching behaviour. $H_{8b(alt)}$: There is a negative relationship between relationship depth and switching behaviour.
$H_{9a(null)}$: There is no relationship between relationship breadth and switching intention. $H_{9a(alt)}$: There is a negative relationship between relationship breadth and switching intention. $H_{9b(null)}$: There is no relationship between relationship breadth and switching behaviour. $H_{9b(alt)}$: There is a negative relationship between relationship breadth and switching behaviour.

Figure 4.1 and Figure 4.2 diagrammatically represent the above hypotheses for switching intention and switching behaviour.

Figure 4.1: The switching intention model hypotheses

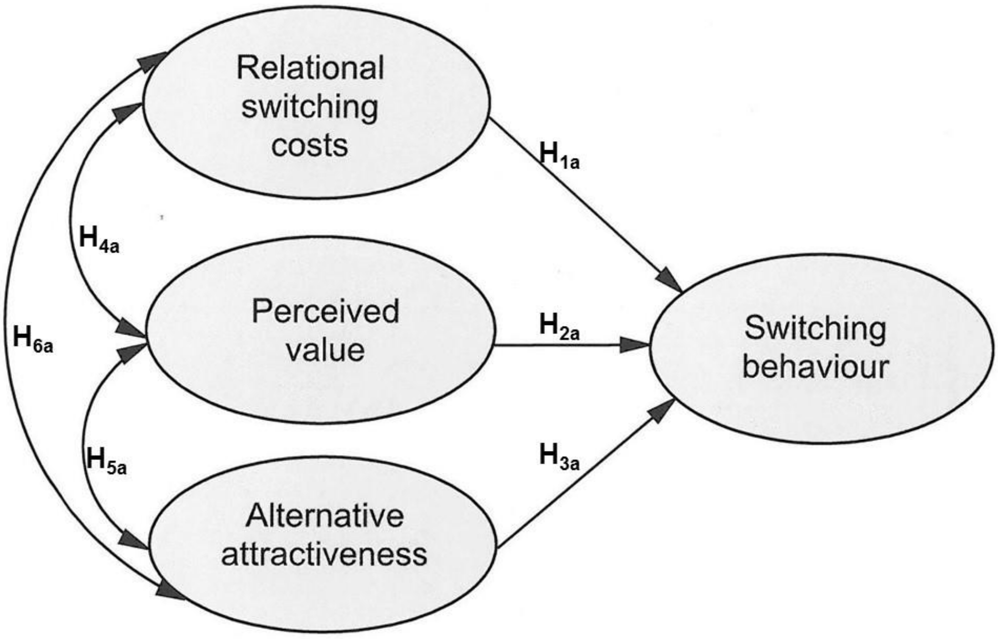
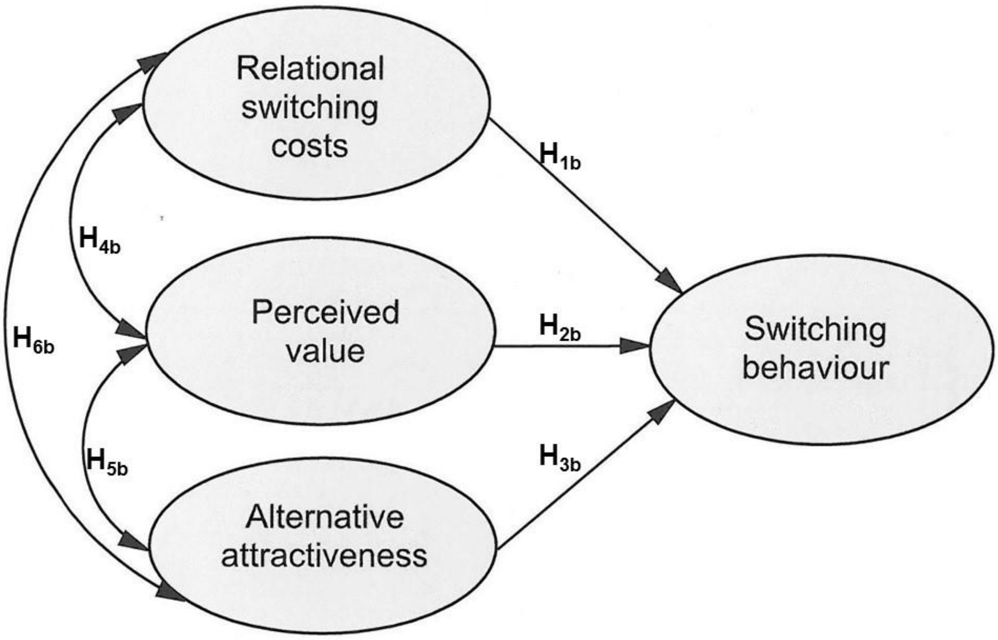


Figure 4.2: The switching behaviour model hypotheses



After hypothesis formulation, conditions for rejecting the null hypothesis are determined.

4.7.2.2 Specification of the level of significance

Since the purpose of hypothesis testing is to reject the null hypothesis, the circumstances under which the null hypothesis will be rejected or fail to be rejected, must be specified (Diamantopoulos & Schlegelmilch, 2000:137). On occasion, the null hypothesis is rejected when it is true, or the false null hypothesis fails to be rejected (Diamantopoulos & Schlegelmilch, 2000:137). Such mistakes lead to decision errors. Two errors that occur are Type I error or Type II error (Cooper & Schindler, 2014:435; Diamantopoulos & Schlegelmilch, 2000:138; McDaniel & Gates, 2013:475). Type I error (alpha error or α error) occurs when the null hypothesis is rejected when it is actually true (Cooper & Schindler, 2014:435; Diamantopoulos & Schlegelmilch, 2000:138; Hair *et al*., 2014:9). Conversely, if the null hypothesis is not rejected when it should be rejected, that is, the researcher failed to reject the false null hypothesis, a Type II error (beta error or β error) has occurred (Cooper & Schindler, 2014:435; Diamantopoulos & Schlegelmilch, 2000:138; Leedy & Ormrod, 2010:279). The two errors can be summarised as follows:

Type I error: $H_{(null)}$ is rejected when $H_{(null)}$ is true
Type II error: $H_{(null)}$ is not rejected while $H_{(null)}$ is false

Researchers attempt to avoid committing either error, nonetheless complete avoidance is difficult. If the possibility of committing Type I error is lowered, the probability of committing a Type II error increases, and vice versa (Diamantopoulos & Schlegelmilch, 2000:138). Committing a Type I error is considered more serious than committing a Type II error, since the null hypothesis should not be rejected unless strong evidence is available to do so (Diamantopoulos & Schlegelmilch, 2000:139). To decrease the probability of committing a Type I error, the alpha value (α) or level of significance is decreased (Diamantopoulos & Schlegelmilch, 2000:139; Leedy & Ormrod, 2010:279).

The level of significance indicates the maximum risk that the researcher is willing to take to make a Type I error. The less risk the researcher is willing to assume, the lower the significance level (Diamantopoulos & Schlegelmilch, 2000:139). A 5% level of significance ($\alpha = 0.05$) indicates that the null hypothesis will only be rejected if it is true 5 times out of 100 (Diamantopoulos & Schlegelmilch, 2000:139). In other words, there is only a 5% probability of rejecting the true null hypothesis (Cooper & Schindler, 2014:438). To decrease the risk of the error, a significance level of 0.01 ($\alpha = 0.01$) can be used (Cooper & Schindler, 2014:438). The level of significance must be chosen before data collection (Diamantopoulos & Schlegelmilch, 2000:140; Zikmund & Babin, 2013:373). A 5% level of significance ($\alpha = 0.05$) was chosen for the current study.

The accuracy of the significance test can be specified by using a confidence interval (Bradley, 2013:325). A confidence interval of either 0.95 or 0.99 is generally acceptable. A confidence interval of 0.99 indicates that there is only one chance in 100 that the true null hypothesis will be rejected. In other words, the researcher can be 99% confident that the true null hypothesis will not be rejected (Bradley, 2013:325). In the case of a 0.95 confidence interval, the level of significance is 0.05 (Diamantopoulos & Schlegelmilch, 2000:148). Similarly, when the confidence interval is 0.99, the level of significance is 0.01 (Paret, 2012). A 0.95 confidence interval was chosen for the current study.

The probability value (*p*-value) is compared to the significance level (α) to determine whether to reject the null hypothesis (Cooper & Schindler, 2014:438). Probability values are explained below.

I) Probability values (p-value)

The probability value (*p*-value) indicates the probability that the null hypothesis is true (Paret, 2012; Zikmund & Babin, 2013:373). Malhotra (2009:490) mentions that the *p*-value is “the probability of observing a value of the test statistic as extreme as, or more extreme than, the value actually observed, assuming $H_{(null)}$ is true”. As the probability that the result occurred by chance (i.e.: due to sampling error) decreases, the *p*-value also decreases (McDaniel & Gates, 2013:503).

To determine whether to ‘reject’ or ‘not reject’ the null hypothesis, the *p*-value is compared to α, the significance value (Cooper & Schindler, 2014:439). If the *p*-value is less than or equal to the significance level, the test result is significant and the null hypothesis is rejected. If the *p*-value is greater than the significance level, the null hypothesis can not be rejected, and the result is non-significant (Cooper & Schindler, 2014:439; Diamantopoulos & Schlegelmilch, 2000:139; Zikmund & Babin, 2013:373). The above can be summarised as follows:

Reject $H_{(null)}$ if the *p*-value is less than or equal to the level of significance (*p*-value is ≤ α)
Do not reject $H_{(null)}$ if the *p*-value is greater than the level of significance (*p*-value is > α).

The lower the *p*-value, the stronger the evidence to reject the null hypothesis (Diamantopoulos & Schlegelmilch, 2010:146). Albright, Winston and Zappe (2009:503) suggest the following guidelines to interpret the significance of results:

Table 4.8: Guidelines to interpret significance

***p*-value**	**Significance**
p-value > 0.1	weak or no significance
p-value < 0.1	weak to moderate evidence of significance
p-value < 0.05	strong evidence of significance
p-value < 0.01	convincing evidence of significance
p < 0.001	overwhelming evidence of significance

If the test result is significant, it must be established whether the result is only statistically significant or whether the result in fact has practical significance.

II) Statistical significance

A hypothesis is accepted or rejected based on information gathered from the sample that was tested. The sample will likely vary from the population, thus researchers must determine whether or not the differences are statistically significant (Cooper & Schindler, 2014:430). Whether the hypothesis can be rejected depends on whether a significant difference exists between the findings from the sample and the possible findings from a census (Bradley, 2013:324). Once statistical significance has been determined, the researcher has to determine whether the result is meaningful from a managerial point of view. Therefore results that are statistically significant are not necessarily of any practical significance (Cooper & Schindler, 2014:431).

III) Power of the test

The power of a test determines the probability that the null hypothesis is rejected when it should be (Kline, 2011:34; Malhotra, 2009:489). Thus the number of cases must be large enough to allow for enough statistical power to estimate all of the parameters in a SEM model. Parameters represent the anticipated relationship paths that will be tested (Hair *et al*., 2014:574-575). Since SEM is a large-sample technique (Byrne, 2010:329; Thomson, 2000:272), to determine the sample size required for SEM, the 'rule-of-thumb' states that there should be approximately 10 times as many cases as there are parameters that need to be estimated (Schreiber, 2008:85). N_1 = 1,025 observed cases were realised for the switching intention sample, and the switching model has 46 parameters to be estimated. Therefore the number of cases is large enough (46 x 10 = 460; 460 < 1,025). Since 460 is much less than 1,025, the tests will have sufficient statistical power. Regarding the switching behaviour sample, due to the low number of observed cases (N_2 = 135), statistical power is of concern.

To derive a result for the hypothesis test, a comparison is made between the level of significance and the probability value.

4.7.2.3 Rejection or non-rejection of the null hypothesis

To determine whether the null hypothesis should be rejected, the probability value (*p*-value) and the significance level (α) are compared (Cooper & Schindler, 2014:439). If the *p*-value < α, reject $H_{(null)}$ (Malhotra, 2009:491). If the *p*-value > α; do not reject $H_{(null)}$ (Malhotra, 2009:517). The alpha-level was set at α = 0.05 for the study.

Lastly, the hypothesis test results are interpreted.

4.7.2.4 Drawing conclusions

The final step in the hypothesis testing procedure is to draw conclusions from the test results and express the statistical decision in terms of the marketing research problem.

The ensuing section describes the various multivariate data analysis techniques used to analyse the data. The section begins with exploratory factor analysis, and concludes with structural equation modeling (SEM).

4.7.3 Phase 6.3: Multivariate data analysis

Multivariate analysis refers to statistical techniques that analyse more than two variables simultaneously (Boslaugh, 2013:112; Hair *et al*., 2014:4). Multivariate data analysis techniques are classified into dependence and interdependence techniques (Hair *et al*., 2014:11). Dependence techniques have a dependent variable explained or predicted by a set of independent variables, for example, multiple regression or structural equation modeling (SEM). Interdependence techniques do not define a single variable as being either dependent or independent, but instead simultaneously analyse all of the variables, for example, factor analysis (Hair *et al*., 2014:14). Factor analysis, an interdependence technique, is first explained, followed by two dependence techniques, namely multiple regression and structural equation modelling (SEM).

4.7.3.1 Exploratory factor analysis

Factor analysis is a multivariate interdependence technique with the main purpose of data reduction (Boslaugh, 2013:291; Mooi & Sarstedt, 2011:202; Pallant, 2011:181; Zikmund *et al*., 2009:593). Mooi and Sarstedt (2011:202) explain that factor analysis "identifies unobserved variables (factors) that explain patterns of correlations within a set of observed variables."

Before further explaining factor analysis, a slight digression is needed to clarify the terms 'observed variables' and 'unobserved variables'. Each individual item on the measurement scale for which data were collected is an observed variable, also known as manifest variables, indicator variables or measured variables (Byrne, 2010:4; Hair *et al*., 2014:544; Kline, 2011:8; Schreiber, 2008:84). For the remainder of the discussion, the term 'manifest variable' will be used. Unobserved variables are the constructs that are measured. Each construct is measured using a measurement scale, which in essence is a combination of manifest variables. Constructs are 'unobserved' because they can not be measured directly, and are thus measured using a combination of manifest variables (Byrne, 2010:4; Hair *et al*., 2014:544; Kline, 2011:8). Unobserved variables are also known as 'latent variables' (Schreiber, 2008:83), which is the term that will be used for the remainder of the discussion.

Thus, using the above terms, factor analysis is able to identify relationship patterns between a set of manifest variables and statistically group the manifest variables into a smaller set of latent variables (factors/components) based on component intercorrelations, with a minimal loss of information (Hair *et al*., 2014:16; Pallant, 2011:181; Zikmund *et al*., 2009:593). The intention is to identify the least amount of factors that explain the most variance (change) or covariation among a large number of manifest variables (Byrne, 2010:5; Mooi & Sarstedt, 2011:202; Zikmund *et al*., 2009:595). Factor analysis is thus useful to develop and refine measurement scales (Pallant, 2011:181).

Factor analysis, also known as exploratory factor analysis (EFA) is used to gather information regarding interrelationships about variables when the interrelationships are unknown (Zikmund *et al*., 2009:593). As the name implies, EFA is used to explore the data. In EFA, the manifest variables are not assigned to a particular latent variable (Byrne, 2010:5). Thus EFA is used to explore unknown relationships between latent and manifest variables, and is able to determine how the factors (constructs/latent variables) are correlated (linked) and how strong the correlations are by considering the factor loadings (Byrne, 2010:5; Hair *et al*., 2014:602-603). Furthermore, the data provides the researcher with the suggested number of factors, as derived from the statistical results, and not from theory (Hair *et al*., 2014:603).

To conduct an EFA, the following steps are generally followed (Hair *et al*., 2014:95; Mooi & Sarstedt, 2011:206; Pallant (2011:182):

- Determine the data suitability for EFA,
- Choose the method of factor extraction,
- Determine the number of factors,
- Rotate the factors, and

- Interpret the factors.

The steps followed to conduct an EFA are discussed in the ensuing paragraphs.

Step 1: Determine the data suitability for EFA

To determine data suitability, the sample size and item intercorrelation strength are first examined (Pallant, 2011:182). Regarding sample size, generally, the larger the sample size, the more reliable the results (Boslaugh, 2013:299). Hair *et al*. (2014:100) suggest a minimum sample size of 100 cases. Apart from sample size, the ratio of participants to items should also be considered (Pallant, 2011:183). A suggested rule-of-thumb is that there should be ten times as many observations as the number of variables to be analysed (Boslaugh, 2013:299; Hair *et al*., 2014:100; Mooi & Sarstedt, 2011:207).

Once the sample size is deemed adequate, the item intercorrelations are assessed to determine whether there are any correlations present by inspecting the correlation coefficients, Bartlett's (1954) test of sphericity and The Kaiser-Meyer-Olkin measure of sampling adequacy.

The strength of association between two variables is indicated by the correlation coefficient (Hair *et al*., 2014:152-153). The correlation coefficient ranges between -1 and +1 (Mooi & Sarstedt, 2011:89). The sign indicates the direction of the relationship. A negative sign indicates that as one variable increases, the other decreases, while a positive sign indicates that as one variable increases, the other also increases. A correlation coefficient of 0.3 indicates a weak relationship. Ideally the relationship strength should be 0.5 or greater (Mooi & Sarstedt, 2011:89; Tabachnick & Fidell, 2013:619). Should the assessment indicate that all of the correlations are low or equal, conducting an EFA should be reconsidered (Hair *et al*., 2014:101). Therefore, in order for factor analysis to be conducted, a visual inspection of the correlation matrix should reveal inter-item correlations greater than 0.3 (Hair *et al*., 2014:101; Mooi & Sarstedt, 2011:207).

Bartlett's (1954) test of sphericity indicates whether statistically significant correlations exist between (at least some of) the variables in the correlation matrix (Hair *et al*., 2014:102; Pallant, 2011:183). The Bartlett's test of sphericity should be significant ($p < 0.05$) (Mooi & Sarstedt, 2011:217).

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (MSA) (Kaiser, 1970, 1974) is a third measure used to evaluate item intercorrelation strength (Hair *et al*., 2014:102; Mooi & Sarstedt, 2011:207; Pallant, 2011:183). The KMO index ranges from 0 to 1. The closer the KMO is to 1, the higher the correlation (Hair *et al*., 2014:102; Mooi & Sarstedt, 2011:207). Table 4.9 summarises the thresholds for the KMO index (Hair *et al*., 2014:102; Mooi & Sarstedt, 2011:207).

Table 4.9: Kaiser-Meyer-Olkin (KMO) thresholds

KMO/MSA value	Adequacy of the correlations
Below 0.50	Unacceptable
0.50–0.59	Miserable
0.60–0.69	Mediocre
0.70–0.79	Middling
0.80–0.89	Meritorious
0.90 and higher	Marvelous

Source: adapted from Hair *et al.* (2014:102) and Mooi & Sarstedt (2011:208).

The minimum suggested threshold for the KMO is 0.60 (Tabachnick & Fidell, 2013:620). Mooi and Sarstedt (2011:207) suggest that the KMO statistic should be the deciding factor as to whether the data are suitable for further analysis. Hair *et al*. (2014:102) suggest that individual variables should be examined and all variables in the "unacceptable" range should be deleted before factor analysis can continue.

Factor analysis assumes that variables are correlated, which thereby implies that the variables have a linear relationship (Pallant, 2011:187). Thus it is important to confirm the aforementioned assumption. Therefore the assumption of linearity is investigated before conducting factor analysis. Since compiling scatterplots for the interrelationships between all of the variables would be a lengthy process, Tabacknick and Fidell (2013:84) suggest randomly checking a few relationships. Should the relationships be linear, the likelihood that the other relationships are linear is high, since the sample size assumption was met (Pallant, 2011:187). However, should any scatterplots show irregularities, further investigation is required.

Outliers are observations that are very different from the rest of the data being analysed (Boslaugh, 2013:96). Therefore outliers should be identified and possibly removed before further analysis.

Step 2: Choose the method of factor extraction

Factor extraction intends to discover the smallest number of factors that can represent the interrelationships among variables (Pallant, 2011:183). The underlying factors are extracted (identified) using a variety of approaches, for example, principal components analysis; principal axis factoring; image factoring; maximum likelihood factoring; alpha factoring; unweighted least squares; and generalised least squares (Mooi & Sarstedt, 2011:212; Pallant, 2011:183). Principal axis factoring (PAF), also called common factor analysis (Mooi & Sarstedt, 2011:211) was used in the current study for factor extraction. PAF is used when there is little knowledge regarding unique as well as common variance of each variable (Hair *et al*., 2014:105-106; Mooi & Sarstedt, 2011:202). PAF is most appropriate to identify underlying factors that indicate communalities between variables (Mooi & Sarstedt, 2011:202). PAF is also preferable when the assumption of multivariate normality is violated (Costello & Osborne, 2005:2).

Step 3: Determine the number of factors

A variety of techniques are available to aid the decision regarding the number of factors to retain (Pallant, 2011:184). Kaiser's criterion and the scree test are two popular methods which were implemented in the current study (Pallant, 2011:184). Kaiser's criterion, also known as the eigenvalue rule or the Guttman-Kaiser criterion, suggests that only factors with an eigenvalue greater than or equal to 1.0 should be further investigated (Boslaugh, 2013:293; Mooi & Sarstedt, 2011:212; Pallant, 2011:184). A factor's eigenvalue represents the total variance explained by that factor (Mooi & Sarstedt, 2011:209; Pallant, 2011:184; Zikmund *et al*., 2009:594).

Catell's scree test (Catell 1966) uses a visual approach to determine which factors to retain (Boslaugh, 2013:293; Pallant, 2011:184). The scree test plots each factor's eigenvalue on a graph (Boslaugh, 2013:293; Pallant, 2011:184). The eigenvalue is plotted on the y-axis and the factor that is associated with the eigenvalue is plotted on the x-axis (Mooi & Sarstedt, 2011:213). The scree plot typically indicates a distinct 'elbow' or break. All the factors above the elbow should be retained, as these factors explain most of the variance in the data (Boslaugh, 2013:293; Mooi & Sarstedt, 2011:213; Pallant, 2011:184). In cases where the elbow is not clear, the Kaiser criterion can be used to make the decision as to how many factors to retain (Mooi & Sarstedt, 2011:213).

Finally, researchers use their discretion to decide how many factors to use to best describe the underlying relationships (Pallant, 2011:183). Ideally the factors should explain 50% to 75% of the total variance (Mooi & Sarstedt, 2011:213).

Step 4: Factor rotation

The purpose of factor rotation to simplify factor analysis in order to ease identification of variables that load on to factors (Mooi & Sarstedt, 2011:213-214; Zikmund *et al*., 2009:594). Rotation does not change the underlying meaning. On the contrary, the purpose of rotation is to facilitate interpretation by simplifying the factor matrix's rows and columns (Hair *et al*., 2014:110). Two rotation approaches are orthogonal and oblique rotation. Orthogonal rotation requires the assumption that the underlying constructs are uncorrelated, whereas oblique rotation allows for factors to be correlated (Pallant, 2011:185). Each rotation approach uses a variety of techniques. Orthogonal rotation can be conducted using Varimax, Quartimax or Equamax rotation, while oblique rotation can be conducted using Promax or Direct Quartimin Oblique rotation (Hair *et al*., 2014:113-114; Mooi & Sarstedt, 2011:215; Pallant, 2011:185). Varimax is the most commonly used orthogonal rotation procedure. Varimax rotation intends to simplify the columns of the factor matrix (Hair *et al*., 2014:113). Direct Quartimin Oblique rotation is the most commonly used oblique rotation technique (Mooi & Sarstedt, 2011:215). Oblique rotation, specifically Direct Quartimin Oblique rotation with Kaiser Normalisation, was used in the study to allow the factors to correlate (Costello & Osborne, 2005:3).

Step 5: Interpret the factors

After rotation, the factors are interpreted by considering the factor loadings. Factor loadings indicate the strength of the correlations between the manifest variables and the latent constructs (Boslaugh, 2013:292; Byrne, 2010:5-6; Zikmund *et al*., 2009:594). If factors are correlated, it is said that they "load" onto one another (Zikmund *et al*., 2009:593).

To interpret the EFA results, whether PCA or PAF were conducted, the factor loadings are examined to determine which variables correlate strongly to each factor (Mooi & Sarstedt, 2011:213-214). Factor loadings should be at least 0.4 (Hair *et al*., 2014:136). Factor loadings greater than 0.7 are the objective of a factor analysis, since such high loadings indicate a well-defined structure (Hair *et al*., 2014:136). By considering the highest factor loadings, each variable is assigned to a factor. Once all the variables have been assigned to a factor, the researcher considers the meaning of the "set of variables" and names the factor (Mooi & Sarstedt, 2011:213-214). After the EFA, reliability and validity of the measurement scale are assessed (see Section 4.5.3).

One of the main research objectives was to develop a switching intention model and linked to that, to investigate interrelationships between the switching antecedents in the model. The use of multivariate data analysis was best-suited to examine the research objectives, since multivariate techniques analyse three or more variables in an attempt to identify relationships between the variables (Bradley, 2013:320). Multivariate analysis methods such as multiple regression, multivariate analysis of variance (MANOVA) and factor analysis are able to examine only one relationship at a time, using a limited number of variables (Hair *et al*., 2014:541). However, a more complex multivariate technique, namely SEM, is a single comprehensive technique that is able to examine a set of interrelated variables and a series of dependence relationships simultaneously (Hair *et al*., 2014:542). SEM is an extension of multivariate analysis techniques, but in particular, an extension of factor analysis and multiple regression analysis (Hair *et al*., 2014:542). The next section focuses on SEM.

4.7.3.2 Structural equation modeling (SEM)

SEM is a multivariate data analysis technique that assists researchers to understand complex relationships between variables (Hair *et al*., 2014:546; Schumacker & Lomax, 2010:2). SEM can be used to test and confirm theory by measuring how well theory fits reality (Hair *et al*., 2014:554; Schreiber, 2008:84). The results can then be used to further theory development (Anderson & Gerbing, 1988:411).

To test relationships and confirm theory, SEM conducts statistical analyses to explain the resemblance between theory (conceptual model) and reality (the observed data) (Schreiber, 2008:84). In 'SEM speak', SEM compares an observed covariance matrix (the observed data) to a conceptual covariance matrix (the conceptual model) (Schreiber, 2008:84; Soureli *et al*., 2008:13). The raw data collected from the sample is changed in to an unstandardised correlation matrix, known as a covariance matrix, so that the data can be analysed (Weston & Gore, 2006:729; Wheaton, n.d.:5). As such, SEM is used to determine whether the conceptual model produces a covariance matrix that is consistent with the covariance matrix produced by the sample data, known as the observed covariance matrix or sample covariance matrix (Byrne, 2010:70; Wheaton, n.d.:5). The higher the resemblance between the conceptual covariance matrix and the observed covariance matrix, the better the conceptual model fits the sample data (Schreiber, 2008:84), which ultimately means that theory and reality are in agreement. Therefore it can be said that the objective of SEM is to explain covariance and how covariance translates into the fit of a model (Hair *et al*., 2014:561). Consequently SEM has also become known as covariance structure analysis or covariance structure modeling (Bollen, 1995:xix; Hair *et al*., 2014:561; Kline, 2011:7; Rigdon, 1998:251; Schumacker & Lomax, 2010:189).

I) Advantages of SEM

SEM uses a confirmatory approach for data analysis, which means that SEM uses a hypothesis-testing approach and inferential statistics to analyse theory (Byrne, 2010:3). SEM is confirmatory since SEM aspires to verify a combination of hypothesised relationships between variables (Wheaton, n.d.:5). Most multivariate techniques are exploratory and therefore are not able to test hypotheses (Byrne, 2010:3). SEM on the other hand is able to test and confirm existing relationships and hypothesised (new) relationships between dependent variables (DV) and independent variables (IV) (Schreiber, 2008:85). SEM is also able to analyse all of the interrelated IVs and DVs in the model simultaneously, in order to determine whether the hypothesised model is consistent with the data (Byrne, 2010:3; Soureli *et al*., 2008:11). Furthermore, SEM is also able to calculate the strength and direction of the multiple dependent relationships.

SEM analysis manifest variables (observed variables) and latent variables (unobserved variables) simultaneously, while other multivariate techniques are only able to measure manifest variables (Byrne, 2010:3; Fornell & Larcker, 1981:49; Rigdon, 1998:251). The terms 'observed variables' and 'unobserved variables' were explained previously in Section 4.7.3.1. The ability to simultaneously analyse latent variables and manifest variables is extremely advantageous. This is because SEM examines the validity and reliability of the items for each latent variable, while also testing direct and indirect relationships between the latent variables (Schreiber, 2008:85). Therefore it can be said that SEM conducts path analysis and factor analysis simultaneously, while also assessing measurement instrument validity and reliability.

Another unique feature of SEM is that SEM makes provision for errors (Byrne, 2010:3; Fornell & Larcker, 1981:49; Iacobucci, 2009:674; Rigdon, 1998:253). Unlike other multivariate techniques, SEM provides estimates for error variance parameters, which enables SEM to assess and correct measurement error during the estimation process and provide accurate estimates of error variance parameters (Byrne, 2010:3; Hair *et al*., 2014:590; Rigdon, 1998:253). Traditional multivariate techniques can not assess for, nor correct, measurement error.

As can be concluded from the above advantages, SEM is a powerful data analysis technique, hence its popularity in academic research in general, and marketing research in particular (Byrne, 2010:4; Rigdon, 1998:251). Certain assumptions need to be adhered to in order to conduct SEM. The assumptions are discussed in the next section.

II) SEM assumptions

Certain critical assumptions must be met to ensure that SEM results are accurate (Byrne, 2010:102). The assumptions include the assumption of multivariate normality, the assumption that the data are continuous, and that sample size must be relatively large (Byrne, 2010:329; Klem, 2000:233; Kline, 2011:60). SEM is a large-sample technique which implies that a large sample size is required when using SEM (Byrne, 2010:329; Thomson, 2000:272). The more complex the measurement model, the larger the sample size required. Hair *et al*. (2014:572-574) consider any sample consisting of 500 or more respondents to be a large sample. As mentioned in the data collection section (Section 4.6.5), N_1 = 1,025 cases were observed for the switching intention sample, and is thus considered to be a large sample (1,025 > 500), thereby meeting the large sample size assumption. As for the switching behaviour sample, the number of observed cases was N_2 = 135. Therefore, in the case of the switching behaviour sample, the assumption of large sample size was violated, meaning that SEM would not be accurate for the switching behaviour sample.

In terms of the data being on a continuous scale, if a measurement scale has five or more categories, ordinal data approach the characteristics of interval data (Cooper & Schindler, 2014:252). (Refer to the explanation in Section 4.5.7.3). Therefore interval scales meet the assumption of continuous data, which is imperative for SEM analysis (Byrne, 2010:329; Klem, 2000:233; Kline, 2011:60). In the current study, all of the Likert-type scales, as is the typical approach used in marketing literature, are considered to be measured with interval data (Bradley 2013:203). An 11-point Likert-type scale was used for the current study. Due to the high number of scale points the assumption of continuous (interval) data was met for both the switching intention sample and switching behaviour sample.

Apart from using a large sample and meeting the assumption of continuous data, the assumption of multivariate normality distribution must also be met (Byrne, 2010:329; Klem, 2000:233; Kline, 2011:60). To assess multivariate normality, the assumption of univariate normality distribution must first be satisfied (Byrne, 2010:103; Kline, 2011:60). To test for univariate normality, the measures of symmetry, namely, skewness and kurtosis, were examined (Byrne, 2010:103; Kline, 2011:60). (See Section 4.7.1.3 for a detailed explanation of measures of symmetry). Skewness impacts tests of means, but kurtosis impacts tests of variance and covariance (Byrne, 2010:103). Therefore when using SEM, kurtosis is of particular importance since SEM is based on covariance structure analysis (Byrne, 2010:103; Hair *et al*., 2014:561).

A kurtosis value that is greater than or equal to 7 indicates an "early departure from normality" (Byrne, 2010:103). (Kurtosis ≥ 7 indicates nonnormal distribution; kurtosis < 7 indicates normal distribution). If the kurtosis indicates nonnormal distribution, the critical ratio (CR) value must be assessed (Byrne, 2010:104). If the CR value is greater than 5, the data are nonnormally distributed (Byrne, 2010:104). (CR > 5 indicates nonnormal distribution; CR < 5 indicates normal distribution). In this study, the assessment of univariate normality indicated a nonnormal distribution, since the kurtosis value for relationship depth was greater than 7 (8.836) and the corresponding CR value was above 5 (57.747). Even though the relationship depth variable indicated a nonnormal distribution, normal distribution could still be assumed due to the large sample size and the 11-point Likert-type scale, which gives a more precise measurement due to continuous data.

The test for multivariate normality indicated nonnormal distribution (multivariate kurtosis = 265.773; CR = 125.457). Typical estimation techniques used in SEM, namely maximum likelihood (ML) and normal theory generalised least squares (GLS) require the assumptions for continuous data and multivariate normality to be met (Byrne, 2010:329). However, Byrne (2010:330) notes that in practice, most data do not meet the assumption of multivariate normality. Consequently, SEM researchers developed techniques which take the violation of the assumption of multivariate normality into account (Byrne, 2010:330). Bootstrapping is one such technique that is used to deal with the presence of multivariate nonnormal data (Byrne, 2010:330).

Bootstrapping determines whether the sample statistic is a good estimator of the population parameter (Schumacker & Lomax, 2010:234). Kline (2011:42) refers to bootstrapping as a computer-based resampling method, since bootstrapping uses the original sample to "create multiple subsamples from an original database" (Byrne, 2010:331). Bootstrapping then compares "parametric values over repeated samples that have been drawn (with replacement) from the original sample" (Byrne, 2010:331). That is, every time a sample is drawn, the distribution is recalculated. As a result, the stability of the model parameters can be established (Byrne, 2010:332) which in turn indicates that the parameter estimates can be reported with confidence. If the bootstrapping and ML estimates are close, convergence is demonstrated and the ML estimates can be reported with confidence. Chapter 5 elaborates on the implementation of ML and bootstrapping.

Apart from knowing the complex capabilities of SEM and the criteria required to perform SEM, a basic understanding of the model development and testing procedure is required. The following section provides an overview of the fundamental concepts used in building and testing SEM models.

III) Development and testing of the structural equation model

The eventual goal of test a structural equation model is to compare how closely a conceptual model resembles the sample data (Byrne, 2010:66; Schreiber, 2008:84). Six stages are generally followed to test the model (Kline, 2011:91-92; Weston & Gore, 2006:729-745). The first stage involves postulating a conceptual model, based on theory and/or previous empirical research (Byrne, 2010:7). Next, the model is specified, in other words, the theory is modelled into mathematical equations and a conceptual diagram to demonstrate how the theory has been conceptualised (Byrne, 2010:3; Hoyle, 1995:2; Kline, 2011:92; Schumacker & Lomax, 2010:55). Because the relationships can be expressed as equations, the conceptual model can be tested statistically (Byrne, 2010:3; Kline, 2011:93). All the variables and relationships to be tested are included in the diagram (Schumacker & Lomax, 2010:55). Prior to data collection, model identification takes place to confirm that the model can be tested (Hoyle, 1995:4; Kline, 2011:93).

After the data are collected and edited, coded and captured, model estimation is used to simultaneously derive parameter estimates and fit indices (Chou & Bentler, 1995:37; Hair *et al*., 2014:575; Hoyle, 1995:5). Next the model is examined to determine how closely the conceptual model fits the observed data. To do so, various fit indices are examined. A model that shows adequate fit confirms the relationships hypothesised in the conceptual model (Byrne, 2010:3). However, a perfect fit is highly unlikely. Model fit can be improved using model modification, which involves adding or deleting variables (Hoyle, 1995:6; Schumacker & Lomax, 2010:64). Modification is, however, only attempted if the modification can be justified by theory (Klem, 2000:245; Schreiber, 2008:90). Once adequate model fit is achieved, the parameter estimates are interpreted and reported (Hoyle, 1995:9; Kline, 2011:92). The sections to follow explain the SEM model building process in more detail.

i) Model specification

In order to conduct SEM, the model to be estimated is first specified (Hoyle, 1995:2). Model specification involves allocating the manifest variables to the appropriate latent variables (Kline, 2011:92; Schumacker & Lomax, 2010:114). The model to be estimated has two components, namely the measurement model and the structural model (Anderson & Gerbing, 1988:411; Hair *et al*., 2014:550; Hoyle, 1995:1; Schreiber, 2008:84; Schumacker & Lomax, 2010:114). The measurement model is a confirmatory model, because the relationships between the manifest and latent variables are known (Anderson & Gerbing, 1988:411; Byrne, 2010:6; Hair *et al*., 2014:550; Iacobucci, 2009:675; Klem 2000:247; Schumacker & Lomax, 2010:114). The measurement model is thus an extension of CFA (Schreiber, 2008:84). The structural model is an extension of multiple regression analysis and indicates the predicted causal relationships between the constructs (Anderson & Gerbing, 1988:411; Hair *et al*., 2014:560; Iacobucci, 2009:674; Schreiber, 2008:84). The measurement model forms the core of the full structural model and therefore is specified first.

In the measurement model, all of the individual constructs to be included must be defined, and a thorough literature review is required to explain each construct (Schreiber, 2008:91). The constructs for this study were defined and explained in Chapter 3. Next, a suitable measurement scale must be identified to operationalise each construct. The use of existing measurement scales is preferable, due to validity and reliability issues (Hair *et al*., 2014:605). The choice of appropriate measurements scales was discussed in Section 4.5. Furthermore, each measurement scale item (manifest variable) must be specified, that is, 'allocated' to the appropriate latent variable, which is why the measurement model is considered confirmatory (Hoyle, 1995:3; Iacobucci, 2009:675;

Schreiber, 2008:84). Lastly, the measurement model also includes all the error terms associated with the manifest variables in the measurement model (Wheaton, n.d.:11).

Once the measurement model is specified, the structural model is specified by including the anticipated paths between the dependent and independent latent variables. The paths indicate the complete set of relationships among all the latent variables, including causal direction (Byrne, 2010:7; Hair *et al*., 2014:644; Schumacker & Lomax, 2010:114). Specification of the expected relationships is known as directionality (Kline, 2011:98). Since SEM is used to test theory, the identified relationships in the structural model should be based on theory (Anderson & Gerbing, 1988:411). Next, the measurement model and the structural model are combined in to the full SEM model (Iacobucci, 2009:677).

SEM models are formally specified using either a series of equations or a schematic representation of the equation using a combination of symbols (Byrne, 2010:9; Klem, 2000:243; Kline, 2011:92). Most often SEM model diagrams are used for simplification (Hair *et al*., 2014:628; Kline, 2011:92). To represent the model schematically, SEM notation uses Greek characters to represent latent variables and Greek alphabetic characters to represent manifest variables (Hair *et al*., 2014:605; MacCallum, 1995:24). Latent variables are symbolised by ovals, also called ellipses, while manifest variables are symbolised by rectangles (Byrne, 2010:9; Hair *et al*., 2014:604; Klem, 2000:228; Kline, 2011:95; Rigdon, 1996:2; Schreiber, 2008:83). A distinction is made between two types of latent variables: dependent (endogenous) latent variables are represented by 'eta' (η) and independent (exogenous) latent variables are represented by 'xi' (ξ) (Byrne, 2010:5; Klem, 2000:232; Rigdon, 1996:2). Similarly, manifest variables associated with exogenous latent variables are represented by an 'X' and are distinguished from manifest variables associated with endogenous latent variables, which are represented by a 'Y' (Rigdon, 1996:2).

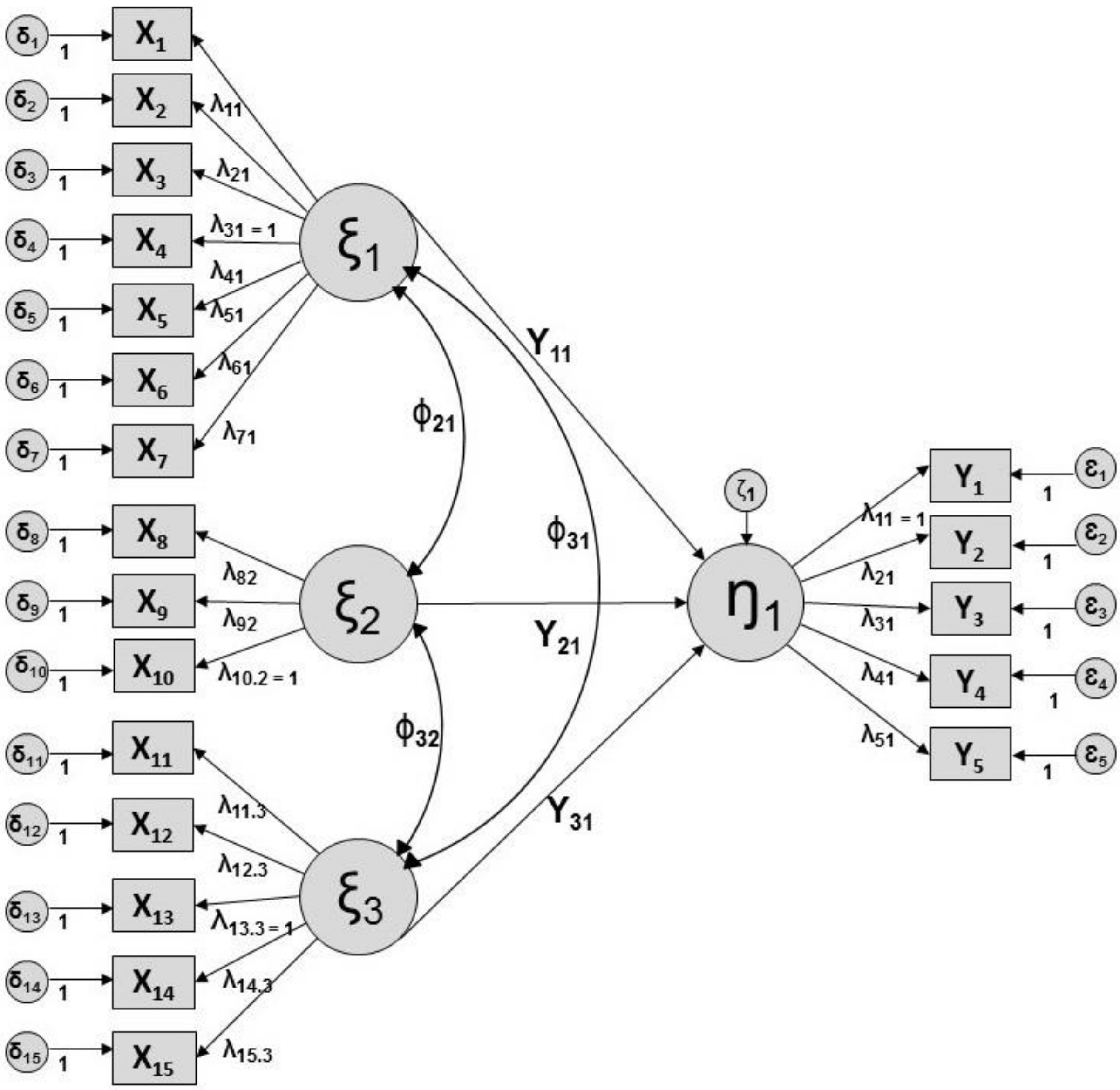
Paths represent relationships between variables. A straight path reflects a dependence relationship, while a curved line indicates a relationship between two variables (Schreiber, 2008:84). The direction of the relationship is indicated by the arrows (Schreiber, 2008:84). A straight path with a single-headed arrow implies that one variable has an impact on another variable (Byrne, 2010:9; Hair *et al*., 2014:551; Schreiber, 2008:84). Dual-headed arrows imply a relationship between the two variables, indicating that the two variables covary (Byrne, 2010:9; Hair *et al*., 2014:551; Kline, 2011:95; Rigdon, 1998:56). The covariance is indicated by 'phi' (ϕ) (Klem, 2000:233; Rigdon, 1996:2).

The SEM diagram also specifies the structural path parameters. A relationship from an exogenous variable toward an endogenous variable is represented by a straight path with a single-head arrow toward the endogenous variable and the 'gamma' (Y) symbol (Klem, 2000:232). 'Beta' (β) path parameters, from one endogenous variable to another, are not applicable to the current study. The factor loadings for parameters representing the relationship paths between latent and manifest variables are indicated by 'lambda' (λ) (Klem, 2000:233; Rigdon, 1996:2). Factor loadings for parameters associated with endogenous latent variables are represented by 'lambda y' (λ_y). Factor loadings for parameters associated with exogenous latent variables are indicated by 'lambda x' (λ_x) (Klem, 2000:233; Rigdon, 1996:2). Parameters must be specified as either free or fixed (Hair *et al*., 2014:574-575; Hoyle, 1995:3). SEM analysis estimates free parameters (Hoyle, 1995:3; Kline, 2011:102). However, to facilitate model identification (which is explained in Section 4.7.3.2), a metric scale must be assigned to all latent variables and residuals in the SEM model (Byrne, 2010:34; Kline, 2011:124). Due to the fact that latent variables and residuals are unobserved, they are not measured directly (Byrne, 2010:4) and therefore do not have a definite metric scale (Byrne, 2010:34). To compensate for the absence of a metric scale, unmeasured latent variables are mapped onto their related manifest indicator variables during model specification (Byrne, 2010:34). To perform the 'mapping' procedure, one of the regression paths from the latent variable to the manifest variable is constrained to a nonzero value, usually 1.0 (Byrne, 2010:35).

Each manifest variable is associated with a measurement error term. Error terms associated with exogenous manifest variables are represented either by a small circle or 'delta' (δ) and have a single-headed arrow pointing toward the exogenous manifest variable (Klem, 2000:233; Schreiber, 2008:84; Rigdon, 1996:3). Similarly, 'epsilon' (Ɛ) or a small circle is used for error terms associated with endogenous manifest variables and also have a single-headed arrow pointing toward the endogenous manifest variable (Klem, 2000:233; Rigdon, 1996:2). Measurement error indicates the extent to which the manifest variable measures something which is not what the latent variable was supposed to measure (Schumacker & Lomax, 2010:185). Thus error terms are added to manifest variables to account for variance. While the errors themselves are not of interest, the variances and covariances of the errors are important (Klem, 2000:231). The variance of each measurement error must be estimated in SEM to assess measurement error (Schumacker & Lomax, 2010:166). Including the measurement error into the analysis is what sets SEM apart from other data analysis techniques, since SEM is able to account for measurement error and can correct measurement error, which no other data analysis technique is able to do (Byrne, 2010:3; Iacobucci, 2009:674). Furthermore, SEM allows measurement error terms to covary (Rigdon, 1994:277). Error term covariances associated with exogenous manifest variables are represented by 'theta delta' (θ_δ); error term covariances associated with endogenous manifest variables are represented by 'theta-epsilon' (θ_ε) (Klem, 2000:233).

The SEM model also indicates structural prediction errors (Iacobucci, 2009:676). Exogenous variables are allowed to covary freely (and are always assumed to covary) (Kline, 2100:100; Rigdon, 1996:2). In contrast, endogenous variables are not free to vary (Kline, 2011:103). Thus provision is made for unexplained variance (disturbance) in the endogenous latent variable. The residual (disturbance) in prediction associated with endogenous latent variables is denoted by 'zeta' (ζ) (Klem 2000:232; Rigdon, 1996:2). The SEM model specified for the current study is represented in Figure 4.3.

Figure 4.3: Specification of the conceptual SEM model



Finally, it should be noted that SEM models can be either recursive or nonrecursive. The SEM model for this study is recursive, since all the causal effects are unidirectional. Nonrecursive models have correlations that include feedback loops (Hair *et al*., 2014:647-648; Kline, 2011:106).

After model specification, model identification is conducted to determine whether it is theoretically possible to test the SEM model (Byrne, 2010:34; Kline, 2011:93). An identified model is testable and able to find a unique solution for each parameter (Byrne, 2010:34).

An unidentified model cannot be tested empirically; "the parameters are subject to arbitrariness, thereby implying that different parameter values define the same model" (Byrne, 2010:34). Model identification determines whether the model is underidentified, overidentified, or just-identified. An explanation of the three levels of model identification is preceded by an explanation of how parameter estimates and degrees of freedom are used to establish the level of model identification.

ii) Model identification

In order to identify a SEM model, the degrees of freedom of the model must be at least zero ($df_M \geq 0$) (Kline, 2011:124) and the number of parameters to be estimated must be fewer than the number of observations (MacCallum, 1995:29). In the context of model identification, the 'number of observations' refers to the number of entries in the sample covariance matrix and not sample size (Kline, 2011:101). Evaluation of the parameter estimates is explained below.

iii) Parameter estimates

Parameters represent the anticipated relationship paths that will be tested (Hair *et al*., 2014:574; Rigdon, 1996:2). Thus parameters represent all of the regression coefficients, variances and covariances, and standard errors (Chou & Bentler, 1995:37; Klem, 2000:243; Schreiber, 2008:87). To calculate the total number of parameters to be estimated (Byrne, 2010:33), the regression coefficients (parameter factor loadings), variances (error variances and factor variances) and factor covariances are added together. The fixed parameters are deducted from the calculation.

For the current model the total regression coefficients included the 3 Y (gamma) relationships between the exogenous and endogenous variables and 3 covariances (ϕ) between the exogenous latent variables. There were 15 parameter factor loadings for the exogenous latent variables (λ_x) and 5 parameter factor loadings for the endogenous latent variable (λ_y). Parameters should be specified as either free or fixed (Hair *et al*., 2014:574). One parameter per latent variable (both exogenous and endogenous) should be fixed (Hoyle, 1995:3). Therefore four fixed parameters were deducted, leaving 19 parameters. There were 15 error variances (δ) for the exogenous manifest variables and 5 error variances (Ɛ) for the endogenous manifest variables. Lastly, there were a total of 4 factor variances, 3 for the exogenous latent variables (ξ) and one for the endogenous latent variable (η). Therefore, a total of 46 parameters were estimated for the current model. Once the parameter estimates are known, the degrees of freedom (*df*) are determined.

iv) Degrees of freedom

Degrees of freedom (*df*) indicate "the amount of mathematical information available to estimate model parameters" (Hair *et al*., 2014:577). One *df* is lost for every parameter that is estimated (Hair *et al*., 2014:608). A large *df* value implies a fairly robust estimate which is fairly representative of the overall sample of respondents (Hair *et al*., 2014:153). Therefore the larger the *df*, the more generalisable the results (Hair *et al*., 2014:172). A general rule-of-thumb is that the total number of parameter estimates must be less than the degrees of freedom in order to build a model. For the current study, the *df* for the model are 164, which is more than the 46 parameters that are to be estimated.

v) Levels of identification

If a value is obtained for each parameter, the model is just-identified (Hair *et al*., 2014:608; Hoyle, 1995:4). As explained by Byrne (2010:35), the parameter estimates correspond precisely with the data. A just-identified model is able to yield a unique solution for each parameter, however, such models can never be rejected because they have zero *df* (Hoyle, 1995:4; Kline, 2011:102; MacCallum, 1995:28). Meaning that any results obtained would not contribute to research (Byrne, 2010:35).

An underidentified model can not be estimated and by implication can not be empirically analysed (Hoyle, 1995:4; Kline, 2011:102). The number of parameters to be estimated are greater than the number of observations (Byrne, 2010:35). Consequently, observed data are unable to obtain a single unique value for one or more parameters and thus an infinite number of solutions are possible (Byrne, 2010:35; Hoyle, 1995:4). Furthermore, the *df* will be negative ($df_M < 0$) (Hair *et al*., 2014:608; Kline, 2011:102).

Lastly, if the observed data can be manipulated in a variety of ways to obtain parameter estimate values, the model is overidentified (Hoyle, 1995:4). An overidentified model has fewer parameter estimates than observations and positive *df* ($df_M > 0$) (Byrne, 2010:35; Kline, 2011:102). An overidentified model implies that discrepancies exist between the data and the model (Kline, 2011:102). Thus the model can be rejected, which makes it scientifically useful (Byrne, 2010:35). Therefore, in order for a model to be estimated, the model must be either just-identified or overidentified (Hoyle, 1995:4). The current model is overidentified because the $df > 0$ ($df = 164$) (Kline, 2011:102).

Once the data were collected, the complete structural (conceptual) model is compared to the sample data to test whether the proposed relationships are in the anticipated direction, and significant. To do so, estimation using maximum likelihood was conducted and the fit indices were examined.

vi) Estimation

Once the model is specified and identified, estimation takes place (Hoyle, 1995:5; Klem, 2000:243). Estimation is the procedure used to derive parameter estimates and goodness-of-fit statistics (Chou & Bentler, 1995:37; Hair *et al*., 2014:575). In SEM, goodness-of-fit indices and parameter estimates are obtained simultaneously (Chou & Bentler, 1995:37). To conduct estimation, the appropriate estimation technique must be chosen (Hair *et al*., 2014:575). The estimation technique is the mathematical algorithm that is used to identify the estimates for each parameter (Hair *et al*., 2014:575). The parameter estimates and goodness-of-fit χ^2 test statistic derived depend on the estimation procedure chosen (Chou & Bentler, 1995:38). The estimation technique chosen for this study was maximum likelihood (ML). ML is the most commonly used estimation method in SEM (Anderson & Gerbing, 1988:413; Hu & Bentler, 1999:2; Klem, 2000:233; Kline, 2011:154; Sharma & Kim, 2013:1; Schreiber, 2008:87). As previously mentioned, ML requires a large sample and assumes multivariate normality distribution (Kline, 2011:60; Hu & Bentler, 1999:2; Schumacker & Lomax, 2010:60). Several software programmes are available for estimation. Popular software packages include AMOS, EQS, Lisrel and Mplus (Hair *et al*., 2014:575; Rigdon, 1998:266; Schumacker & Lomax, 2010:8). The software programme AMOS was used to perform the data analysis, because the University of Pretoria has a site licence for IBM SPSS Statistics version 22 and AMOS is available as an add-on to SPSS (Hair *et al*., 2014:575).

Once the parameter estimates and goodness-of-fit indices are obtained through estimation, the model is analysed to determine validity and reliability and to establish multivariate normality. However, a limitation of AMOS is that data are analysed on the assumption of being multivariate normal. The assessment of measurement scale validity and reliability was discussed in Section 4.5.3. Likewise, the assessment of multivariate normality was discussed in Section *II) SEM assumptions*). After all the assumptions of normality have been met, or otherwise accounted for, the sample data are fitted to the structural model to determine fit. Hence a description of the evaluation of fit and various fit indices used to establish fit follows.

vii) Evaluation of fit

To determine whether the sample covariance matrix matches the population covariance matrix, the significance of parameter estimates and the overall model should be evaluated (Byrne, 2010:66-67; Weston & Gore, 2006:744). When evaluating parameter estimates, three considerations are: i) parameter estimate feasibility; ii) appropriateness of the standard errors; and iii) statistical significance of the parameter estimates (Byrne, 2010:67).

First, taking theory into account, parameter estimates should have the correct sign (positive or negative) and correlation strength. If the parameter sign is different than expected, or the parameter estimate shows correlations > 1.00, the variance should first be examined before continuing with model evaluation (Byrne, 2010:67). Next, since standard errors indicate sampling error, standard errors should be negligible (Byrne, 2010:67; Kline, 2011:33). If not, the standard errors should first be investigated further. Third, the test statistic or critical ratio (CR) should be significant to confirm that the parameter estimates are statistically different from zero (Byrne, 2010:68). Further investigation is needed if this is not the case.

If a model is able to precisely reproduce a covariance matrix, it can be said that there is good model fit. Various indicators, known as fit indices, are used to show how closely the model (population covariance matrix) resembles the sample covariance matrix (Schermelleh-Engel, Moosbrugger & Műller, 2003:24; Schreiber, 2008:88). SEM is able to calculate the model fit, and is able to suggest how to change the model to bear closer resemblance to the data using fit indices.

viii) Model fit indices

Model fit is assessed by a variety of fit indices (Schreiber, 2008:88). Consideration of a 'bouquet' of fit indices is imperative, since each fit index evaluates a different aspect of model fit, and together the fit indices provide complementary information (Iacobucci, 2010:90; Whitten & Wakefield, 2006:234). Therefore an 'overall picture' is necessary to determine model fit, and dependence on one 'all-or-nothing' fit statistic is not recommended (Schumacker & Lomax, 2010:63; Thomson, 2000:271). On the other hand, Hooper, Coughlan and Mullen (2008:56) advise that reporting all fit indices that are available is unnecessary.

There is much debate as to which fit indices should be reported (Iacobucci, 2010:90). However, researchers seem to agree that the chi-square value (χ^2), the associated degrees of freedom (*df*), the ratio of chi-square to degrees of freedom (χ^2/df) and the *p*-value (α) must be reported to indicate overall fit (Hair *et al*., 2014:577-578; Hooper *et al*., 2008:56; Iacobucci, 2010:90; Schreiber, 2008:88; Strasheim *et al*., 2007:105). Schreiber, Nora, Stage, Barlow and King (2006:327) suggest considering the type of data when reporting model fit. For continuous data, the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI) and the Tucker Lewis Index (TLI) and the Standardised Root Mean Square Residual (SRMR) should be reported. The same indices apply to categorical data, except SRMR, which should be replaced with the Weighted Root Mean Square Residual (WRMR).

The aforementioned indices can be classified as either absolute or incremental fit indices (Hair *et al*., 2014:577-578; Hu & Bentler, 1995:82). Overall fit indices assessed and reported in the current study were χ^2 and the associated *df*, the χ^2/df ratio and the *p*-value (α). Absolute fit indices, namely RMSEA and SRMR, and incremental fit indices, CFI and TLI, were also assessed and reported. The three categories of fit indices are described in more detail in the sections to follow.

Overall fit indices

The chi-square (χ^2) statistic is the original fit index used for structural models, so it is the first goodness-of-fit index that is usually reported and forms the foundation of most other fit indices (Hooper *et al*., 2008:53; Newsom, 2012:1). The χ^2 compares the model to the sample data to test whether the sample covariance matrix is the same as the hypothesised population covariance matrix (Iacobucci, 2010:91; Rigdon, 1998:268; Whitten & Wakefield, 2006:234).

A significant χ^2 value indicates that a difference exists between the observed sample data and the conceptual model, which by implication indicates poor fit (Schreiber, 2008:88; Schumacker & Lomax, 2010:85; Thomson, 2000:269; Whitten & Wakefield, 2006:234). Unlike other significance tests, a nonsignificant χ^2 value is sought, since the nonsignificant χ^2 value indicates good fit (Barrett, 2007:816; Hair *et al*., 2014:577-578). For example, if p > 0.05, the model is considered to have a good fit (Barrett, 2007:816; Rigdon, 1998:269). Since the purpose of SEM is to determine how close the fit is between the observed data and the conceptual model, a nonsignificant χ^2 value is preferred. Thus the χ^2 is often referred to as a 'badness-of-fit' index, since a significant χ^2 result indicates poor fit (Schreiber, 2008:88).

Sensitivity to sample size is a limitation of χ^2 (Barrett, 2007:816; Gerbing & Anderson, 1985:421; Fornell & Larcker, 1981:40; Hooper *et al*., 2008:54; Iacobucci, 2010:92; Strasheim *et al*., 2007:105). Typically the larger the sample size, the more precise the parameter estimation (Iacobucci, 2010:91). However, in the case of χ^2, as sample size increases, χ^2 could indicate significance, even if there is no significance (Type I error), which may lead to erroneous conclusions (Iacobucci, 2010:91; Newsom, 2012:1; Schreiber, 2008:88; Schumacker & Lomax, 2010:86). Therefore χ^2 is an unreliable fit index for large samples (Hooper *et al*., 2008:54; Schermelleh-Engel *et al*., 2003:33). Kenny (2014) suggests that samples greater than 400 can be considered large samples, whereas Hair *et al*. (2014: 572-574) consider samples larger than 500 be large.

Furthermore, the χ^2 statistic is affected by model complexity and the size of the correlations in the model – the stronger the correlations, the poorer the fit (Kenny, 2014; Whitten & Wakefield, 2006:234). The degree of normality also affects χ^2 as multivariate normality is assumed, meaning that any deviation from normality may lead to a model being rejected even though the model may fit well (Hooper *et al*., 2008:54; Kenny, 2014).

Due to the limitations of the χ^2 fit index, a number of other fit indices were developed based on the adjusted χ^2 statistic (Byrne, 2010:77; Hooper *et al*., 2008:54). The adjusted indices quantify the degree of discrepancy that exists between the models instead of only indicating whether the model is a good fit or not (Barrett, 2007:816; Mackay, 2012:159). Consequently the ratio of the χ^2 value to the degrees of freedom (χ^2/df) is a popular ratio to estimate model fit (Chen & Cheng, 2012:812).

a) Chi-square/degrees of freedom ratio (χ^2/df)

Degrees of freedom (*df*) are used as indicators for parameter estimation. Unlike χ^2, degrees of freedom are not influenced by sample size (Hair *et al*., 2014:577). Therefore using the χ^2/df ratio is an important consideration when testing SEM models. The objective when fitting a model is “to achieve the highest predictive accuracy with the most degrees of freedom” (Hair *et al*., 2014:172). Thus *df* also give an indication of model overfitting.

Schreiber (2008:89) suggests that a χ^2/df ratio less than or equal to 5 ($\chi^2/df \leq 5.00$) indicates adequate fit. However, more conservative thresholds suggest that the ratio should be less than or equal to 2 ($\chi^2/df \leq 2.00$) (Schermelleh-Engel *et al*., 2003:33; Yang & Peterson, 2004:810).

Absolute indices

Absolute fit indices directly measure how well the specified measurement model reproduces the observed data (Hair *et al*., 2014:578). Unlike incremental fit indices, absolute fit indices do not use a reference model to assess fit (Hooper *et al*., 2008:53; Hu & Bentler, 1999:2). Absolute fit indices indicate what proportion of the covariances in the sample data are explained by the model, in other words, these indices point out (for lack of better words) 'how much'/to what degree' the model explains the observed data (Kline, 2011:195).

a) Root Mean Square Error of Approximation (RMSEA)

RMSEA is different to most fit indices as it considers not only how well the sample used for estimation fits the data, but also considers how well the model fits the population (Hair *et al*., 2014:579). In so doing, RMSEA attempts to account for sample size and model complexity (Hair *et al*., 2014:579). So it is not surprising that Byrne (2010:80) regards RMSEA as "one of the most informative criteria in covariance structure modeling". Consequently RMSEA has become a popular fit index and is widely reported (Kenny, 2014).

RMSEA is "expressed per degree of freedom" (Byrne, 2010:80), therefore this index is sensitive to model complexity and more specifically, is sensitive to the number of parameter estimates in the model. Therefore, MacCallum (1995:30) refers to RMSEA as "a measure of lack of fit per degree of freedom", while Whitten and Wakefield (2006:236) refer to RMSEA as "a measure of the discrepancy per degree of freedom". Weston and Gore (2006:742) explain that RMSEA corrects for model complexity. Therefore, if two models are compared, the simpler model will have a better RMSEA. RMSEA is calculated using the following formula:

$$\text{RMSEA} = \frac{\sqrt{(x^2 - df)}}{\sqrt{[df(\text{N} - 1)]}}$$

where N = sample size and *df* = degrees of freedom of the model (Kenny, 2014; Kline, 2011:205). The degrees of freedom of the model are one less than the sample size

(N – 1), therefore RMSEA decreases when there are more degrees of freedom or a larger sample size (Kline, 2011:205). Byrne (2010:80) and Kenny (2014) caution that RMSEA becomes inaccurate with small samples.

RMSEA is reported with its associated confidence intervals to assess the precision of RMSEA estimates (Byrne, 2010:81; Hooper *et al*., 2008:54; MacCallum, Browne & Sugawara, 1996:134). A 90% confidence interval is commonly reported for RMSEA (Byrne, 2010:81; Schreiber, 2008:93; Strasheim *et al*., 2007:106). The wider the confidence interval, the lower the precision (Kline, 2011:206). If the RMSEA is small and the confidence interval is wide “the estimated discrepancy value is quite imprecise” and the degree of fit can not be accurately determined. If the RMSEA is small and the confidence interval is narrow, the RMSEA shows a good fit (Byrne, 2010:81). The wider the confidence interval, the lower the precision (Kline, 2011:206). As is the norm a 90% confidence interval was chosen (and reported) for the RMSEA for the current study.

Byrne (2010:81-82) cautions that the confidence intervals may be influenced by sample size and model complexity. As suggested by MacCallum *et al*. (1996), if the number of parameters to be estimated is large and the sample size is small, the confidence interval will be wide. The more complex the model (that is, the more parameters to be estimated), a larger sample size is required to obtain a narrow confidence interval.

RMSEA is considered a badness-of-fit index due to a value of zero indicating the best fit (Kline, 2011:205; Schreiber, 2008:88). RMSEA cut-offs can be summarised as follows (Byrne, 2010:80; Kenny, 2014; MacCallum *et al*., 1996:134): values between 0.00 and less than 0.05 indicate good fit; values between 0.05 and less than 0.08 indicates a reasonable fit (reasonable errors of approximation in the population); values ranging from 0.08 to 0.10 indicate mediocre fit, while values greater than 0.10 indicate poor fit. The lower bound of the 90% confidence interval should be close to 0 and the upper bound of the 90% confidence interval should be smaller than 0.08 (Kenny, 2014).

b) Standardised Root Mean Square Residual (SRMR)

SRMR uses covariance residuals to identify measurement model problems (Hair *et al*., 2014:579; Kline, 2011:208; Weston & Gore, 2006:742). The error in prediction for every covariance creates a residual. Therefore SRMR is calculated for every possible covariance (Hair *et al*., 2014:579).

SRMR is the square root of the difference between the residuals of the sample covariance matrix and the residuals of the population covariance matrix (Hooper *et al*., 2008:54). In other words, the SRMR is the standardised difference between the observed and predicted covariances (Hair *et al*., 2014:579; Kenny, 2014; Kline, 2011:208).

SRMR is based on Root Mean Square Residual (RMR). RMR is the average of the residuals between individual observed and estimated covariance and variance terms. The range of the RMR is based upon the number of points on a measurement scale. If the measurement instrument has scales with different amounts of points, the RMR is difficult to interpret (Hooper *et al*., 2008:54; Kline, 2011:209). Consequently the SRMR was developed to standardise the scale points and is therefore a more meaningful index to interpret (Hooper *et al*., 2008:55).

An advantage of SRMR is that it is relatively less sensitive to violations of distributional assumptions (Iacobucci, 2010:91). However, Kenny (2014) cautions that SRMR is greater for small sample size and low *df* and has no penalty for model complexity.

SRMR ranges from 0 to 1, where zero indicates perfect fit (Byrne, 2010:77; Hooper *et al*., 2008:55; Iacobucci, 2010:91; Kenny, 2014). SRMR is a 'badness-of-fit' index, since larger values signal poor fit (Hair *et al*., 2014:579). Ideally SRMR should be less than 0.05 (Byrne, 2010:77). However, values less than or equal to 0.08 are acceptable (Hooper *et al*., 2008:55; Hu & Bentler, 1999:1; Kenny, 2014). Note that SRMR will be lower in models based on large sample sizes and also when the model has a high number of parameters to be estimated (Hooper *et al*., 2008:55).

Incremental indices

Incremental fit indices compare the specified model to an alternative baseline model to assess fit (Byrne, 2010:78; Hair *et al*., 2014:580; Kline, 2011:196). Therefore incremental fit indices are also known as comparative fit indices or baseline comparisons (Byrne, 2010:78; Hair *et al*., 2014:580; Hooper *et al*., 2008:55; Kline, 2011:196). Unlike absolute fit indices, incremental fit indices compare the χ^2 value to a baseline model (Hooper *et al*., 2008:55). The baseline model is also known as the null model or the independence model (Kline, 2011:196; Schreiber, 2008:88).

Incremental fit indices are distinguished by the fact that all these fit indices have values ranging between approximately 0 and 1, where 1 indicates perfect fit (Byrne, 2010:78; Whitten & Wakefield, 2006:234). The CFI is 'normed' so that CFI values can not be below 0 or above 1. The TLI is 'nonnormed' because, on occasion, TLI values may be larger than 1 or slightly below 0 (Newsom, 2012:2).

a) Comparative fit index (CFI)

CFI compares the sample covariance matrix to a baseline model (Hooper *et al*., 2008:55; Schreiber, 2008:88; Whitten & Wakefield, 2006:236). CFI is one of the fit indices that is least affected by sample size, and has therefore become a popular fit index to report (Hooper *et al*., 2008:55). CFI takes sample size into account and attempts to adjust for model complexity (Byrne, 2010:78; Hooper *et al*., 2008:55; Iacobucci, 2010:91; Thomson, 2000:270; Whitten & Wakefield, 2006:236). CFI was derived from Bentler and Bonett's (1980) Normed Fit Index (NFI) (Byrne, 2010:78; Hair *et al*., 2014:580). NFI was measured using the ratio of the difference between χ^2 for the fitted model and χ^2 for the null model divided by χ^2 for the null model. NFI is calculated using the following formula (Kenny, 2014):

$$\mathrm{NFI} = \frac{x^2(\text{null model}) - x^2(\text{proposed model})}{x^2(\text{null model})}$$

However, NFI could not cope with model complexity and also underestimated fit in small samples (Byrne, 2010:78; Kenny, 2014). Consequently CFI was developed to make provision for model complexity and make provision for sample size (Byrne, 2010:78; Hair *et al*., 2014:580). CFI is computed in a similar manner to NFI, but calculates $\chi^2 - df$ whereas NFI calculates only χ^2. CFI is calculated using the following formula (Kenny, 2014):

$$\mathrm{CFI} = \frac{(x^2 - df)(\text{null model}) - (x^2 - df)(\text{proposed model})}{(x^2 - df)(\text{null model})}$$

Since larger CFI values indicate good fit, CFI is considered a goodness-of-fit indicator (Iacobucci, 2010:91). CFI values close to 1 indicate good fit while values close to 0 indicate the worst possible fit (Hooper *et al*., 2008:55; Hopwood, 2007:268; Iacobucci, 2010:91). Originally values larger than 0.90 were considered an indication of good fit (Byrne, 2010:78). However, convention has deemed that the cut-off be increased to 0.95 to indicate good fit (Hu & Bentler, 1999:4; Newsom, 2012:2; Schreiber, 2008:90).

b) Tucker Lewis Index (TLI)

TLI is also known as the Nonnormed Fit Index NNFI (Hooper *et al*., 2008:55; Kenny, 2014:4; Schreiber *et al*., 2010:327). As is characteristic of incremental fit indices, TLI compares a fitted model and a null model (Hooper *et al*., 2008:55). TLI is similar to CFI in that it was developed to compensate for the sensitivity of the Normed Fit Index (NFI) to sample size and model complexity (Hooper *et al*., 2008:55; Hu & Bentler, 1999:3; Kenny 2014). The difference between TLI and CFI is that CFI is normed and TLI in nonnormed. Also, in the calculation, TLI uses χ^2/df while CFI uses $\chi^2 - df$. TLI is calculated as follows (Kenny, 2014):

$$\mathrm{TLI} = \frac{x^2/df(\text{null model}) - x^2/df(\text{proposed model})}{x^2/df(\text{null model}) \ - 1}$$

The lower the χ^2/df ratio, the better the fit, provided that the result is not less than 1 (Kenny, 2014). Due to the TLI index range occasionally exceeding 1 or being below 0, the TLI is a ‘nonnormed’ index (Newsom, 2012:2). Hooper *et al*. (2008:55) note that when values exceed 1, the results become difficult to interpret.

TLI is relatively unaffected by sample size (Newsom, 2012:3). TLI depends on the average size of correlations in the data. Therefore TLI will be low if the average correlations are low (Kenny, 2014). Hooper *et al*. (2008:55) caution that TLI may indicate poor fit if used on small samples, even though other fit indices indicate relatively good fit.

Conventionally, the cut-off for TLI was a value larger than 0.90, however, there seems to be consensus that the TLI should be greater than or equal to 0.95 (Hooper *et al*., 2008:55; Hu & Bentler, 1999:1; Newsom, 2012:2; Schreiber, 2008:90).

Kenny (2014) suggests that, because the TLI and CFI are highly correlated, only one of the two need to be reported, and suggests that TLI is the preferred index. However, as per current trends, both are reported in the study. The goal of fit indices is to assist researchers to determine whether or not specified models are acceptable. Table 4.10 provides a summary of the acceptable ranges for all of the above-mentioned goodness-of-fit indices.

Table 4.10: Summary of acceptable goodness-of-fit indices

Goodness-of-fit indices		
Overall Fit Indices		
Fit Index	**Acceptable Threshold Levels**	**Description**
Chi-square (χ^2)	Non-significant χ^2 ($p > 0.05$) exact fit Significant χ^2 ($p < 0.05$) poor fit	
Chi-square/degrees of freedom ratio (χ^2/df)	χ^2/df ratio ≤ 2.00 (good fit) χ^2/df ratio ≤ 5.00 (adequate fit)	Adjusts for sample size
Absolute Fit Indices		
Fit Index	**Acceptable Threshold Levels**	**Description**
Root Mean Square Error of Approximation (RMSEA)	Values < 0.03 (excellent fit) Values < 0.05 (good fit) Values between 0.05 and 0.08 (reasonable fit) Values between 0.08 and 0.10 (mediocre fit) Values > 0.10 (poor fit)	Use in conjunction with 90% confidence interval
RMSEA confidence interval (upper & lower limit)	Lower bound: close to 0.00; Upper bound: < 0.08	Narrow confidence interval indicates good fit
Standardized Root Mean Residual (SRMR)	Value = 0 (perfect fit) Value < .05 (good fit) Value ≤ 0.08 (acceptable fit)	Low values indicate good fit

Goodness-of-fit indices		
Incremental Fit Indices		
Fit Index	**Acceptable Threshold Levels**	**Description**
Comparative fit index (CFI)	Value ≥ 0.90 (acceptable fit) Value ≥ 0.95 (good fit)	Range: 0 (no fit) to 1 (perfect fit)
Tucker-Lewis index (TLI) OR Non-normed Fit Index (NNFI)	Value ≥ 0.90 (acceptable fit) Value ≥ 0.95 (good fit)	Range: 0 (no fit) to 1 (perfect fit) Nonnormed (values can fall outside 0-1 range)

Source: Adapted from Hooper *et al*. (2008:58), Schreiber (2008:89) and Schumacker & Lomax (2010:76).

Fit indices may be influenced by misspecification, small samples, violation of normality and the estimation method used (Schermelleh-Engel *et al*., 2003:53). The number of variables, model complexity, a misspecified measurement mode, a misspecified path model or both are other factors which may cause 'misfit' (Kenny, 2014; McDonald & Ho, 2002:75). Thus Schermelleh-Engel *et al*. (2003:53) are of the opinion that, although fit indices examined may indicate poor fit, the possibility exists that the model may in fact fit the data.

Sometimes the various model fit indices provide conflicting conclusions as to whether the model reproduces the covariance matrix (Schermelleh-Engel *et al*., 2003:53). Some indices may indicate good fit, while at the same time, another fit index may indicate poor fit. Moreover, no suggestions exist in the literature regarding a method to overcome the aforementioned limitation. Schreiber *et al*. (2006:327) suggest that "if the vast majority of the indexes indicate a good fit, then there is probably a good fit".

A perfect fit between the conceptual model and sample data is rarely achieved (Byrne, 2010:7; Weston & Gore, 2006:744). Consequently, the original hypothesised model may be modified to improve fit (Schreiber *et al*., 2006:327). In an attempt to improve the model, modification indices may be used to identify aspects of the model that could be adjusted to possibly improve fit (Schumacker & Lomax, 2010:94).

ix) Model modification

Fit indices point out how closely the specified model resembles the sample data. Poor model fit essentially means that the sample data and the conceptual model do not match precisely (Schreiber, 2008:84). Thus, should the researcher decide to attempt to improve the model, the postulated conceptual model is, in essence, rejected. Nonetheless, the purpose of SEM is not necessarily to achieve good fit, but to test theory (Hair *et al*., 2014:582; Kline, 2011:189). Researchers are cautioned not to attempt improving model fit by compromising ultimate testing of a theory (Hair *et al*., 2014:582). The reason being that a data-driven model can not be generalised across samples (Weston & Gore, 2006:745). Therefore, should model modification be attempted, the process should be theory-driven and not data-driven (Klem, 2000:245; Schreiber, 2008:90).

The main rationale for using model modification is to determine the cause of the poor fit, whether the model can be changed, and if so, how the model can be changed to better describe the sample data (Byrne, 2010:8). Model modification is an exploratory process, and not a confirmatory process, as was the case when using SEM (Schreiber *et al*., 2006:330). Any difference between the sample covariance matrix and the population covariance matrix is indicated by modification indices (Byrne, 2010:86). Modification indices give clues as to what adjustments can be made to the model to improve fit.

a) Modification indices (MIs)

The purpose of inspecting the modification index (MI) is to estimate how much the overall model χ^2 value will decrease if a single path is added to the model (Kline, 2011:217). The MI is a chi-square statistic with a single degree of freedom, $\chi^2(1)$ (Byrne, 2010:86; Kline, 2011:217). MIs estimate the expected decrease in the overall model χ^2 if that parameter were freely estimated (Byrne, 2010:86; Kline, 2011:217). Thus a MI is calculated for each fixed parameter, should the fixed parameter be a freely estimated in a subsequent calculation (Byrne, 2010:86; Hair *et al*., 2014:621).

All paths with large modification indices should be inspected to decide whether to keep or delete the path (Iacobucci, 2009:678). The greater the MI value, the higher the likelihood that modifying the path will improve the overall model fit (Kline, 2011:217). A general rule-of-thumb is that any modification index greater than 10 is regarded as large. A large modification index points out which parameters, if estimated, would improve model fit (Iacobucci, 2009:678). Modification indices are generated by the software programme used for the data analysis (Schreiber, 2008:90). The AMOS programme computes the predicted change for each parameter (Byrne, 2010:86; Iacobucci, 2009:678). Parameter estimates should be changed one at a time (Iacobucci, 2009:678).

After model modification, the original model and the modified model are compared (Schreiber, 2008:90). The χ^2 value and χ^2/df ratio of the two models are compared as well as various goodness-of-fit indices. Depending on the results, the researcher decides whether to continue further modification or keep the modified model. Further modification should only be attempted if theoretically justifiable (Schermelleh-Engel *et al*., 2003:62; Schreiber, 2008:90).

4.8 CONCLUSION

In this chapter the research design that was followed to conduct empirical analysis, and the methodology used during each phase of the research process that was followed to conduct empirical analysis, were discussed and applied to the current study where applicable. The chapter commenced with a summary of the research problem and objectives, while the process of primary data collection was discussed in-depth. Various statistical techniques that were used in this study were addressed, with the focus being the analysis technique to be used to measure the conceptual switching intention model, namely structural equation modelling (SEM). The following chapter presents the empirical findings of this study.

CHAPTER 5

RESEARCH RESULTS AND INTERPRETATION

5.1 INTRODUCTION

To attain results to answer the three primary objectives of the study, the research design discussed in Chapter 4 was followed. The empirical findings are discussed in this chapter, which begins with an account of the descriptive statistics obtained to describe both the switching intention sample (N_1) and the switching behaviour sample (N_2). As previously mentioned, the survey was sent to 55,224 online panel members. A total of 1,668 questionnaires were returned, thus a 3% response rate was realised. After data editing, a usable sample of N_1 = 1,025 for switching intention and N_2 = 135 for switching behaviour was obtained.

To ascertain the validity of the measurement scales, the exploratory factor analysis procedure and the accompanying results are presented. The procedure used to establish measurement scale reliability, using Cronbach's alpha, is then discussed.

Thereafter, the Structural Equation Modeling (SEM) technique used to empirically test the conceptual switching intention model (RO1), is explained. The SEM model was measured using the switching intention sample (N_1) data. Maximum likelihood (ML) was used to obtain parameter estimates. Due to poor fit indices obtained, model modification was conducted in an attempt to obtain better model fit. Bootstrapping confirmed that the parameter estimates were valid. Finally, robust maximum likelihood as conducted using the EQS package, due to nonnormality of the data.

The next section discusses the comparison of the conceptual switching intention model and actual switching behaviour data (RO2). The switching behaviour data could not be fitted to the conceptual switching intention model, since the number of cases obtained for the switching behaviour sample (N_2 = 135) were far less than the number of cases required for parameter estimation. Thus stepwise regression was used for the comparison.

Multiple regression was used to explore the role of relationship characteristics, namely relationship length, depth and breadth, and their influence on both switching intention and switching behaviour (RO3).

Finally, hypothesis testing was used to obtain results for the secondary objectives. The direct influence of the switching antecedents on switching intention and on switching behaviour were tested, followed by an investigation of the interrelationships between the switching antecedents in both the switching intention and switching behaviour contexts. Finally, the direct influence of relationship characteristics on switching intention switching behaviour were measured.

Before discussing the results, two points should be mentioned. Firstly, the sections to follow report the research results of the switching intention sample (N_1) and the switching behaviour sample (N_2) separately. However, results for each sample are discussed under the same sub-section. Secondly, note that for the purposes of data collection, both Telkom Mobile and '8ta' (the former name of Telkom Mobile), were included in the questionnaire so as not to confuse respondents. As mentioned in Chapter 2, 8ta was rebranded to Telkom Mobile (Telkom, 2013) at the time of data collection. However, for the remainder of the analysis, only Telkom Mobile will be referred to.

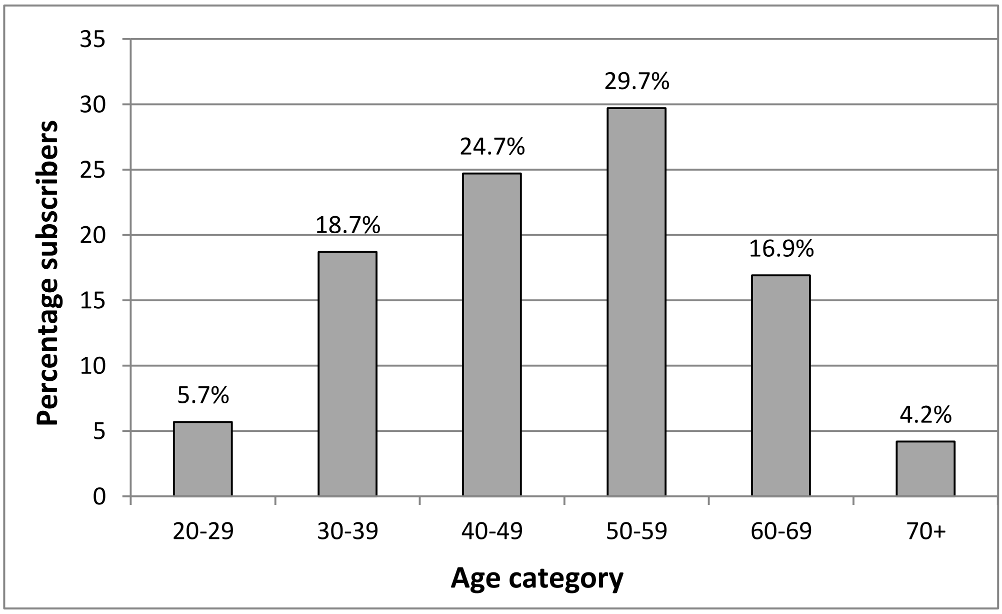
5.2 SAMPLE PROFILES

To gain an overall representation of the respondents, a sample profile was compiled. First, the switching intention sample (N_1) profile is described, followed by the profile for the switching behaviour sample (N_2). Each section includes the descriptive statistics in the same sequence. The demographics provided in the sample profiles include age, gender, ethnicity, preferred language, residency by province, level of education, employment status, personal monthly income and monthly household income. As previously mentioned, the data was supplemented with additional demographic data that was available on the Consulta Research database at the time of the survey. Due to outdated demographic data, a number of responses were missing. Therefore the demographic information is reported only indicating the valid percentage, so as to provide information regarding only the respondents for whom information was available on the database.

5.2.1 Switching intention sample (N_1) profile

Intriguingly, most respondents in the switching intention sample (N_1) were aged 50-59 years (*n* = 297; 29.7%). Considering that the survey was web-based, such a high number of respondents in the 50-59 year age category was unexpected. A report by 'mybroadband' found that most internet users were persons aged 25-44 years (Muller, 2010), while another found that the 15-24 year age group had the highest internet usage (Horrocks, 2013). In contrast, respondents aged 20-29 were one of the smallest categories (*n* = 57; 5.7%), only slightly larger than respondents aged 70 and older (*n* = 42; 4.2%). The remainder of the respondents were aged 40-49 years (*n* = 247; 24.7%), 30-39 years (*n* = 187; 18.7%) and 60-69 years (*n* = 169; 16.9%). The average age of all the respondents was 49.25 years (*M* = 49.5; *SD* = 12.24). The results are shown in Figure 5.1.

Figure 5.1: Subscriber age profile (switching intention sample, N_1)



Of the switching intention sample (N_1) respondents that indicated their gender (785), 38.6% (303) were female, and 61.4% (482) were male. Research conducted by 'mybroadband' regarding demographic profiles of internet users also indicated that more males (55%) used the internet than females (45%) (Muller, 2010). Interestingly, Horrocks (2013) also found that in South Africa, mostly men use the internet.

With regard to ethnicity, the majority respondents were White (*n* = 616; 79%), followed by African (*n* = 70; 9%). The remaining 64 respondents were Coloured (*n* = 29; 3.7%), Indian (*n* = 23; 2.9%) and Asian (*n* = 12; 1.5%). No ethnic description was available for 3.8% (30) of the respondents.

South Africa has 11 official languages. In line with the Consulta panel, only seven of the official South African languages are represented in the switching intention sample (N_1). The majority respondents were English (*n* = 319; 62.3%). The next largest language group was Afrikaans (*n* = 177; 34.6%), followed by isiXhosa (*n* = 4; 0.8%), Sepedi (*n* = 4; 0.8%), Setswana (*n* = 4; 0.8%), isiZulu (*n* = 3; 0.6%) and Xitsonga (*n* = 1; 0.2%), which together comprise 3.1% of the sample.

Regarding level of education, the majority respondents were either graduates (*n* = 303; 43.6%) or had completed secondary schooling (*n* = 187; 26.9%). Respondents with postgraduate qualifications, such as an Honours, a Masters or a Doctoral degree comprised 25.9% (*n* = 180) of the sample. A small percentage of respondents were busy with tertiary education (*n* = 25; 3.6%). Of interest is the fact that such a high percentage of the respondents were graduates.

Considering employment status (*n* = 506), most respondents were employed (*n* = 334; 66%). Quite a large number of the sample were self-employed (*n* = 112; 22.1%). The remaining respondents were either retired (*n* = 52; 10.3%) or unemployed (*n* = 8; 1.6%).

Of the respondents that answered the *personal monthly income* question (588), most respondents earned a monthly income of between R16,001 and R20,000 (*n* = 139; 23.6%), followed closely by 23.3% (137) of the respondents earning between R25,001 and R 40,000. The next highest personal monthly income group earned between R11,001 and R16,000 (*n* = 83; 14.1%). The remaining respondents either earned a personal monthly income below R11,000 (*n* = 99; 16.8%), or above R60,001 (*n* = 130; 22.1%). The results are presented in Table 5.1.

Table 5.1: Personal monthly income (switching intention sample, N_1)

Personal monthly income	Frequency	Valid percent (N_1 = 588)
R 1 - R6,000	32	5.4
R 6,001 - R8,000	21	3.6
R 8,001 - R11,000	46	7.8
R11,001 - R16,000	83	14.1
R16,001 - R25,000	139	23.6
R25,001 - R40,000	137	23.3
R40,001 - R60,000	65	11.1
R60,001 - R100,000	43	7.3
R100,001 and more	22	3.7
Total	588	100
Missing	437	
	1025	
	Median (*Mdn*)	24 195.65
	Mean (*M*)	31 357.99
	Standard deviation (*SD*)	26 108.78

The highest *monthly household income* earned by the switching intention sample (N_1) was between R25,001 and R40,000 (*n* = 76; 25.9%). Unlike their personal monthly income, the next highest category was a monthly household income of between R40,001 and R60,000 (*n* = 58; 19.8%). The third highest monthly household income group earned between R16,001 and R25,000 (*n* = 49; 16.7%). The remaining respondents earned either below R16,000 (*n* = 63; 21.5%) or above R60,001 (*n* = 47; 16.0%). Table 5.2 presents the monthly household income results.

Table 5.2: Monthly household income (switching intention sample, N_1)

Monthly household income	Frequency	Valid percent (N_1 = 293)
R 1 - R6,000	8	2.7
R 6,001 - R8,000	4	1.4
R 8,001 - R11,000	18	6.1
R11,001 - R16,000	33	11.3
R16,001 - R25,000	49	16.7
R25,001 - R40,000	76	25.9
R40,001 - R60,000	58	19.8
R60,001 - R100,000	28	9.6
R100,001 and more	19	6.5
Total	293	100
Missing	732	
	1025	
	Median (*Mdn*)	31 828.00
	Mean (*M*)	39 489.76
	Standard deviation (*SD*)	29 243.92

To measure relationship characteristics, respondents were asked questions about the three components of relationship characteristics, namely relationship length, depth and breadth. The switching intention sample (N_1) profile concludes with a brief description of each relationship characteristic aspect.

Respondents were asked to indicate the length of time that they had a contract their MNO to determine relationship length. Surprisingly, the largest portion of respondents had a contract with their MNO for more than 15 years (*n* = 265; 25.9%). Many respondents had a contract for between 8 and 12 years (*n* = 201; 19.6%) or between 12 and 15 years (*n* = 198; 19.3%). Very few respondents had a contract for less than 6 months (*n* = 1; 0.1%). A small number of respondents had a contract with their MNO for either 6 to 12 months (*n* = 16; 1.6%) or 12 to 18 months (*n* = 18; 1.8%). Considering the sample age profile, and the fact that most respondents were between 50 and 59 years of age, having had a contract with their MNO for more than 15 years is consistent with the development of the South African mobile telecommunications industry. Mobile phones became accessible to South Africans in 1994 (Hodge, 2005:495), thus having a contract for more than 15 years is quite possible. Of interest would be to further investigate whether the respondents had been with the same MNO for the full time period of 15 years and up, or had switched before commencing the present contract that has continued for more than 15 years. Another aspect to investigate would be to determine whether the respondents remained with the MNO because they were happy or due to convenience. The results for the relationship length scale are shown in Table 5.3.

Table 5.3: Relationship length (switching intention sample, N_1)

Relationship length (N_1)	n	%
Less than 6 months	1	0.1
6 to 12 months	16	1.6
12 to 18 months	18	1.8
18 to 24 months	39	3.8
2 to 5 years	132	12.9
5 to 8 years	155	15.1
8 to 12 years	201	19.6
12 to 15 years	198	19.3
Longer than 15 years	265	25.9
	1025	**100**

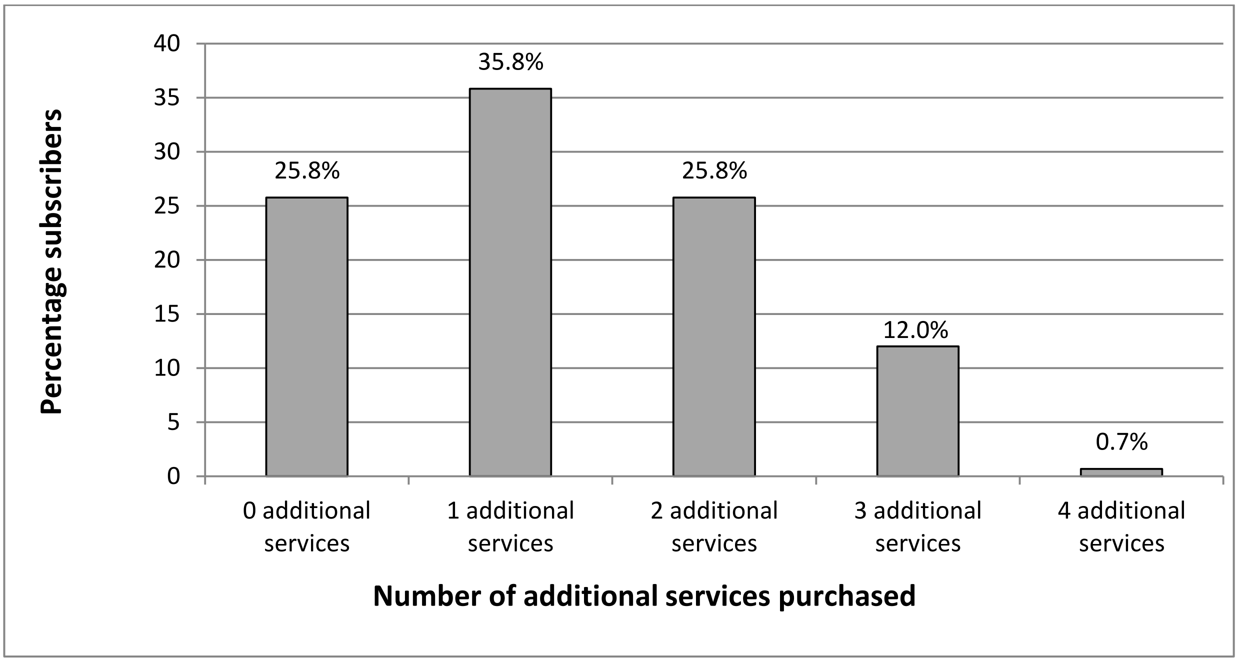
The next relationship characteristic investigated was relationship depth. The purpose of asking the question was to determine how much money the subscriber spent monthly with the MNO. The more money spent monthly implies a deeper relationship. Most subscribers (*n* = 207; 20.2%) spent between R401 and R600 per month with their MNO. A large number of subscribers (*n* = 172; 16.8%) spent slightly less per month (between R201 and R400), while other subscribers spent between R601 and R800 per month (*n* = 166; 16.2%). In total, 38.7% of the respondents (*n* = 396) spent R801 or more per month on mobile telecommunication, whereas 8.2% (*n* = 84) spent approximately R200 or less per month on their mobile phone bill. See Table 5.4 for a summary of the results.

Table 5.4: Relationship depth (switching intention sample, N_1)

Relationship depth (N_1)	n	%
R 0 – R 200	84	8.2
R 201 – R 400	172	16.8
R 401 – R 600	207	20.2
R 601 – R 800	166	16.2
R 801 – R1,000	101	9.9
R1,001 – R1,250	88	8.6
R1,251 – R1,500	67	6.5
R1,501 – R1,750	29	2.8
R1,751 – R2,000	37	3.6
R2,001 – R2,500	20	2.0
R2,501 – R3,000	23	2.2
R3,001 – R3,500	12	1.2
R3,501 – R4,000	5	0.5
R4,001 – R4,500	2	0.2
R4,501 – R5,000	3	0.3
Above R5,001	9	0.9
	1025	**100**

After relationship length and depth, the third relationship characteristic, relationship breadth, was analysed. Relationship breadth was determined by examining the number of additional services that subscribers purchased. Furthermore, if respondents indicated that they had in fact purchased additional services, they were asked to indicate which specific additional services they had purchased. Even though a small number of respondents did not acquire any additional services (n = 264; 25.8%), most acquired either one additional service (n = 367; 35.8%) or two additional services (n = 264; 25.8%). The number of additional services purchased are shown in Figure 5.2.

Figure 5.2: Number of additional services purchased (switching intention sample, N_1)



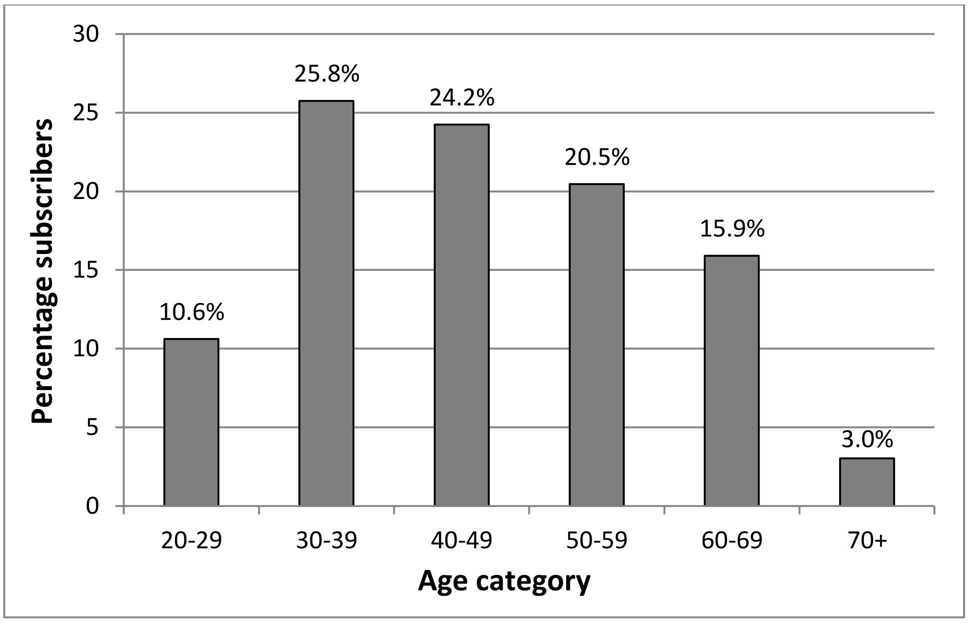
Of the additional services purchased, the most popular were data bundles (*n* = 631; 48.8%), SMS bundles (*n* = 370; 28.6%) and roaming (*n* = 253; 19.6%). Additional services mentioned by the respondents included additional airtime (*n* = 18; 1.4%), BlackBerry Internet Service (BIS) (*n* = 12; 0.9%), the purchase of a notebook or tablet with a data contract (*n* = 4; 0.3%) or mobile phone insurance (*n* = 2; 0.2%). Data bundles, roaming and SMS bundles may have been indicated as being the highest categories of additional services purchased because they were the three options provided in the survey. However, additional airtime was certainly a noticeable new category in the "other" category, suggesting that communication is still very important to subscribers.

The switching behaviour sample profile follows in the next section, in the same sequence as the switching intention sample profile (N_1).

5.2.2 Switching behaviour sample profile (N_2)

As indicated in Figure 5.3, the largest age category for the switching behaviour sample (N_2) was the 30-39 year age category (*n* = 34; 25.8%). The finding is surprising, as it is in stark contrast to the switching intention sample (N_1) where the 50-59 year age group was the largest. The number of switching behaviour respondents seem to decrease as the age categories increase: 40-49 years (*n* = 32; 24.2%), 50-59 years (*n* = 27; 20.5%), 60-69 years (*n* = 21; 15.9%), 70 years and older (n = 4; 3%); suggesting that as age increases, respondents may be less inclined to switch. Of further interest is the fact that the 20-29 year age group was very small (*n* = 14; 10.6%) in comparison to the bulk of the switching behaviour sample. The average age of the switching behaviour respondents was 46.07 years (*M* = 46.07; *SD* = 13.18).

Figure 5.3: Subscriber age profile (switching behaviour sample, N_2)



In the switching behaviour sample (N_2), 33% of the respondents (*n* = 29) were female; 67% (*n* = 59) were male. The gender distribution is similar to the results found in the switching intention sample (N_1), and also in line with previous research indicating that more males have internet access (Horrocks, 2013; Muller, 2010).

In terms of ethnicity, most respondents (*n* = 63; 72.4%) were White. A somewhat smaller number of respondents were African (*n* = 9; 10.3%). The other ethnic groups were Indian (*n* = 6; 6.9%), Coloured (*n* = 4; 4.6%) and Asian (*n* = 1; 1.1%). The results are very similar to the switching intention sample (N_1), except that there are a comparatively larger number of Indians in the switching behaviour sample (N_2) and less Coloureds than in the switching intention sample (N_1). No ethnic descriptions were available for a small number of respondents (*n* = 4; 4.6%).

As with the switching intention sample (N_1), the bulk of the switching behaviour respondents (N_2) were English (*n* = 35; 64.8%) and Afrikaans (*n* = 17; 31.5%). There was a very small representation of two other languages: Sepedi (*n* = 1; 1.9%) and Sesotho (*n* = 1; 1.9%). isiXhosa, isiZulu and Setswana, which were represented in the switching intention sample (N_1), were absent for the switching behaviour sample (N_2).

Regarding level of education, the majority respondents were graduates (*n* = 38; 50.7%) or had a postgraduate qualification (*n* = 19; 25.3%). Some respondents had completed secondary schooling (*n* = 13; 17.3%), while others were undergraduates (*n* = 5; 6.7%). Of interest is the fact that such a high percentage of the switching behaviour respondents are graduates and postgraduates. There are comparatively more postgraduate respondents in the switching behaviour sample (N_2) than in the switching intention sample (N_1). Thus the results suggest that level of education influences switching intention.

In terms of employment status, as was the case with the switching intention sample (N_1), most switching behaviour respondents (N_2) were employed (*n* = 36; 67.9%) and 20.8% (*n* = 11) were self-employed. The remaining respondents were either unemployed (*n* = 1; 1.9%) or retired (*n* = 5; 9.4%).

The highest *personal monthly income* in the switching behaviour sample (N_2) was between R25,001 and R40,000 (*n* = 18; 28.6%). The next two highest personal monthly income groups earned between R16,001 and R25,000 (*n* = 9; 14.3%) and between R8,001 and R11,000 (*n* = 9; 14.3%). The remaining 19% of respondents (*n* = 12) earned above R40,001, between R11,001 and R16,000 (*n* = 7; 11.1%), or below R8,000 (*n* = 8; 12.7%). Table 5.5 presents a summary of the personal monthly income of the switching behaviour sample.

Table 5.5: Personal monthly income (switching behaviour sample, N_2)

Personal monthly income	Frequency	Valid percent (N_2 = 63)
R 1 - R6,000	4	6.3
R 6,001 - R8,000	4	6.3
R 8,001 - R11,000	9	14.3
R11,001 - R16,000	7	11.1
R16,001 - R25,000	9	14.3
R25,001 - R40,000	18	28.6
R40,001 - R60,000	6	9.5
R60,001 - R100,000	5	7.9
R100,001 and more	1	1.6
Total	63	100
Missing	72	
	135	
	Median (*Mdn*)	23 166.67
	Mean (*M*)	28 722.22
	Standard deviation (*SD*)	23 603.54

Very little data was available regarding the *monthly household income* of the switching behaviour sample (26). Nonetheless, the highest monthly household income was between R25,001 and R40,000 (n = 7; 26.9%). The same number of respondents (n = 5; 19.2%) earned either between R16,001 and R25,000 or between R60,001 and 100,000. The remaining respondents had a monthly household income of either R16,000 or less (n = 5; 19.2%), or a monthly household income of between R40,001 and R60,000 (n = 3; 11.5%), or above R100,000 (n = 1; 3.8%). The monthly household income results are presented in Table 5.6.

Table 5.6: Monthly household income (switching behaviour sample, N_2)

Monthly household income	Frequency	Valid percent (N_2 = 26)
R 1 - R6,000	2	7.7
R 6,001 - R8,000	0	0.0
R 8,001 - R11,000	2	7.7
R11,001 - R16,000	1	3.8
R16,001 - R25,000	5	19.2
R25,001 - R40,000	7	26.9
R40,001 - R60,000	3	11.5
R60,001 - R100,000	5	19.2
R100,001 and more	1	3.8
Total	26	100
Missing	109	
	135	
	Median (*Mdn*)	31 500.00
	Mean (*M*)	39 942.31
	Standard deviation (*SD*)	29 863.47

To conclude the switching behaviour sample (N_2) profile, the three components of relationship characteristics, namely relationship length, depth and breadth are briefly discussed.

The switching behaviour sample respondents (N_2) were required to indicate how long they had a contract with their previous MNO. In sharp contrast to the switching intention sample (N_1) , most switching behaviour sample (N_2) respondents were with their previous MNO for only 2 to 5 years (*n* = 33; 24.4%), whereas most switching intention respondents had a contract with their MNO for 15 years or more (*n* = 265; 25.9%). As was the case for the switching intention sample (N_1), the second longest period for which switching behaviour respondents (N_2) had a contract with their MNO was 8 to 12 years (*n* = 26; 19.3%). A few of the switching behaviour respondents had contracts with their previous MNO for 5 to 8 years (*n* = 24; 17.8%). A rather surprising result is that 11.9% of the respondents (*n* = 16) switched after being with their MNO for 15 years or more. Table 5.7 shows the results for the switching behaviour sample's relationship length.

Table 5.7: Relationship length (switching behaviour sample, N_2)

Relationship length (N_2)	**n**	**%**
Less than 6 months	4	3.0
6 to 12 months	6	4.4
12 to 18 months	2	1.5
18 to 24 months	11	8.1
2 to 5 years	33	24.4
5 to 8 years	24	17.8
8 to 12 years	26	19.3
12 to 15 years	13	9.6
Longer than 15 years	16	11.9
	135	**100**

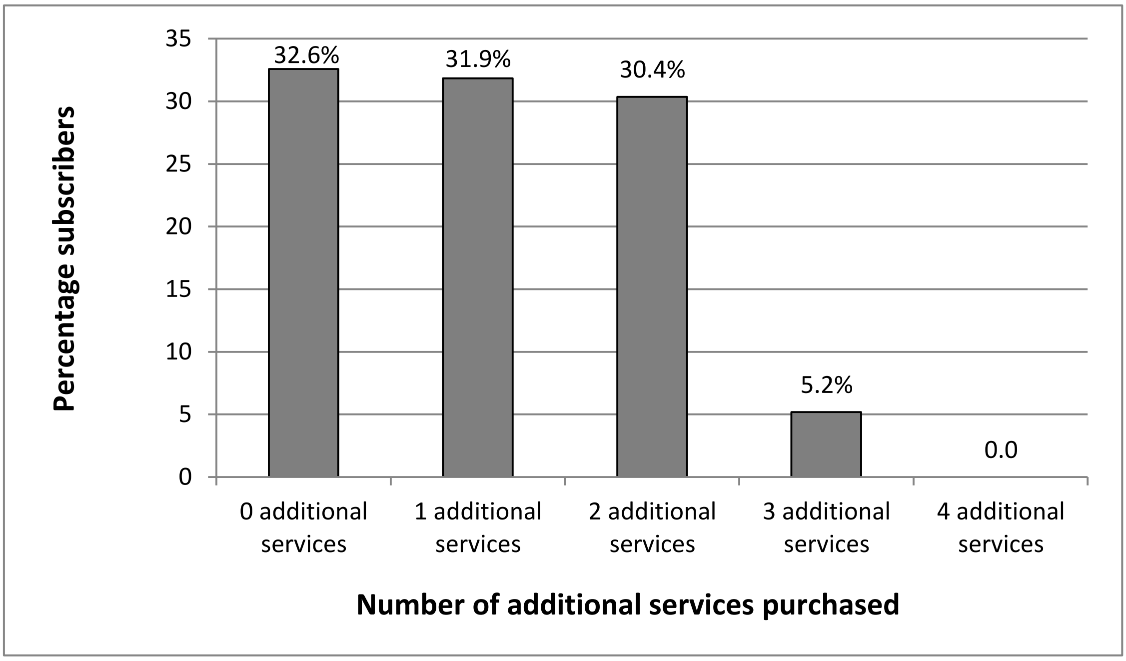
Most of the switching behaviour respondents (*n* = 32; 23.7%) indicated that their monthly bill with their previous MNO was approximately R201 to R400 per month. A large number of respondents indicated that their monthly bill was between R401 and R600 per month (*n* = 26; 19.3%). The next two largest categories indicated that their monthly bill at their previous MNO was either R100 per month (*n* = 19; 14.1%) or R700 per month (*n* = 19; 14.1%). The remaining 28.7% spent R900 or more per month on mobile telecommunication at their previous MNO. Tin comparison to the majority in the switching intention sample (N_1) that spent between R401 and R600 per month, most of the switching behaviour (N_2) respondents' monthly bill was between R201 to R400 per month. Table 5.8 shows the results for relationship depth in the switching behaviour sample (N_2).

Table 5.8: Relationship depth (switching behaviour sample, N_2)

Relationship depth (N_2)	n	%
R 0 – R 200	19	14.1
R 201 – R 400	32	23.7
R 401 – R 600	26	19.3
R 601 – R 800	19	14.1
R 801 – R1,000	12	8.9
R1,001 – R1,250	5	3.7
R1,251 – R1,500	6	4.4
R1,501 – R1,750	6	4.4
R1,751 – R2,000	3	2.2
R2,001 – R2,500	0	0.0
R2,501 – R3,000	3	2.2
R3,001 – R3,500	0	0.0
R3,501 – R4,000	2	1.5
R4,001 – R4,500	1	0.7
R4,501 – R5,000	0	0.0
Above R5,001	1	0.7
	135	**100**

As with the switching intention sample (N_1), the number of additional services that the switching behaviour sample (N_2) subscribers purchased was an indication of relationship breadth. In contrast to the switching intention sample (N_1), overall less switching behaviour respondents (N_2) purchased additional services from their previous MNO (n = 44; 32.6%). Nonetheless, more than half of the subscribers that purchased additional services purchased either one (n = 43; 31.9%) or two additional services (n = 41; 30.4%). A small percentage subscribers acquired three additional services (n = 7; 5.2%), but none of the switching behaviour sample respondents purchased more than three additional services. Figure 5.4 shows the results for relationship breadth in the switching behaviour sample (N_2).

Figure 5.4: Number of additional services purchased (switching behaviour sample, N_2)



As was the case with the switching intention sample (N_1), the most popular additional services purchased by the switching behaviour sample (N_2) were data bundles (n = 68; 46.6%), SMS bundles (n = 47; 32.2%) and roaming (n = 25; 17.1%). Also possibly due to the inclusion of these three options in the questionnaire. Additional airtime (n = 3; 2.1%) and BlackBerry Internet Service (BIS) (n = 3; 2.1%) were equally popular. The switching behaviour sample (N_2) did not mention any other types of additional services.

Following the descriptions of the MNOs and the samples, the descriptive statistics of the measurement scales are presented in the next section.

5.3 MOBILE NETWORK OPERATORS

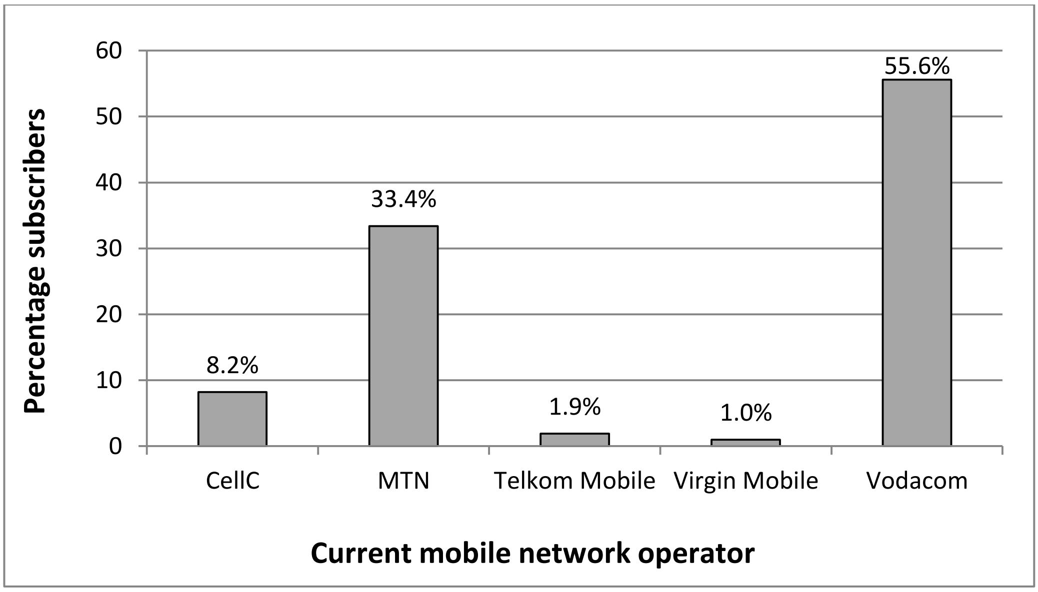
For the purpose of the study, switching was investigated in the mobile telecommunications context. Therefore questions were asked to determine with which MNO the respondents had a contract and for the switching behaviour sample (N_2), from which MNO they had switched. The results are discussed in the ensuing paragraphs.

5.3.1 Main mobile network operator

In 2012 mobile penetration was over 128 percent in South Africa (Deloitte Digital SA, 2013), implying that some subscribers may have a contract with more than one MNO. Thus the purpose of the first question was to determine which MNO respondents considered as their *main* service provider, so that respondents answered the remainder of the survey questions based only on a single MNO.

The switching intention sample (N_1 = 1025) results indicated that the majority respondents had a contract with Vodacom (*n* = 570; 56.6%), followed by MTN (*n* = 342; 33.4%). Together, these two MNOs comprise 89% of the total number of switching intention respondents. The result is in line with figures for South Africa as a whole, since the two dominant mobile network operators in South Africa are Vodacom and MTN (Deloitte Digital SA, 2013; Kruger & Mostert, 2012:45). The remaining 11% of respondents subscribed to Cell C (*n* = 84; 8.2%), Telkom Mobile (*n* = 19; 1.9%) and Virgin Mobile (*n* = 10; 1.0%) respectively. Results indicating the main MNO for the switching intention sample are shown in Figure 5.5.

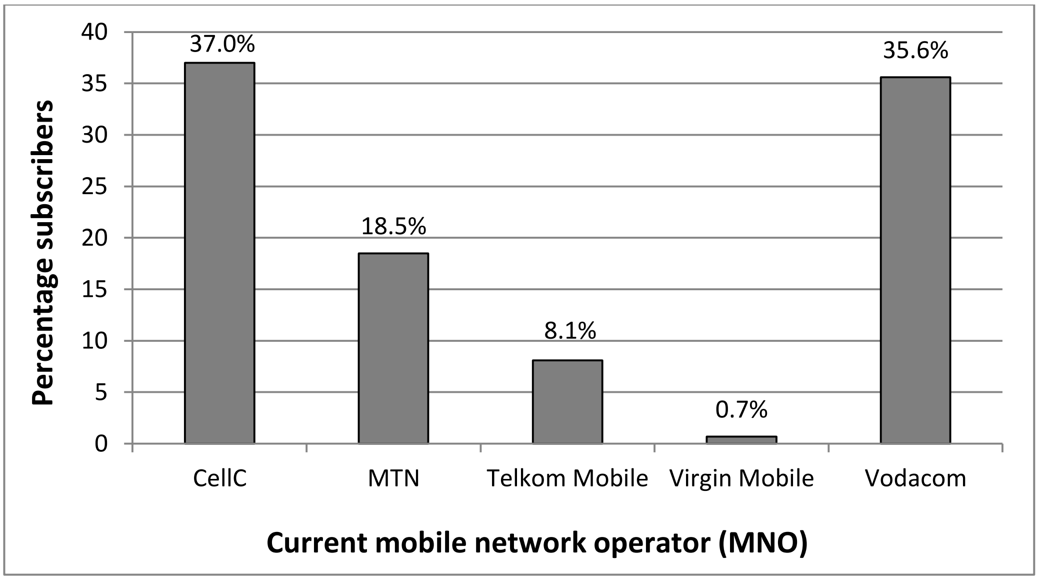
Figure 5.5: Main MNO with whom the switching intention sample (N_1) have a contract



In contrast to the switching intention sample, most respondents in the switching behaviour sample (N_2 = 135) had a contract with Cell C (*n* = 50; 37%). Nonetheless, as with the switching intention sample, a large number of switching behaviour respondents (N_2) also had a contract with Vodacom (*n* = 48; 35.6%). Thus combined, 72.6% of the switching behaviour sample had contracts with the two aforementioned MNOs. Of the remaining respondents, 18.5% (*n* = 25) had a contract with MTN, Telkom Mobile (*n* = 11; 8.1%) or Virgin Mobile (n = 1; 0.7%).

The result is interesting since Cell C is the dominant MNO in the switching behaviour sample (N_2), even though nationally, it is the third-largest MNO (Deloitte Digital SA, 2013). The results suggest that most respondents switched from Vodacom to Cell C, as there was a sharp increase in the number of Cell C subscribers and a substantial decrease in the number of Vodacom subscribers in the switching behaviour sample. Also of interest is the fact that the number of Telkom Mobile subscribers in the switching behaviour sample was larger relative to the switching intention sample. In comparison, the number of Virgin Mobile subscribers remained relatively constant. The results indicating the main MNO for the switching behaviour sample are shown in Figure 5.6.

Figure 5.6: Main MNO with whom the switching behaviour sample (N_2) have a contract

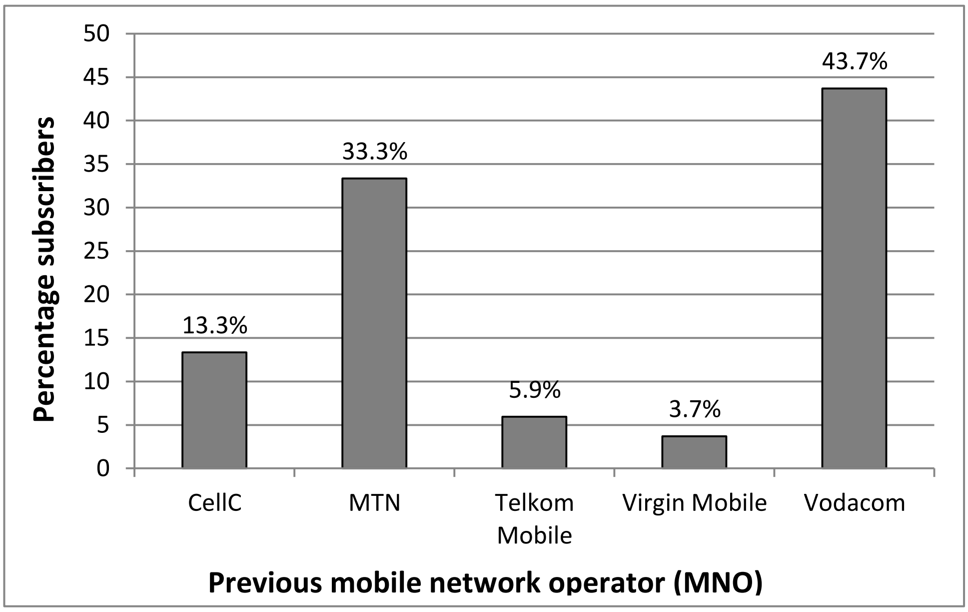


Results in the next section are for the switching behaviour sample (N_2) only.

5.3.2 Mobile network operator switched from

Only the switching behaviour sample (N_2) respondents were asked to indicate from which MNO they had switched. The majority respondents switched from Vodacom (*n* = 59; 43.7%) which supports the aforementioned speculation that most respondents that switched were previously Vodacom subscribers. Many respondents switched from MTN (*n* = 45; 33.3%) and a small number switched from Cell C (*n* = 18; 13.3%). The minority respondents switched from Telkom Mobile (*n* = 8; 5.9%) and Virgin Mobile (*n* = 5; 3.7%). The results are shown in Figure 5.7.

Figure 5.7: MNO from whom the switching behaviour sample (N_2) switched



To further investigate from which MNO respondents switched, a cross-tabulation was drawn for the switching behaviour sample (N_2) to determine from which MNO the respondents in the switching behaviour sample had switched, and to which MNO they had switched. The results are provided in Table 5.9.

Table 5.9: Cross-tabulation of MNO switched from/MNO switched to (N_2)

		MNO switched to (current MNO)					Total
		Cell C	MTN	Telkom Mobile	Virgin Mobile	Vodacom	
MNO switched from (previous MNO)	Cell C	3	4	1	1	12	21
	MTN	14	9	4	0	27	54
	Telkom Mobile	0	2	1	0	6	9
	Virgin Mobile	1	1	0	0	3	5
	Vodacom	35	18	6	0	15	74
	Total	53	34	12	1	63	**163**

A discrepancy was noticed in the cross-tabulation (Table 5.9). The purpose of the cross-tabulation was to indicate which MNO the respondents switched from and which MNO the respondents switched to, therefore each block which indicates ‘MNO switched from’ and ‘MNO switched to’ for the same MNO should have a ‘zero’ value. For example, the block which indicates ‘switched from MTN to MTN’ should not have a value. However, in total, 28 respondents indicated that they ‘switched to' the same MNO that they had switched from. In other words, no switch had actually taken place. The possibility exists that the respondents misinterpreted the question and that they had in actual fact switched to another type of contract, but had remained with the same MNO. Therefore, even though the results indicate that a total of 21 Cell C customers switched to other MNOs, only 18 in actual fact switched, since three respondents mentioned that they switched from Cell C, to Cell C. As a result of the discrepancy found in the ‘MNO switched from/MNO switched to’ cross-tabulation, all of the results for the switching behaviour sample were recalculated and reported using 135 respondents and not the original 163 respondents. The updated cross-tabulation is presented in Table 5.10.

Table 5.10: MNO switched from/MNO switched to cross-tabulation (N_2)

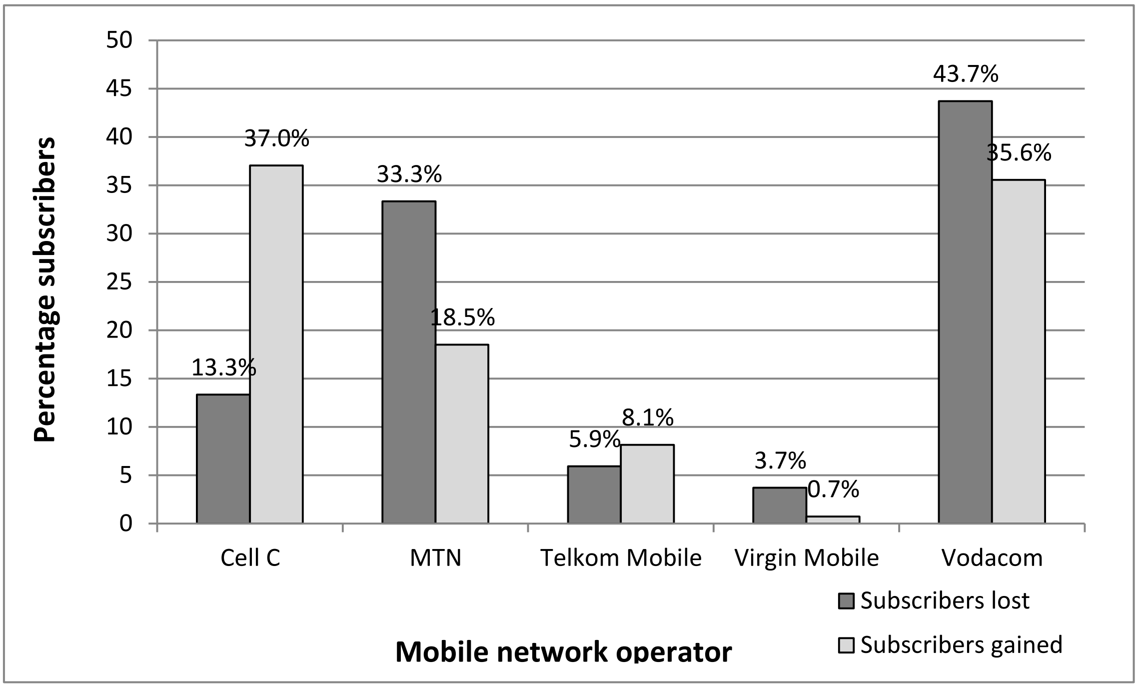
		MNO switched to (current MNO)					Total
		Cell C	MTN	Telkom Mobile	Virgin Mobile	Vodacom	
MNO switched from (previous MNO)	Cell C	X	4	1	1	12	18
	MTN	14	X	4	0	27	45
	Telkom Mobile	0	2	X	0	6	8
	Virgin Mobile	1	1	0	X	3	5
	Vodacom	35	18	6	0	X	59
	Total	50	25	11	1	48	**135**

Further investigation showed that most switching behaviour sample (N_2) respondents were Vodacom subscribers (*n* = 59) switched to Cell C (*n* = 35; 59.3%), while fewer switched to MTN (*n* = 18; 30.5%). Of the subscribers that switched from MTN (*n* = 45), most switched to Vodacom (*n* = 27; 60%), while fewer switched to Cell C (*n* = 14; 31.1%). Most Cell C subscribers that switched (*n* = 18), moved to Vodacom (*n* = 12; 66.7%), while a small number of Cell C subscribers moved to MTN (*n* = 4; 22.2%). The results suggest that the majority of MTN (60%) and Cell C (66.7%) subscribers switched to Vodacom and that most Vodacom subscribers (59.3%) switched to Cell C. Thus it would appear that in general, subscribers that were with an MNO other than Vodacom, had a tendency to choose Vodacom over the other available MNOs.

The total number of current MTN subscribers in the switching behaviour sample (N_2) (*n* = 25; 18.5%) was less than the total number of subscribers that switched from MTN (*n* = 45; 33.3%) to an alternative MNO. Similarly, Vodacom also had less current subscribers (*n* = 48; 35.6%) than subscribers that switched from Vodacom to another MNO (*n* = 59; 43.7%). Likewise, the number of current Virgin Mobile subscribers in the switching behaviour sample (*n* = 1; 0.7%) was less than the number of subscribers that chose to switch from Virgin Mobile to another MNO (*n* = 5; 3.1%). The results suggest that these three MNOs lost more subscribers than they gained. Even though Vodacom and MTN are the dominant MNOs in South Africa (Deloitte Digital SA, 2013), both MNOs should investigate the high number of switchers and determine their reason(s) for switching, in order to develop a suitable customer retention strategy.

The results further suggest that both Cell C and Telkom Mobile gained more subscribers than they lost. Cell C lost 13.3% (*n* = 18) subscribers, but gained a substantial number of customers (*n* = 50; 37%). Even though on a much smaller scale, Telkom Mobile lost less subscribers (*n* = 8; 0.7%) than they gained (*n* = 8; 3.7%). Figure 5.8 shows a comparison of subscribers lost versus subscribers gained for each MNO.

Figure 5.8: Subscribers lost versus subscribers gained (switching behaviour sample, N_2)



5.4 MEASUREMENT SCALE DESCRIPTIVE STATISTICS AND INTERPRETATION

The purpose of Section 4 in the measurement instrument was to ask respondents their opinion regarding: their intention to switch from their MNO; to enquire about their relationship with their MNO; to determine whether respondents perceived that their MNO's service offering was value-for-money; and to ascertain whether respondents regarded any other MNOs as offering better services. The section to follow discusses and interprets each measurement scales individually. The switching intention sample (N_1) results are first discussed, followed by an account of the switching behaviour sample (N_2) results.

The descriptive statistics which include the median (*Mdn*), mean (*M*), standard deviation (*SD*) as well as the frequencies and valid percentages for each measurement item are provided. As mentioned in the research methodology chapter, Likert-type scales are strictly ordinal, but are regarded in marketing literature to be interval scales. When Likert scales have five or more categories, the ordinal data "approach the characteristics required for interval measurement" (Cooper & Schindler, 2014:252) and are thus considered continuous data. Therefore even though the results do not report the true arithmetic mean, the mean and standard deviation are reported together. An 11-point Likert-type scale was used to measure switching intention, switching behaviour, relational switching costs, perceived value and alternative attractiveness. The scale was numbered from 0 to 10, where 0 = do not agree at all, and 10 = completely agree. The measurement scale items, including the results, are presented in separate tables for each construct.

5.4.1 Switching intention measurement scales (N_1)

The switching intention sample (N_1) respondents were asked questions regarding their intention to switch to another MNO in the future. The questions are presented in Table 5.11 below. Most respondents did not expect to remain with their current MNO for the foreseeable future (*M* = 2.50, *SD* = 2.12), thus implying a high intention to switch. However, when asked whether they intended to switch to another MNO as soon as their contract with their current MNO expired, respondents were hesitant to do so (*M* = 3.09; *SD* = 3.05). Respondents were unsure whether they would switch to a MNO that offered better services (*M* = 5.20, *SD* = 3.50). Nonetheless, the respondents had not considered changing from their current MNO to another MNO (*M* = 3.92, *SD* = 3.40) and were unlikely to switch as a result of experiencing problems with their current MNO (*M* = 3.38, *SD* = 3.21). The results for the switching intention scale are shown in Table 5.11.

Table 5.11: Descriptive statistics for the switching intention scale (switching intention sample, N_1)

Switching intention (N_1 = 1025)			Do not agree at all	1	2	3	4	5	6	7	8	9	Completely agree	Median (*Mdn*)	Mean (*M*)	Standard deviation (*SD*)
A5_1	I expect to stay with my current mobile network for the foreseeable future	n	318	162	165	82	67	100	26	31	17	15	42	2	2.51	2.73
		%	31.0	15.8	16.1	8.0	6.5	9.8	2.5	3.0	1.7	1.5	4.1			
A5_2	When my contract with my current mobile network expires, I am likely to switch to another mobile network	n	275	144	138	85	57	119	38	45	41	27	56	2	3.09	3.05
		%	26.8	14.0	13.5	8.3	5.6	11.6	3.7	4.4	4.0	2.6	5.5			
A5_3	I have often considered changing from my current mobile network to another mobile network	n	230	128	104	75	44	100	63	68	79	49	85	3	3.92	3.40
		%	22.4	12.5	10.1	7.3	4.3	9.8	6.1	6.6	7.7	4.8	8.3			
A5_4	I am likely to switch to a mobile network that offers better services	n	160	84	60	49	41	138	58	85	115	91	144	5	5.20	3.50
		%	15.6	8.2	5.9	4.8	4.0	13.5	5.7	8.3	11.2	8.9	14.0			
A5_5	I am likely to switch to another mobile network because I have experienced problems with my current mobile network	n	247	151	136	80	50	104	50	49	51	38	69	2	3.38	3.21
		%	24.1	14.7	13.3	7.8	4.9	10.1	4.9	4.8	5.0	3.7	6.7			

Secondly, respondents were asked questions regarding their relationship with their MNO. The purpose of the question was to determine whether the respondent would experience relational switching costs should they decide to end their relationship with their current MNO.

The majority respondents seemed apathetic to any questions related to personal relational switching costs. The staff at their current MNO did not matter to them (*M* = 3.88, *SD* = 3.20) and they would not miss dealing with the staff at their current MNO, should they switch to another MNO (*M* = 3.93, *SD* = 3.17). Furthermore, they did not like talking to the staff at their current MNO (*M* = 3.96, *SD* = 3.15) and would not feel more comfortable interacting with the staff working for their current MNO than they would be if they switched to another MNO (*M* = 4.15, *SD* = 3.11).

In contrast, respondents appeared to have a rather neutral opinion regarding the MNO's brand. Respondents showed slight preference toward liking the public image of their MNO (*M* = 5.57, *SD* = 2.95) and being supportive of their MNO as a firm (*M* = 5.47, *SD* = 3.09). However, respondents were neutral regarding caring about their MNO's brand/company name (*M* = 5.01, *SD* = 3.22). Results for the relational switching costs scale are shown in Table 5.12.

Table 5.12: Descriptive statistics for the relational switching costs scale (switching intention sample, N_1)

Relational switching costs (N_1 = 1025)			Do not agree at all	1	2	3	4	5	6	7	8	9	Completely agree	Median (*Mdn*)	Mean (*M*)	Standard deviation (*SD*)
A6_1	I would miss dealing with the staff at my current mobile network if I switched to another mobile network	n	200	114	98	83	52	201	49	56	58	31	83	4	3.93	3.17
		%	19.5	11.1	9.6	8.1	5.1	19.6	4.8	5.5	5.7	3.0	8.1			
A6_2	I am more comfortable interacting with the staff working for my current mobile network than I would be if I switched to another mobile network	n	172	115	87	76	41	245	52	62	57	39	79	5	4.15	3.11
		%	16.8	11.2	8.5	7.4	4.0	23.9	5.1	6.0	5.6	3.8	7.7			
A6_3	The staff at my current mobile network matter to me	n	201	138	98	69	42	200	44	57	61	36	79	4	3.88	3.20
		%	19.6	13.5	9.6	6.7	4.1	19.5	4.3	5.6	6.0	3.5	7.7			
A6_4	I like talking to the staff at my current mobile network	n	193	123	95	68	56	211	51	61	54	35	78	4	3.96	3.15
		%	18.8	12.0	9.3	6.6	5.5	20.6	5.0	6.0	5.3	3.4	7.6			
A6_5	I like the public image that my current mobile network has	n	90	49	46	48	50	231	104	105	117	72	113	5	5.57	2.95
		%	8.8	4.8	4.5	4.7	4.9	22.5	10.1	10.2	11.4	7.0	11.0			
A6_6	I support my current mobile network as a firm	n	101	59	46	63	42	236	71	101	100	77	129	5	5.47	3.09
		%	9.9	5.8	4.5	6.1	4.1	23.0	6.9	9.9	9.8	7.5	12.6			
A6_7	I care about my current mobile network's brand/company name	n	132	84	50	68	53	211	82	76	85	61	123	5	5.01	3.22
		%	12.9	8.2	4.9	6.6	5.2	20.6	8.0	7.4	8.3	6.0	12.0			

Next, the respondents were asked about the value that they received from the service that they purchased from their MNO at the time of the survey. Even though the respondents seemed to have a rather neutral opinion regarding perceived value in general, most respondents gave the impression that the total monthly bill from their current MNO was acceptable (*M* = 5.80, *SD* = 2.89). The possible reason for the 'neutral' responses regarding whether the respondent's current MNO offers good value-for-money (*M* = 5.51, *SD* = 2.88) or whether the current MNO offers better value-for-money for the same service at another MNO (*M* = 5.14, *SD* = 2.92) could be that respondents had not thought about or compared other options prior to answering the survey.

Of interest is the fact that most respondents indicated that their current MNO offered good value-for-money (*n* = 121; 11.8%) and when compared to other MNOs, respondents also agreed that their current MNO offered better value-for-money than what they would pay for the same service at another MNO (*n* = 111; 10.8%). Overall, the perceived value results allude to the fact that the respondents perceived that they received good value-for-money and in this case seem unlikely to switch. The results for the perceived value scale are shown in Table 5.13.

Table 5.13: Descriptive statistics for the perceived value scale (switching intention sample, N_1)

Perceived value (N_1 = 1025)			Do not agree at all	1	2	3	4	5	6	7	8	9	Completely agree	Median (*Mdn*)	Mean (*M*)	Standard deviation (*SD*)
A7_1	My total monthly bill from my current mobile network is acceptable	n	53	43	68	83	69	148	92	128	141	76	124	6	5.80	2.89
		%	5.2	4.2	6.6	8.1	6.7	14.4	9.0	12.5	13.8	7.4	12.1			
A7_2	My current mobile network offers good value for money	n	53	59	75	84	77	167	101	121	111	67	110	5	5.51	2.88
		%	5.2	5.8	7.3	8.2	7.5	16.3	9.9	11.8	10.8	6.5	10.7			
A7_3	My current mobile network offers better value for money than what I would pay for the same service at another mobile network	n	82	57	77	82	73	237	89	93	77	47	111	5	5.14	2.92
		%	8.0	5.6	7.5	8.0	7.1	23.1	8.7	9.1	7.5	4.6	10.8			

Respondents were asked their opinion regarding the difference between their current MNO and other MNOs to determine their view regarding alternative attractiveness. Respondents believed that they would be much more satisfied with other MNOs than with their current MNO (*M* = 3.50, *SD* = 2.59). Respondents also preferred to do business with other MNOs instead of with their current MNO (*M* = 3.52, *SD* = 2.61). In addition, respondents were of the opinion that they would be more satisfied with the service available from other MNOs than the service they receive from their current MNO (*M* = 3.64, *SD* = 2.61). Respondents felt that policies at other MNOs would benefit them much more than the policies at their current MNO (*M* = 3.80, *SD* = 2.50). Overall, the majority respondents had the view that other MNOs would be more fair than their current MNO (*M* = 4.24, *SD* = 2.60).

When comparing their current MNO to other (alternative) MNOs, it appears that respondents overall had a high intention to switch. Thus it seems that alternative attractiveness may be a strong driver of switching intention. The results for the alternative attractiveness scale are shown in Table 5.14.

Table 5.14: Descriptive statistics for the alternative attractiveness scale (switching intention sample, N_1)

Alternative attractiveness (N_1 = 1025)			Do not agree at all	1	2	3	4	5	6	7	8	9	Completely agree	Median (*Mdn*)	Mean (*M*)	Standard deviation (*SD*)
A8_1	All in all, other mobile networks would be more reasonable than my current mobile network	n	101	76	103	119	94	268	84	60	51	26	43	5	4.24	2.60
		%	9.9	7.4	10.0	11.6	9.2	26.1	8.2	5.9	5.0	2.5	4.2			
A8_2	Overall, other mobile networks' policies would benefit me much more than my current mobile network's policies	n	121	98	116	125	111	267	63	43	33	14	34	4	3.80	2.50
		%	11.8	9.6	11.3	12.2	10.8	26.0	6.1	4.2	3.2	1.4	3.3			
A8_3	I would be much more satisfied with the service available from other mobile networks than the service provided by my current mobile network	n	145	109	126	132	86	249	41	52	32	14	39	4	3.64	2.61
		%	14.1	10.6	12.3	12.9	8.4	24.3	4.0	5.1	3.1	1.4	3.8			
A8_4	In general, I would be much more satisfied with other mobile networks than I am with my current mobile network	n	147	121	137	148	74	227	51	38	26	20	36	3	3.50	2.59
		%	14.3	11.8	13.4	14.4	7.2	22.1	5.0	3.7	2.5	2.0	3.5			
A8_5	Overall, other mobile networks would be better to do business with than my current mobile network	n	150	119	146	122	78	241	46	33	34	21	35	3	3.52	2.61
		%	14.6	11.6	14.2	11.9	7.6	23.5	4.5	3.2	3.3	2.0	3.4			

The next section discusses the measurement scale results for the switching behaviour sample (N_2).

5.4.2 Switching behaviour measurement scales (N_2)

The switching behaviour sample (N_2) respondents were asked questions regarding their behaviour relating to their previous MNO. The majority respondents did not expect to stay with their MNO for long when they originally subscribed to their previous MNO (*M* = 2.50, *SD* = 2.12). In contrast, respondents did not intend to switch to another MNO once their contract with their previous MNO expired (*M* = 3.28, *SD* = 3.60). Switching behaviour respondents intended to switch to a MNO that offered better services (*M* = 6.17, *SD* = 3.57), but not necessarily due to regularly experiencing problems with their previous MNO (*M* = 5.45, *SD* = 3.81). However, they did not often consider changing networks when they were with their previous MNO (*M* = 4.51, *SD* = 3.52). A summary of the results for the switching behaviour scale are shown in Table 5.15.

Table 5.15: Descriptive statistics for the switching behaviour scale (switching behaviour sample, N_2)

Switching behaviour (N_2 = 135)			Do not agree at all	1	2	3	4	5	6	7	8	9	Completely agree	Median (*Mdn*)	Mean (*M*)	Standard deviation (*SD*)
B6_1	When I originally joined my previous mobile network, I expected to stay with them for long	n	0	72	14	18	9	1	13	2	5	0	1	1	2.50	2.12
		%	0.0	53.3	10.4	13.3	6.7	0.7	9.6	1.5	3.7	0.0	0.7			
B6_2	I intended to switch to another mobile network as soon as my contract with my previous mobile network expired	n	38	29	13	6	7	7	5	3	5	4	18	2	3.28	3.60
		%	28.1	21.5	9.6	4.4	5.2	5.2	3.7	2.2	3.7	3.0	13.3			
B6_3	I often considered changing networks when I was with my previous mobile network	n	23	17	12	10	6	12	8	11	11	9	16	4	4.51	3.52
		%	17.0	12.6	8.9	7.4	4.4	8.9	5.9	8.1	8.1	6.7	11.9			
B6_4	I intended to switch from my previous mobile network to a mobile network that offered better services	n	12	12	6	6	6	15	9	5	12	13	39	7	6.17	3.57
		%	8.9	8.9	4.4	4.4	4.4	11.1	6.7	3.7	8.9	9.6	28.9			
B6_5	I often had problems with my previous mobile network, which made me decide to switch to my current mobile network	n	18	17	7	6	3	20	8	6	5	5	40	5	5.45	3.81
		%	13.3	12.6	5.2	4.4	2.2	14.8	5.9	4.4	3.7	3.7	29.6			

Regarding relational switching costs, as was the case with the switching intention sample, the majority respondents did not attach high value to the staff relationships. The respondents did not miss dealing with the staff at their previous MNO (*M* = 2.86, *SD* = 3.20). Also, the respondents felt that the staff at their previous MNO did not matter to them (*M* = 2.88, *SD* = 2.89). The respondents did not particularly like talking to the staff at their previous MNO (*M* = 3.10, *SD* = 3.00); and the majority respondents had a rather neutral opinion regarding whether they were more comfortable interacting with the staff working at their current MNO than they were interacting with the staff at their previous MNO (*M* = 5.03, *SD* = 3.48).

The majority respondents were in agreement that they were not concerned about their previous MNO's brand/company name (*M* = 4.29, *SD* = 3.20) and that they did not like their previous MNO's public image (*M* = 4.70, *SD* = 3.19). Lastly, respondents had a neutral opinion as to whether or not they supported their previous MNO as a firm (*M* = 5.04, *SD* = 3.36). These results suggest that relational switching costs in mobile telecommunications are very low, implying that subscribers have a high intention to switch. The results for the relational switching costs scale are shown in Table 5.16 below.

Table 5.16: Descriptive statistics for the relational switching costs scale (switching behaviour sample, N_2)

Relational switching costs (N_2 = 135)			Do not agree at all	1	2	3	4	5	6	7	8	9	Completely agree	Median (*Mdn*)	Mean (*M*)	Standard deviation (*SD*)
B7_1	I miss dealing with the staff at my previous mobile network	n	50	16	11	8	8	20	3	0	5	6	8	2	2.86	3.20
		%	37.0	11.9	8.1	5.9	5.9	14.8	2.2	0.0	3.7	4.4	5.9			
B7_2	I am more comfortable interacting with the staff working for my current mobile network than I was interacting with the staff at my previous mobile network	n	22	7	10	7	5	35	5	4	5	12	23	5	5.03	3.48
		%	16.3	5.2	7.4	5.2	3.7	25.9	3.7	3.0	3.7	8.9	17.0			
B7_3	The staff at my previous mobile network mattered to me	n	42	19	11	12	6	22	6	5	4	5	3	2	2.88	2.89
		%	31.1	14.1	8.1	8.9	4.4	16.3	4.4	3.7	3.0	3.7	2.2			
B7_4	I liked talking to the staff at my previous mobile network	n	42	19	6	8	9	27	2	7	7	5	3	3	3.10	3.00
		%	31.1	14.1	4.4	5.9	6.7	20.0	1.5	5.2	5.2	3.7	2.2			
B7_5	I like the public image that my previous mobile network has	n	24	8	8	6	6	28	13	14	9	9	10	5	4.70	3.19
		%	17.8	5.9	5.9	4.4	4.4	20.7	9.6	10.4	6.7	6.7	7.4			
B7_6	I supported my previous mobile network as a firm	n	26	6	4	7	3	26	14	12	12	11	14	5	5.04	3.36
		%	19.3	4.4	3.0	5.2	2.2	19.3	10.4	8.9	8.9	8.1	10.4			
B7_7	I cared about my previous mobile network's brand/company name	n	27	11	6	10	9	28	11	8	7	8	10	5	4.29	3.20
		%	20.0	8.1	4.4	7.4	6.7	20.7	8.1	5.9	5.2	5.9	7.4			

Contrary to expectations, the switching behaviour sample felt that their current MNO did not offer better value-for-money than their previous MNO (*M* = 3.07; *SD* = 3.13). However, the switching behaviour sample also felt that their previous MNO did not offer good value-for-money (*M* = 4.57, *SD* = 3.18). These results allude to an overall perception that the available mobile telecommunications packages from MNOs in South Africa do not offer value-for-money. Nonetheless, the respondents were in slight agreement that the total monthly bill from their previous MNO was acceptable (*M* = 5.41, *SD* = 3.44). The results for the perceived value scale are shown in Table 5.17.

Table 5.17: Descriptive statistics for the perceived value scale (switching behaviour sample, N_2)

Perceived value (N_2 = 135)			Do not agree at all	1	2	3	4	5	6	7	8	9	Completely agree	Median (*Mdn*)	Mean (*M*)	Standard deviation (*SD*)
B8_1	My total monthly bill from my previous mobile network was acceptable	n	14	13	7	9	8	19	13	6	11	8	27	5	5.41	3.44
		%	10.4	9.6	5.2	6.7	5.9	14.1	9.6	4.4	8.1	5.9	20.0			
B8_2	My previous mobile network offered good value for money	n	20	9	13	10	11	22	16	4	10	6	14	5	4.57	3.18
		%	14.8	6.7	9.6	7.4	8.1	16.3	11.9	3.0	7.4	4.4	10.4			
B8_3	My current mobile network offers better value for money than what I paid for the same service at my previous mobile network	n	44	13	14	11	9	17	6	2	7	6	6	2	3.07	3.13
		%	32.6	9.6	10.4	8.1	6.7	12.6	4.4	1.5	5.2	4.4	4.4			

Overall, the results for the alternative attractiveness scale suggest that the switching behaviour respondents are much happier with their current MNO than they were with their previous MNO, thus they are satisfied that they switched. In general, switching behaviour respondents were much more satisfied with their current MNO than they were with their previous MNO (*M* = 6.47, *SD* = 3.10). Respondents felt that their current MNO was more fair than their previous MNO (*M* = 6.33, *SD* = 3.16). Furthermore, the switching behaviour respondents were much more satisfied with the service available from their current MNO than the service provided by their previous MNO (*M* = 6.28, *SD* = 3.13). Respondents also agreed that their current MNO's policies benefit them much more than their previous MNO's policies (*M* = 6.19, *SD* = 2.99) and that overall their current MNO is better to do business with than their previous MNO (*M* = 6.11, *SD* = 3.12). The results for the alternative attractiveness scale are shown in Table 5.18 below.

Table 5.18: Descriptive statistics for the alternative attractiveness scale (switching behaviour sample, N_2)

Alternative attractiveness (N_2 = 135)			Do not agree at all	1	2	3	4	5	6	7	8	9	Completely agree	Median (*Mdn*)	Mean (*M*)	Standard deviation (*SD*)
B9_1	All in all, my current mobile network is more reasonable than my previous mobile network	n	8	6	9	6	2	26	7	8	20	13	30	7	6.33	3.16
		%	5.9	4.4	6.7	4.4	1.5	19.3	5.2	5.9	14.8	9.6	22.2			
B9_2	Overall, my current mobile network's policies benefit me much more than my previous mobile network's policies	n	7	7	6	6	2	32	9	13	18	8	27	6	6.19	2.99
		%	5.2	5.2	4.4	4.4	1.5	23.7	6.7	9.6	13.3	5.9	20.0			
B9_3	I am much more satisfied with the service available from my current mobile network than the service provided by my previous mobile	n	11	4	6	7	4	20	10	14	21	11	27	7	6.28	3.13
		%	8.1	3.0	4.4	5.2	3.0	14.8	7.4	10.4	15.6	8.1	20.0			
B9_4	In general, I am much more satisfied with my current mobile network than I was with my previous mobile network	n	11	4	3	7	3	21	11	13	17	18	27	7	6.47	3.10
		%	8.1	3.0	2.2	5.2	2.2	15.6	8.1	9.6	12.6	13.3	20.0			
B9_5	Overall, my current mobile network is better to do business with than my previous mobile network	n	11	3	6	10	4	24	15	8	15	12	27	6	6.11	3.12
		%	8.1	2.2	4.4	7.4	3.0	17.8	11.1	5.9	11.1	8.9	20.0			

In the preceding sections, all of the descriptive statistics were discussed. The MNOs with whom the respondents currently have a contract were examined, as well as those from whom the switching behaviour sample switched.

5.5 MEASUREMENT SCALE VALIDITY AND RELIABILITY

Quality research is reliant on the accuracy and quality of measurement scales. Therefore the assessment of measurement scale reliability and validity are an integral part of good research practice (Leedy & Ormrod, 2010:91-92). Even though existing scales were used for the current study, reliability and validity were assessed to confirm that the measurement scales remained reliable and valid in the South African context and in the context of mobile telecommunications.

5.5.1 Validity of the switching intention measurement scales

Measurement scales which were proven valid in previous studies were used, thus the constructs were expected to be valid. Nonetheless, even though the constructs used in this study were derived *a priori*, a decision was made to conduct EFA for several reasons. Firstly, the constructs were not derived from a singular instrument, but from several studies. Secondly, these constructs have not been tested together before, thus constituting a new framework (and instrument). EFA thus allowed the researcher to examine the relationships between variables and assess the unidimensionality of each construct. Finally, and most relevant to this section, EFA evaluates the construct validity of the scales (Williams, Onsman & Brown, 2010:2). Using the five generally accepted steps required to conduct an EFA (Hair *et al*., 2014:95; Mooi & Sarstedt, 2011:206; Pallant, 2011:182), the first step is to determine data suitability.

Data suitability is determined by investigating sample size and item intercorrelation strength (Pallant, 2011:182). The switching intention sample realised was n = 1,025, thus in terms of purely considering the number of cases, the sample size is adequate. In terms of the ratio of cases to items to be factor analysed, all four of the measurement scales together have 20 items (SI = 5; RSC = 7; PV = 3; AA = 5). For the sample size, the ratio of cases to factors is 52:1 (1,025/20). Thus the ratio is greater than 10:1. Furthermore, Bartlett's (1954) test of sphericity was statistically significant ($p < 0.05$) and the KMO value was 0.935, thus above the threshold of 0.60 as suggested by (Tabachnick & Fidell, 2013:620). On the whole, the inter-item correlations were greater than 0.3 (see Table 7.1, Appendix F). Therefore the data is suitable to continue with the EFA.

Once the assumptions were met, the second step of the EFA entailed subjecting the 20 items in the switching intention measurement scales to principal axis factoring (PAF) using IBM SPSS Statistics version 22. PAF is able to identify underlying factors which indicate communalities between variables (Mooi & Sarstedt, 2011:202). PAF is also able to reveal information regarding unique variance and common variance of each variable (Costello & Osborne, 2005:2; Hair *et al*., 2014:106; Mooi & Sarstedt, 2011:202). Therefore PAF was the chosen factor extraction method.

The third step of the EFA considers the number of factors to retain (Pallant, 2011:184). Kaiser's criterion, also known as the eigenvalue rule, suggests that only factors with an eigenvalue greater than or equal to 1.00 are 'retained for further investigation' (Pallant, 2011:184). A factor's eigenvalue represents the total variance explained by that factor (Pallant, 2011:184). The PAF revealed the presence of four components with eigenvalues greater than one. The four factors accounted for 77.33% of the total variance. The first factor emerged with an eigenvalue of 10.191 and explained 50.96% of variance. The second factor emerged with an eigenvalue of 2.949 and explained an additional 14.75% of variance. In total, the two factors accounted 65.7% of the total variance. The third factor emerged with an eigenvalue of 1.301 and explained 6.50% of variance. The fourth factor emerged with an eigenvalue of 1.024 and explained 5.12% of variance.

Catell's (1966) scree test was used as a visual approach to confirm whether the aforementioned four factors should be retained (see Figure 7.1, Appendix F). The scree plot showed a change after the third factor, however, the fourth and fifth factors were close. In cases where the elbow is not clear, the Kaiser criterion can be used to make the decision as to how many factors to retain (Mooi & Sarstedt, 2011:213). Thus, since the eigenvalues suggested the original four factors, all four were retained.

During the fourth step of the EFA, Direct Quartimin Oblique rotation with Kaiser Normalisation was used for factor rotation. Direct Quartimin Oblique rotation is an oblique rotation technique which allows the factors to correlate (Costello & Osborne, 2005:3). Both rotated matrices – the pattern matrix and the structure matrix – were investigated and are presented in Table 5.19. The pattern matrix shows the factor loadings for each variable (Pallant, 2011:198). Items that load highest onto one component are used "to identify and label the component" (Pallant, 2011:198). The structure matrix, which provides information regarding correlations between variables and factors, is only available when conducting Oblique rotation (Pallant, 2011:198). The final step of the EFA involves interpreting the factors by considering the factor loadings (Byrne, 2010:5-6).

High factor loadings indicate that a variable is well represented by a certain factor. The minimum cut-off for factor loadings is 0.4. Ideally factor loadings should be greater than 0.7 (Hair *et al*., 2014:136). Taking into consideration that the correlation between a variable and a factor could be negative, the absolute (numerical) value is interpreted (Mooi & Sarstedt, 2011:214). As can be seen from the matrices in Table 5.19 below, the majority items have values greater than 0.7, indicating that they loaded significantly onto one component in the pattern matrix. The variables (items) also showed strong correlations to specific factors (components) in the structure matrix. Therefore the results of the PAF support the four constructs.

Table 5.19: Pattern matrix and structure matrix of the switching intention (N_1) measurement scales

PATTERN MATRIX					STRUCTURE MATRIX				
	FACTORS					FACTORS			
	Switching intention	Relational switching costs	Perceived value	Alternative attractiveness		Switching intention	Relational switching costs	Perceived value	Alternative attractiveness
A5_2	-0.818	0.066	0.002	-0.071	**A5_2**	-0.835	-0.366	-0.400	-0.618
A5_5	-0.813	-0.027	0.001	-0.001	**A5_5**	-0.826	-0.428	-0.415	-0.583
A5_3	-0.737	-0.021	-0.034	0.022	**A5_3**	-0.748	-0.396	-0.396	-0.523
A5_4	-0.706	-0.032	0.022	0.015	**A5_4**	-0.700	-0.361	-0.335	-0.482
A5_1	-0.508	-0.047	-0.131	-0.146	**A5_1**	-0.698	-0.436	-0.488	-0.594
A6_4	-0.063	0.939	-0.026	0.003	**A6_4**	0.390	0.894	0.502	0.330
A6_3	-0.077	0.911	-0.011	0.020	**A6_3**	0.382	0.875	0.503	0.333
A6_2	-0.004	0.880	-0.033	-0.012	**A6_2**	0.406	0.854	0.481	0.328
A6_1	0.011	0.842	-0.012	-0.032	**A6_7**	0.518	0.845	0.600	0.440
A6_5	0.070	0.728	0.039	0.031	**A6_1**	0.399	0.828	0.476	0.315
A6_7	0.094	0.724	0.116	0.013	**A6_6**	0.517	0.826	0.570	0.435
A6_6	0.110	0.716	0.079	0.022	**A6_5**	0.471	0.798	0.523	0.400
A7_2	0.086	-0.002	0.973	-0.045	**A7_2**	0.532	0.600	0.989	0.545
A7_1	-0.003	-0.005	0.859	0.014	**A7_1**	0.427	0.509	0.862	0.479
A7_3	-0.019	0.174	0.636	0.125	**A7_3**	0.467	0.593	0.798	0.529
A8_3	-0.036	-0.050	0.079	-0.934	**A8_3**	-0.679	-0.403	-0.478	-0.937
A8_2	0.071	0.021	-0.040	-0.914	**A8_4**	-0.714	-0.407	-0.496	-0.927
A8_4	-0.124	-0.021	0.044	-0.855	**A8_5**	-0.703	-0.418	-0.488	-0.914
A8_5	-0.110	-0.051	0.060	-0.848	**A8_2**	-0.581	-0.342	-0.491	-0.878
A8_1	0.045	0.043	-0.164	-0.741	**A8_1**	-0.535	-0.335	-0.520	-0.781

Extraction Method: Principal Axis Factoring   Extraction Method: Principal Axis Factoring

Once the factor analysis was complete, construct validity was assessed. To evaluate construct validity, convergent, discriminant and nomological validity are assessed (Hair *et al*., 2014:124; Malhotra, 2009:316). The Cronbach's alpha reliability coefficient is used to establish convergent validity. In short, convergent validity is dependent on internal consistency and internal consistency is established using the Cronbach's alpha reliability coefficient (Zikmund & Babin, 2013:260). Therefore, if the Cronbach's alpha is acceptable, convergent validity is acceptable, indicating that the switching intention scales in the current study demonstrate convergent validity.

Discriminant validity assesses the correlation between all of the measurement scales in the measurement instrument (Hair *et al*., 2014:124). Ideally constructs should be independent from one another, since each construct should measure a specific concept (Hair *et al*., 2014:124; Kline, 2011:72; Zikmund & Babin, 2013:260). As can be seen from the results of the PAF, the items have high loadings, that is, values greater than 0.4. (Hair *et al*., 2014:136). Thus discriminant validity is established. Thus far construct validity for each construct has been verified. Nomological validity is assessed during testing of the SEM model (see Section 5.6.3).

Following the acceptable validity results, reliability was assessed using Cronbach's alpha.

5.5.2 <u>Reliability of the switching intention measurement scales</u>

Reliability indicates that a measurement scale consistently achieves a certain result (Boslaugh, 2013:10). To evaluate internal consistency, inter-item correlations and item-to-total correlations were calculated (Hair *et al*., 2014:123). All of the inter-item correlations for the relational switching costs, perceived value and alternative attractiveness scales for switching intention were above the 0.30 cut-off (Hair *et al*., 2014:101). All of the aforementioned measurement scales also had greater item-to-total correlations than the suggested 0.50 cut-off (Mooi & Sarstedt, 2011:89; Tabachnik & Fidell, 2013:619).

Cronbach's alpha (α) was used to determine measurement scale reliability (Hair *et al*., 2014:123; Zikmund & Babin, 2013:257). The commonly accepted cut-off criterion for Cronbach's alpha is 0.70 (Peterson, 1994:381). Table 5.20 shows the Cronbach's alpha values for the four measurement scales and also the Cronbach's alpha values that were obtained in the studies from which the scales were sourced. Zikmund and Babin (2013:257) suggest a "range" for the alpha value, where values between 0.80 and 0.96 indicate very good reliability. Since all the Cronbach's alpha values for the current study are above 0.80, the scales have very good reliability.

Table 5.20: Cronbach's alpha reliability values for the switching intention (N_1) measurement scales

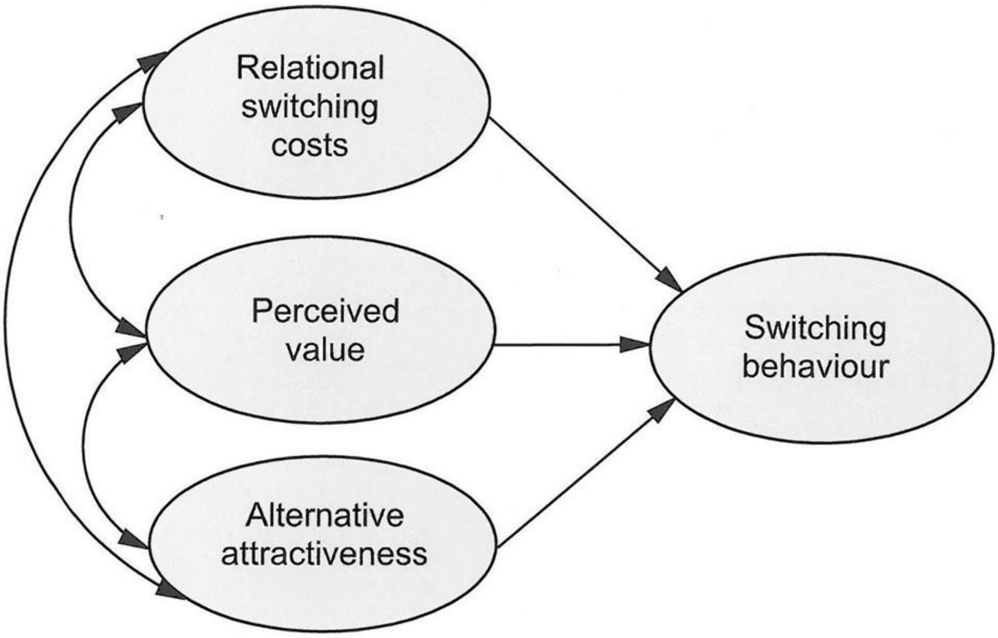
Construct	Original scale reliability	Scale reliability for the switching intention sample (N_1)
Switching intention	α = 0.91	α = 0.871
Relational switching costs	α = 0.87	α = 0.946
Perceived value	α = 0.86	α = 0.917
Alternative attractiveness	α = 0.92	α = 0.948

The section to follow uses multivariate statistical analyses to investigate the three primary objectives of the study. The analysis commences with Research Objective 1 (RO1): testing the switching intention model, using structural equation modelling (SEM). Next, Research Objective 2 (RO2): the comparison of switching behaviour and switching intention is facilitated using various multivariate techniques, for example, multiple regression and factor analysis. The third main objective, namely Research Objective 3 (RO3): to determine the role of relationship characteristics in switching intention and switching behaviour, is examined with the aid of multiple regression. Finally, the secondary objectives related to the three aforementioned main objectives are investigated using hypothesis testing.

5.6 RO1: TESTING THE SWITCHING INTENTION MODEL

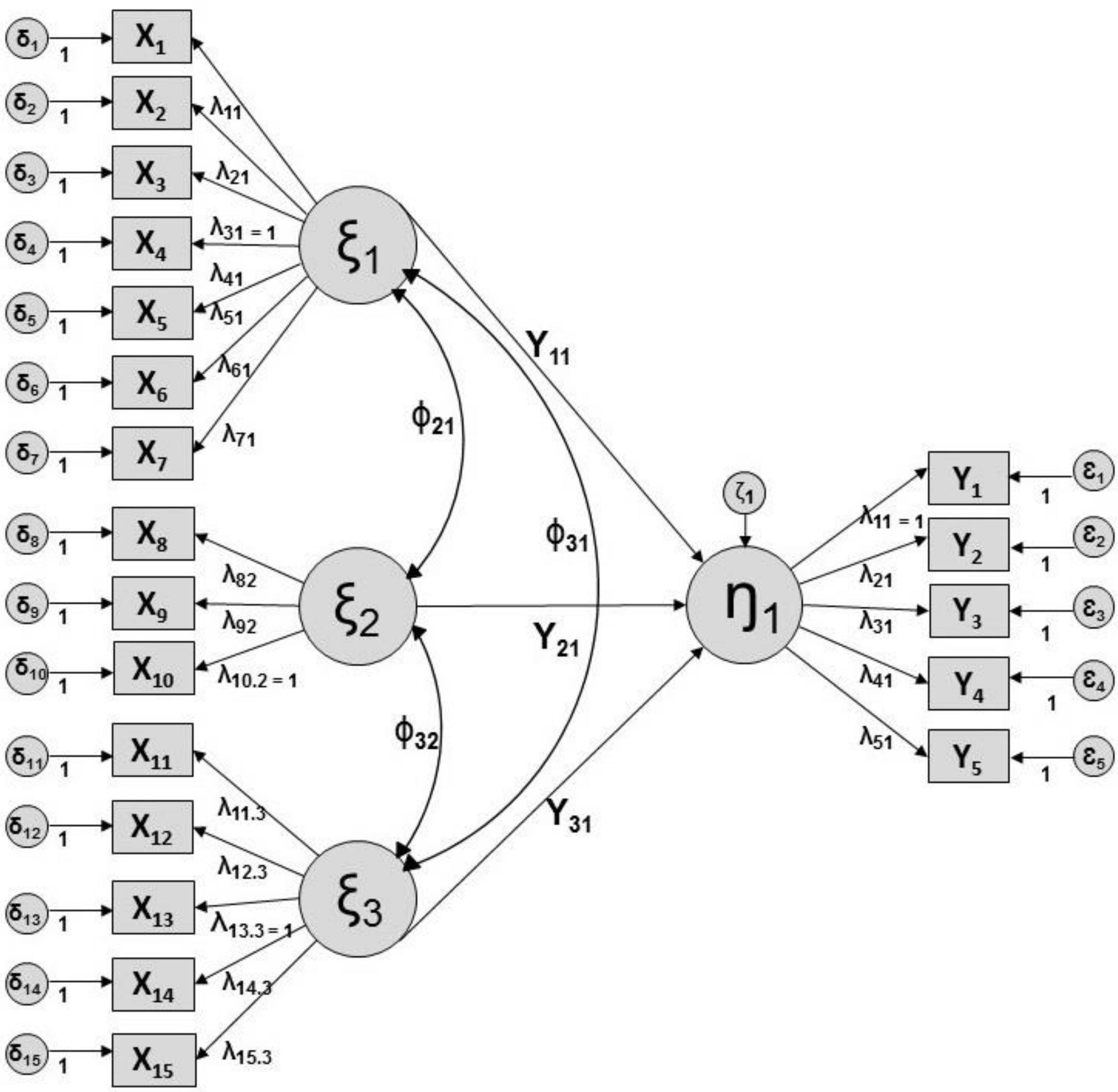
Using the six stages of SEM analysis, Figure 5.9 shows the conceptual switching intention model which was developed using the literature.

Figure 5.9: The conceptual switching intention model



Model specification and identification was discussed in detail in Chapter 4. The specified model is shown in Figure 5.10. In sum, the model had three exogenous latent variables and one endogenous latent variable. The exogenous latent variables were relational switching costs (with seven manifest variables), perceived value (with three manifest variables), and alternative attractiveness (with five manifest variables). The dependent variable (endogenous latent variable) was switching intention, with five manifest variables. Regression weights were calculated from each exogenous latent variable to the endogenous latent variable. Covariances were also calculated among the three exogenous latent variables.

Figure 5.10: Specified switching intention model



Prior to estimation, model identification took place to ensure that there were enough degrees of freedom to estimate the model and to ensure that the number of parameters did not exceed the number of observations (MacCallum, 1995:29). As mentioned in the previous chapter, the current model was overidentified with 164 *df* (Kline, 2011:102). Therefore estimation could proceed. Table 5.21 shows results for the default, saturated and independence models. Each is briefly explained below.

Table 5.21: Default, saturated and independence models

	Number of parameter estimates	Chi-square value (χ^2)	Degrees of freedom (*df*)	*p*-value	χ^2/df
Default model	46	2247.681	164	< 0.001	13.705
Saturated model	210	0.000	0	-	-
Independence model	20	20200.434	190	< 0.001	106.318

The saturated model indicates the maximum number of parameters that can be estimated for the model (Schumacker & Lomax, 2010:41). Since all possible parameters in a saturated model have been fitted to the model, the χ^2-value is zero (0.000). The total number of parameters that could be estimated for the model were 210. The independence model, which is the null model, has no estimated parameters and only indicates the number of observed variables (Schumacker & Lomax, 2010:41), which for the switching intention model was 20. Finally, the number of parameter estimates for the default model (which is the model being assessed), are calculated. The total number of parameter estimates for the default model was 46.

Parameter estimates are derived through estimation (Hair *et al*., 2014:575). As mentioned in Chapter 4, Section 4.7.3.2, maximum likelihood (ML) was used for estimation in the current study. ML requires the assumptions for continuous data and multivariate normality to be met (Byrne, 2010:329). Strictly speaking, the data analysed for each item in each construct in this study was ordinal data. However, due to the large number of scale points used (11-point Likert scale) the data approach the characteristics of interval scales (Cooper & Schindler, 2014:252), implying continuous data, as explained in Section 5.4.

From the assessment of normality, the assumption of kurtosis for individual manifest variables was not violated, since all univariate kurtoses were below 7 (Byrne, 2010:103). However, the large multivariate kurtosis value (248.394) was a concern, since the substantial kurtotic value indicated that the data did not conform to a multivariate normal distribution. Nonetheless, Byrne (2010:330) notes that most data do not meet the assumption of multivariate normality. One approach to deal with the violation of multivariate kurtosis is to report Robust ML fit indices which are not sensitive to categorical variables and nonnormality. However, these fit indices are not available in the AMOS software package. Bootstrapping, which is available in SPSS, is another technique that takes the violation of the assumption of multivariate normality into account, to confirm the stability of the ML estimates (Byrne, 2010:332). Bootstrapping confirms the stability of the ML estimates by estimating confidence intervals and the range of standard errors (Kline, 2011:42). Estimation was thus continued, even though the assumption of multivariate normality was violated, since bootstrapping would be performed once modelling was complete. All parameter estimates were significant ($\alpha = 0.05$; $p < 0.001$). The parameter estimates obtained are summarised in Table 5.22.

Table 5.22: Parameter estimates for the switching intention model

Regressions			Parameter estimates	Standard error	Critical ratio	*p*-value
Switching intention	<---	Relational switching cost	-0.129	0.023	-5.727	< 0.001
Switching intention	<---	Perceived value	-0.098	0.028	-3.489	< 0.001
Switching intention	<---	Alternative attractiveness	0.505	0.028	18.302	< 0.001
A5_1	<---	Switching intention	1			
A5_2	<---	Switching intention	1.265	0.049	26.017	< 0.001
A5_3	<---	Switching intention	1.259	0.054	23.167	< 0.001
A5_4	<---	Switching intention	1.213	0.056	21.604	< 0.001
A5_5	<---	Switching intention	1.296	0.051	25.342	< 0.001
A6_3	<---	Relational switching cost	1			
A6_1	<---	Relational switching cost	0.935	0.027	34.830	< 0.001
A6_2	<---	Relational switching cost	0.943	0.026	36.578	< 0.001
A6_4	<---	Relational switching cost	0.998	0.025	40.088	< 0.001
A6_5	<---	Relational switching cost	0.853	0.025	33.617	< 0.001
A6_6	<---	Relational switching cost	0.923	0.026	35.609	< 0.001
A6_7	<---	Relational switching cost	0.981	0.027	37.012	< 0.001
A7_3	<---	Perceived value	1			
A7_1	<---	Perceived value	1.081	0.032	33.958	< 0.001
A7_2	<---	Perceived value	1.217	0.032	38.527	< 0.001
A8_3	<---	Alternative attractiveness	1			
A8_1	<---	Alternative attractiveness	0.789	0.024	32.393	< 0.001
A8_2	<---	Alternative attractiveness	0.853	0.020	42.134	< 0.001
A8_4	<---	Alternative attractiveness	1.006	0.016	64.222	< 0.001
A8_5	<---	Alternative attractiveness	0.996	0.017	59.348	< 0.001

When evaluating parameter estimates, three considerations are: i) parameter estimate feasibility; ii) appropriateness of the standard errors; and iii) statistical significance of the parameter estimates (Byrne, 2010:67). As indicated in Table 5.22, all standard errors are small and all parameter estimates are statistically significant, suggesting that the parameter estimates are acceptable.

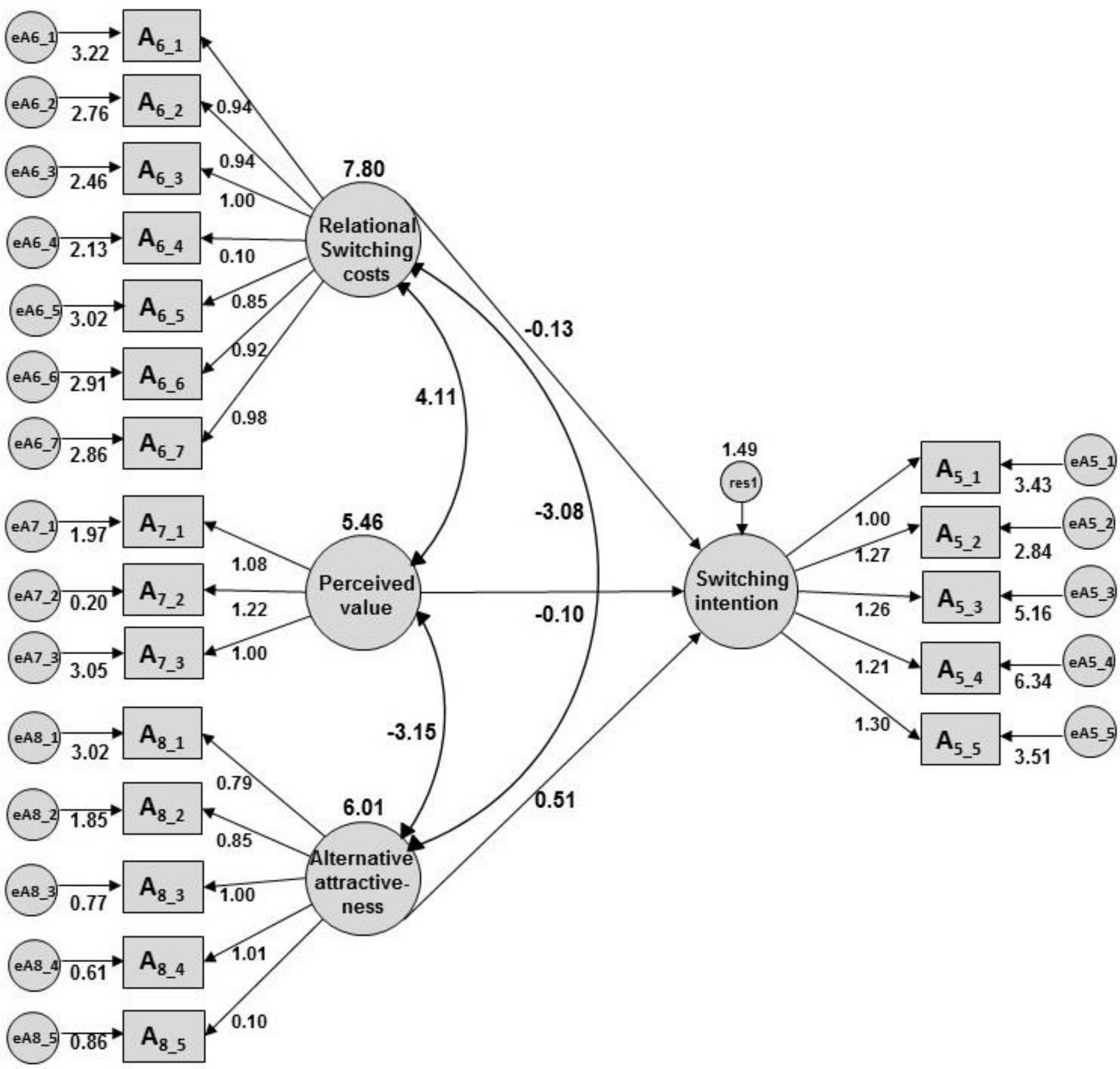
Standardised regression weights indicate relative importance. Alternative attractiveness (0.617) was much larger than the other constructs, which indicated that alternative attractiveness was the most important predictor of switching intention, followed by relational switching costs (-0.180) and perceived value (-0.114). The standardised regression weights are shown in Table 5.23.

Table 5.23: Standardised regression weights for the switching intention model

Standardised regression weights			Parameter estimates
Switching intention	<---	Relational switching cost	-0.180
Switching intention	<---	Perceived value	-0.114
Switching intention	<---	Alternative attractiveness	0.617

The results of the initial analysis are indicated in Figure 5.11 below, which shows the switching intention model and includes the parameter estimates.

Figure 5.11: The switching intention model (including parameter estimates)



A model that shows adequate fit confirms the relationships hypothesised in the conceptual model (Byrne, 2010:3). A variety of goodness-of-fit indices are typically examined to establish model fit (Hoyle, 1995:6). First the overall fit indices, namely χ^2, *df* and χ^2/df were examined, followed by absolute and incremental fit indices.

The simplest way to compare the model to the sample data is to test whether the sample covariance matrix is the same as the hypothesised population covariance matrix, using χ^2 (Iacobucci, 2010:91). However, the model almost never fits when a large sample, usually 500 or more respondents, is used (Hair *et al*. (2014:572-574). In this study there are n = 1,025. Ideally, the χ^2-value should be small and the p-value should be large/non-significant (Fornell & Larcker, 1981:40). A significant χ^2-value indicates that there is a difference between the observed sample data and the conceptual model, which implies 'not exact' fit (Schreiber, 2008:88; Schumacker & Lomax, 2010:85; Thomson, 2000:269). Consequently, according to the χ^2-value, the switching intention model does not fit the model exactly, because the χ^2-value is significant (p-value < 0.001).

Since SEM models typically do not fit using only the χ^2 criterion, the ratio of the χ^2-value to the degrees of freedom (χ^2/df) is another ratio often used to estimate model fit (Chen & Cheng, 2012:812). A χ^2/df ratio less than or equal to 5 ($\chi^2/df \leq 5.00$) indicates adequate fit (Schreiber, 2008:89). However, more conservative thresholds suggest that the ratio should be less than or equal to 2 ($\chi^2/df \leq 2.00$) (Yang & Peterson, 2004:810). The χ^2/df ratio of 13.705 did not meet either of the above criteria; thus the model did not demonstrate adequate fit. Table 5.24 shows the initial overall goodness-of-fit assessment.

Table 5.24: Model fit summary for the switching intention model

Chi-square value (χ^2)	Degrees of freedom (df)	p-value	χ^2/df
2247.681	164	< 0.001	13.705

An assessment of the degrees of freedom indicated that enough *df* (164) were present to continue modelling. Thus goodness-of-fit indices other than the overall fit indices were considered. The RMSEA considers how well the sample fits the data and how well the model fits the population (Hair *et al*., 2014:579). The closer RMSEA is to zero, the better the fit (Kline, 2011:205; Schreiber, 2008:88). Ideally the RMSEA value should be less than 0.05 (MacCallum *et al*., 1996:134). The results indicated with 90% certainty that the true RMSEA value (0.111) in the population lay within the bounds of 0.107 and 0.116. Furthermore, the narrower the upper and lower bounds of the confidence interval, the more precise the result (Kline, 2011:206). The lower limit should be close to 0.00 and the higher limit should be less than 0.08 (Kenny, 2011:6). The RMSEA confidence interval values were too high. The lower limit was very high (0.107) and the upper limit (0.116) should decrease, concluding that the model did not fit the data well.

SRMR considers the residuals between individual observed and estimated covariance and variance terms and uses covariance residuals to identify measurement model problems (Kline, 2011:208). SRMR ranges from 0 to 1.00, where zero indicates perfect fit (Byrne, 2010:77). SRMR = 0.0541 was good, since SRMR should be less than 0.08 (Hu & Bentler, 1999:1).

Incremental fit indices compare the model to a baseline model (Hair *et al*., 2014:580; Kline, 2011:196). CFI values close to 1.00 indicate good fit (Hooper *et al*., 2008:55). Ideally, the CFI and TLI should be greater than 0.95 (Hu & Bentler, 1999:4; Newsom, 2012:2). Values larger than 0.90 were considered an indication of good fit (Byrne, 2010:78). The generally accepted 'newer' cut-off is 0.95 (Hooper *et al*., 2008:55; Hu & Bentler, 1999:1; Schreiber, 2008:90) Thus CFI = 0.896 and TLI = 0.879 could improve. Table 5.25 provides a summary of the aforementioned fit indices.

Table 5.25: Fit indices for the switching intention model

ABSOLUTE FIT INDICES	
Root Mean Square Error of Approximation (RMSEA)	0.111
RMSEA – 90% Confidence Interval (CI)	[0.107; 0.116]
Standardised Root Mean Square Residual (SRMR)	0.0541
INCREMENTAL FIT INDICES	
Comparative Fit Index (CFI)	0.896
Tucker Lewis Index (TLI)	0.879

Once all of the fit indices were considered, it was established that the model fit was not ideal. Thus the modification indices were examined to determine whether a better fit could be achieved. The modification index (MI) shows which parameters could improve model fit (Iacobucci, 2009:678). That is, the MIs indicate which correlations will make the biggest change to the model from a mathematical point of view, with the implication that the changes could be mathematically beneficial but not necessarily theoretically founded. Parameters representing covariances between error terms can be correlated to improve model fit (Byrne, 2010:89; Hooper *et al*., 2008:56). Some researchers discourage the practise (Gerbing & Anderson, 1984 in Hooper *et al*., 2008:56) because covariation of the error terms implies that there is a problem and that something was not specified in the model. Nonetheless, if the correlation of the error terms can be justified theoretically, such a correlation is acceptable (Jöreskog & Long, 1993, in Hooper *et al*., 2008:56; Klem, 2000:231). Note that once modification to the postulated model takes place, the model is no longer confirmatory, but rather exploratory (Schreiber, 2008:90).

A general rule-of-thumb is that any MI greater than 10 could be considered for model modification. All paths with large MIs should be inspected to determine whether retaining or deleting the path could influence model fit. Researchers warn that modification should only be pursued if the change is supported by theory (Klem, 2000:245; Schreiber, 2008:90).

Table 5.26 summarises the highest MIs. It is interesting to note that, of the eight highest MIs, seven were from the relational switching costs scale. The highest MI (469.800) was for the covariance between the error terms eA6_6 and eA6_7, implying that correlating these two error terms would have the largest impact to improve model fit. Therefore correlating the eA6_6 and eA6_7 error terms was theoretically justified, since the manifest variables both measured brand relationship loss. Thus the decision was made to continue to a second switching intention model, and to correlate the eA6_6 and eA6_7 error terms. It is good practise to implement one modification at a time, so that the effect can be monitored and the cause of the change be known.

Table 5.26: Modification indices for the switching intention model

Covariance	Modification Index (MI)	Rank
eA6_6 <--> eA6_7	469.800	1
eA6_5 <--> eA6_6	291.887	2
eA6_3 <--> eA6_4	251.540	3
eA8_2 <--> eA8_1	224.926	4
eA6_2 <--> eA6_1	191.136	5
eA6_5 <--> eA6_7	189.718	6
eA6_2 <--> eA6_7	109.050	7
eA6_4 <--> eA6_6	108.129	8

Once the error terms were correlated, the AMOS output produced the second switching intention model, discussed below.

5.6.1 Switching intention model 2

Since all of the parameter estimates were significant in the first switching intention model, the parameter estimates are not reported again, but are reported with the final model. The assessment of normality is not repeated before continuing with modelling, since bootstrapping will be performed once modelling is complete.

The χ^2-value in the first switching intention model decreased from 2247.681 to 1637.407 in the second switching intention model, which indicated a substantial improvement in model fit. The χ^2/df was still rather high (10.045) compared to the recommended threshold of 5.00 or less (Schreiber, 2008:89). There were enough *df* to continue modifying the model. Table 5.27 indicates the fit of the second switching intention model.

Table 5.27: Model fit summary for switching intention model 2

Chi-square value (χ^2)	Degrees of freedom (*df*)	*p*-value	χ^2/df
1637.407	163	< 0.001	10.045

The RMSEA improved to 0.094, but still did not meet the suggested cut-off value of between 0.05 and 0.08 (MacCallum *et al*., 1996:134). The RMSEA confidence interval also improved [0.090; 0.098]. Interestingly, the SRMR worsened slightly, from 0.0541 to 0.0645. The SRMR should ideally be less than 0.05, however a value of less than or equal to 0.08 is acceptable (Hooper *et al*., 2008:55; Hu & Bentler, 1999:1). Both the CFI and TLI were above the 0.90 cut-off, indicating acceptable fit. Table 5.28 shows a summary of the goodness-of-fit indices for the second switching intention model.

Table 5.28: Fit indices for switching intention model 2

ABSOLUTE FIT INDICES	
Root Mean Square Error of Approximation (RMSEA)	0.094
RMSEA – 90% Confidence Interval (CI)	[0.090; 0.098]
Standardised Root Mean Square Residual (SRMR)	0.0645
INCREMENTAL FIT INDICES	
Comparative Fit Index (CFI)	0.926
Tucker Lewis Index (TLI)	0.914

With the view of improving model fit, further MIs were investigated. Table 5.29 shows suggested modification indices for the second switching intention model.

Table 5.29: Modification indices for switching intention model 2

Covariance	Modification Index (MI)	Rank
eA8_2 <--> eA8_1	224.843	1
eA6_2 <--> eA6_1	117.022	2
eA6_5 <--> eA6_6	114.744	3
eA6_3 <--> eA6_4	98.873	4

The MIs for the second switching intention model shows a strong correlation between the eA8_2 & eA8_1 error terms (224.843). Upon further investigation, it was found that even though the two error terms were mathematically correlated, they were not conceptually related. Question A8_1 deals with MNOs in general, whereas Question A8_2 queries MNO's policies. Therefore the decision was made not to pursue this modification further, despite the correlation having the highest MI.

The next two highest MIs were for eA6_2 & eA6_1 (117.022) and eA6_5 & eA6_6 (114.744). Upon further investigation, it was decided to correlate eA6_5 & eA6_6, even though eA6_2 & eA6_1 had a slightly higher MI. The reason for the decision was that in the previous model, the items relating to brand relationship loss were correlated. It therefore made theoretical sense to also correlate eA6_5 & eA6_6, since these error terms also relate to brand relationship loss. The aforementioned decision abides by the maxim that modelling should be theory-driven and not mathematically-driven. Results for the third switching intention model are discussed in the next section.

5.6.2 Switching intention model 3

As with the previous switching intention model, the parameter estimates are not reported at this stage, and bootstrapping will be performed to assess normality.

After correlating eA6_5 & eA6_6, model fit improved as expected. The χ^2-value decreased from 1637.407 in the previous switching intention model to 1475.480 in the third switching intention model. The change was not as large as the change from the first switching intention model (2247.681) to the second switching intention model (1637.407). Nonetheless, an improvement that was statistically significant was indicated. The χ^2/df was still rather large, but below 10, which is an improvement compared to the previous models. Table 5.30 shows the model fit summary for the third switching intention model.

Table 5.30: Model fit summary for switching intention model 3

Chi-square value (χ^2)	Degrees of freedom (*df*)	*p*-value	χ^2/df
1475.480	162	< 0.001	9.108

RMSEA = 0.089 [0.085; 0.093] improved, indicating mediocre fit (MacCallum *et al.*, 1996:134). The lower limit (0.085) should preferably be close to 0.00, and so was still quite a long way from indicating good fit, but the upper limit (0.093) also improved. Both CFI = 0.934 and TLI = 0.923 improved slightly. Both these indices were above 0.90, indicating acceptable fit, but could improve. Table 5.31 summarises the fit indices for the third switching intention model.

Table 5.31: Fit indices for the switching intention model 3

ABSOLUTE FIT INDICES	
Root Mean Square Error of Approximation (RMSEA)	0.089
RMSEA – 90% Confidence Interval (CI)	[0.085; 0.093]
Standardised Root Mean Square Residual (SRMR)	0.0623
INCREMENTAL FIT INDICES	
Comparative Fit Index (CFI)	0.934
Tucker Lewis Index (TLI)	0.923

The various fit indices showed mixed results. CFI and TLI approached the recommended 0.95 cut-off. SRMR showed acceptable fit. However, the RMSEA only indicated mediocre fit (MacCallum *et al.*, 1996:134). The overall model fit was still poor, therefore the MIs were re-examined to determine whether a better fit could be achieved. Again the MIs showed a very high correlation for eA8_2 & eA8_1 (224.835). However, correlating these two error terms would not be theoretically sound. The MIs indicated that eA6_5 & eA6_7 (139.825) and eA6_2 & eA6_1 had the next highest MIs. Upon taking into consideration that eA6_6 & eA6_7 and eA6_6 & eA6_5 were correlated in the previous two models, it logically follows that eA6_5 & eA6_7 would be correlated. Therefore indicating such a correlation on the model is unnecessary and this correlation was not pursued. Finally, the third highest MI was for eA6_2 & eA6_1 (115.237). Table 5.32 shows suggested modification indices for the third switching intention model.

Table 5.32: Modification indices for switching intention model 3

Covariance	Modification Index (MI)	Rank
eA8_2 <--> eA8_1	224.835	1
eA6_5 <--> eA6_7	139.825	2
eA6_2 <--> eA6_1	115.237	3

There is some evidence that the relational switching cost measurement scale may have two sub-sections, as according to Burnham *et al.* (2003) and Hu and Hwang (2006). Since all three of the error terms in the brand relationship loss sub-section were already correlated successfully to improve model fit, the final MI suggesting correlating the eA6_2 & eA6_1 error terms, which are part of the personal relationship loss sub-section of the scale, was pursued to determine whether better model fit could be achieved. Thus correlation of the aforementioned error terms was theoretically founded. The results following the correlation are discussed in the next section.

5.6.3 Switching intention model 4

The results for the final switching intention model are discussed below. The parameter estimates are included since this is the final switching intention model. The *p*-values for all of the parameter estimates are less than 0.001. Thus, not only are the results significant, the results are highly significant. According to Albright *et al*. (2009:503) a *p*-value of 0.001 shows overwhelming evidence that the results are significant. Table 5.33 provides a summary of the parameter estimates for the fourth switching intention model.

Table 5.33: Parameter estimates for the switching intention model 4

Regressions			Parameter estimates	Standard error	Critical ratio	*p*-value
Switching intention	<---	Relational switching cost	-0.106	0.021	-5.060	< 0.001
Switching intention	<---	Perceived value	-0.112	0.028	-3.991	< 0.001
Switching intention	<---	Alternative attractiveness	0.511	0.028	18.456	< 0.001
A5_1	<---	Switching intention	1			
A5_2	<---	Switching intention	1.267	0.049	25.999	< 0.001
A5_3	<---	Switching intention	1.260	0.054	23.147	< 0.001
A5_4	<---	Switching intention	1.214	0.056	21.589	< 0.001
A5_5	<---	Switching intention	1.297	0.051	25.294	< 0.001
A6_3	<---	Relational switching cost	1			
A6_1	<---	Relational switching cost	0.893	0.024	36.541	< 0.001
A6_2	<---	Relational switching cost	0.909	0.023	39.418	< 0.001
A6_4	<---	Relational switching cost	0.999	0.021	48.278	< 0.001
A6_5	<---	Relational switching cost	0.762	0.024	31.137	< 0.001
A6_6	<---	Relational switching cost	0.810	0.024	34.349	< 0.001
A6_7	<---	Relational switching cost	0.877	0.026	34.299	< 0.001
A7_3	<---	Perceived value	1			
A7_1	<---	Perceived value	1.081	0.032	33.953	< 0.001
A7_2	<---	Perceived value	1.217	0.032	38.465	< 0.001
A8_3	<---	Alternative attractiveness	1			
A8_1	<---	Alternative attractiveness	0.789	0.024	32.396	< 0.001
A8_2	<---	Alternative attractiveness	0.853	0.020	42.136	< 0.001
A8_4	<---	Alternative attractiveness	1.006	0.016	64.218	< 0.001
A8_5	<---	Alternative attractiveness	0.996	0.017	59.340	< 0.001

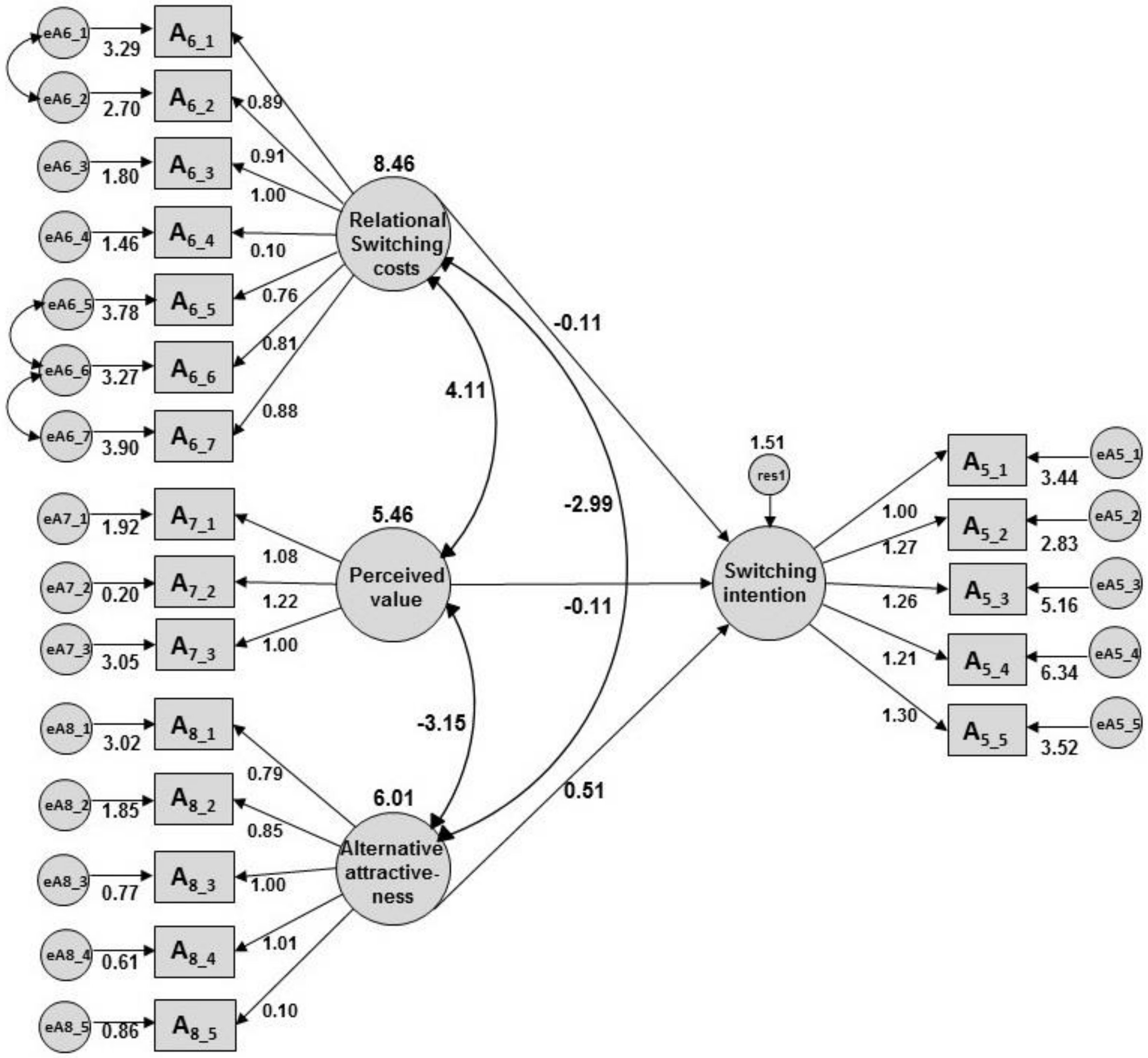
When considering relative importance of the constructs by examining the standardised regression weights, the results are similar to the first switching intention model, however, the relationships are slightly stronger. Alternative attractiveness (0.625) remained the most important influencer of switching intention, followed by relational switching costs (-0.154) and perceived value (-0.130). Therefore it can be concluded that alternative attractiveness is the main driver of switching intention and the main reason that customers switch. The standardised regression weights are shown in Table 5.34.

Table 5.34: Standardised regression weights for switching intention model 4

Standardised regression weights			Parameter estimates
Switching intention	<---	Relational switching cost	-0.154
Switching intention	<---	Perceived value	-0.130
Switching intention	<---	Alternative attractiveness	0.625

The final switching intention model, including parameter estimates, is depicted in Figure 5.12. All of the constructs in the switching intention model were correlated, supporting nomological validity for the model (Pihlström & Brush, 2008:743). The structural part of the SEM is well-suited to assess nomological validity (Anderson & Gerbing, 1988:411; Schumacker & Lomax, 2010:114), because nomological validity essentially assesses relationships between variables as posited by theory, as does SEM (Malhotra, 2009:317).

Figure 5.12: Switching intention model 4 (including parameter estimates)



The final model shows that the χ^2-value decreased (1475.480 – 1348.01 = 127.379). The χ^2/df decreased to 8.373. Table 5.35 provides the model fit summary for the fourth switching intention model.

Table 5.35: Model fit summary for the switching intention model 4

Chi-square value (χ^2)	Degrees of freedom (*df*)	*p*-value	χ^2/df
1348.101	161	< 0.001	8.373

Both CFI = 0.941 and TLI = 0.930 improved, indicating adequate fit by remaining above the 0.90 cut-off (Byrne, 2010:78) and approaching the 0.95 threshold (Schreiber, 2008:90). RMSEA = 0.085 [0.081; 0.089] showed poor fit (MacCallum *et al.*, 1996:134), but improved from the previous models. The lower and upper limits for RMSEA were too high to indicate adequate fit. The initial model indicated acceptable SRMR, however SRMR = 0.0611 in the final model exceeded the 0.05 threshold (Byrne, 2010:77). Nonetheless the SRMR still indicated acceptable fit, since it was less than 0.08. Table 5.36 shows a summary of the goodness-of-fit indices for the fourth switching intention model.

Table 5.36: Fit indices for switching intention model 4

ABSOLUTE FIT INDICES	
Root Mean Square Error of Approximation (RMSEA)	0.085
RMSEA – 90% Confidence Interval (CI)	[0.081; 0.089]
Standardised Root Mean Square Residual (SRMR)	0.0611
INCREMENTAL FIT INDICES	
Comparative Fit Index (CFI)	0.941
Tucker Lewis Index (TLI)	0.930

The significant MIs identified for the fourth switching intention model (eA8_2 & eA8_1 = 224.847), were also identified in the previous analyses and were deemed inappropriate to correlate. Table 5.37 shows suggested modification indices for the fourth switching intention model.

Table 5.37: Modification indices for the switching intention model 4

Covariance	Modification Index (MI)	Rank
eA8_2 <--> eA8_1	224.847	1
eA6_2 <--> eA6_1	115.237	2

Even though the various fit indices showed mixed results, the fourth switching intention model sufficed. Any further correlations would have led to 'over-fitting' the model to the data. In other words, any further model fitting would be data-driven instead of theory-driven. Thus the fourth switching intention model was not modified any further.

Bearing in mind that each fit index reveals different information, it is possible that for the same model, the various fit indices may show mixed results (Whitten & Wakefield, 2006:237). Some indices may show acceptable fit, while others may indicate moderate or poor fit. For example, RMSEA compares how well the sample fits the data and how well the model fits the population. SRMR assists to identify measurement problems by providing information regarding inter-item correlations. CFI and TLI compare the covariance matrix to a baseline (null) model. Taking into consideration that each fit index reveals different information, it is highly likely that some aspects fit well and others, not as well. Weston and Gore (2006:743) confirm that fit indices can contradict one another. For this reason a bouquet of indices are reported (Iacobucci, 2010:90; Whitten & Wakefield, 2006:234) as was done in the preceding section.

The final switching intention model was evaluated using bootstrapping to confirm the robustness of the parameter estimates of the model. Robustness indicates that a statistical technique is able to perform reasonably well despite the violation of underlying statistical assumptions (Hair *et al*., 2014:34).

5.6.4 Bootstrapping

Due to the severe leptokurtic kurtosis indicated for the final switching intention model (248.394), bootstrapping was conducted to confirm the stability of the ML estimates. Bootstrapping is used as an aid for nonnormal data. An explanation regarding bootstrapping is provided in Chapter 4 (see Section 4.7.3.2). Bootstrapping was conducted using a 90% confidence interval, which is the SPSS default. The bootstrap upper and lower limits were close to one another. The ML parameter estimate values were within the lower and upper bounds of the 90% confidence interval obtained using bootstrapping. All *p*-values obtained were significant. Therefore bootstrapping confirmed the stability and reliability of the parameter estimates.

The parameter estimates obtained through bootstrapping were almost identical to the estimates obtained using ML (see Table 5.38). Bootstrapping confirmed that the parameter estimates were valid because the bootstrapping and ML estimates were identical and demonstrated convergence. If the data converge when the ML parameter estimates are compared to the bootstrap estimates, and the difference is very small, then even though the data is not continuous, and the assumption of multivariate normality has been violated, bootstrapping confirms that the values can be trusted. Thus the estimates could be reported with confidence. Researchers such as Sharma and Kim (2013:1) have noted that ML relies on bootstrapping if the distribution assumptions have been violated.

Table 5.38: Parameter estimates obtained using maximum likelihood versus parameter estimates obtained using bootstrapping

			Parameter estimates (Maximum Likelihood)		Parameter estimates (Bootstrapping)	
			Estimate	*p*-value	Upper	Lower
A5_1	<---	Switching intention	1		1	1
A5_2	<---	Switching intention	1.323	< 0.001	1.241	1.433
A5_3	<---	Switching intention	1.308	< 0.001	1.174	1.450
A5_4	<---	Switching intention	1.270	< 0.001	1.146	1.407
A5_5	<---	Switching intention	1.337	< 0.001	1.211	1.475
A6_3	<---	Relational switching cost	1		1	1
A6_1	<---	Relational switching cost	0.886	< 0.001	0.839	0.930
A6_2	<---	Relational switching cost	0.903	< 0.001	0.861	0.941
A6_4	<---	Relational switching cost	1.001	< 0.001	0.972	1.025
A6_5	<---	Relational switching cost	0.744	< 0.001	0.698	0.787
A6_6	<---	Relational switching cost	0.789	< 0.001	0.742	0.834
A6_7	<---	Relational switching cost	0.854	< 0.001	0.805	0.898
A7_3	<---	Perceived value	1		1	1
A7_1	<---	Perceived value	1.009	< 0.001	0.954	1.068
A7_2	<---	Perceived value	1.058	< 0.001	1.022	1.100
A8_3	<---	Alternative attractiveness	1		1	1

			Parameter estimates (Maximum Likelihood)		Parameter estimates (Bootstrapping)	
			Estimate	***p*-value**	**Upper**	**Lower**
A8_1	<---	Alternative attractiveness	0.785	< 0.001	0.734	0.830
A8_2	<---	Alternative attractiveness	0.852	< 0.001	0.811	0.891
A8_4	<---	Alternative attractiveness	1.003	< 0.001	0.980	1.028
A8_5	<---	Alternative attractiveness	0.992	< 0.001	0.960	1.020

Finally, in addition to using bootstrapping, the EQS package was used to obtain the robust ML fit indices, due to nonnormality of the data. The EQS results are discussed below.

5.6.5 Robust ML using EQS

The internal statistical consultation services at the University of Pretoria (UP) use the AMOS package. UP does not have a site license for EQS, but certain individuals at UP do, thus with special permission, robust fit indices were obtained using ML in the EQS package.

Satorra and Bentler (1994) developed a scaling correction to improve the chi-square (χ^2) approximation of goodness-of-fit test statistics under conditions of nonnormality when using ML in SEM (Satorra & Bentler, 2001:507). The Satorra-Bentler χ^2-value is available in some standard computer software packages, for example the EQS programmes (Curran, West & Finch, 1996:18; Satorra & Bentler, 2001:507). The results are presented in Table 5.39.

Table 5.39: Model fit summary for EQS

Satorra-Bentler scaled chi-square (S-Bχ^2)	Degrees of freedom (*df*)	*p*-value	χ^2/df
966.6097	161	< 0.001	6.004

Regarding fit indices, a significant *p*-value indicates poor fit (Schreiber, 2008:88). As the above results show, the *p*-value is < 0.001, which is significant. The χ^2/df ratio should be at least ≤ 5.00 to indicate acceptable fit (Schreiber, 2008:89). The χ^2/df ratio of 6.004 is not much larger than 5, but does not meet the minimum recommended requirement.

However, it is important to take into consideration that variables with a nonnormal distribution, especially distributions with high kurtosis, tend to indicate a Type 1 error as sample size increases (Kenny, 2014). In other words, as the sample size increases, the χ^2-statistic may indicate significance although no significance is present, leading to incorrect interpretation of results (Iacobucci, 2010:91; Kenny, 2014; Newsom, 2012:1; Schreiber, 2008:88; Schumacker & Lomax, 2010:86). The implication is that a model may be erroneously rejected even though it fits, if only the χ^2-statistic is considered. Therefore further fit indices which make provision for the influence of sample size on model fit were examined. Table 5.40 shows various other fit indices for robust ML.

Table 5.40: Fit indices for EQS

ABSOLUTE FIT INDICES	
Root Mean Square Error of Approximation (RMSEA)	0.070
RMSEA – 90% Confidence Interval (CI)	[0.066; 0.074]
INCREMENTAL FIT INDICES	
Comparative Fit Index (CFI)	0.952
Nonnormed Fit Index (NNFI) /*Tucker Lewis Index (TLI)*	0.943

RMSEA = 0.070 [0.066; 0.074] indicates a reasonable fit (MacCallum *et al*., 1996:134). Regarding the RMSEA confidence interval, the confidence interval lower limit should be close to 0 and the upper limit should be smaller than 0.08 (Kenny, 2011:6). Thus the upper limit is within the acceptable threshold. The NNFI (TLI) = 0.943 is very close to the 0.95 threshold (Hu & Bentler, 1999:4; Newsom, 2012:2) and exceeds the 0.90 threshold, which was previously considered to be an acceptable indication of good fit (Byrne, 2010:78). CFI = 0.952 exceeds the 0.95 threshold (Hu & Bentler, 1999:4), indicating good fit. Table 5.41 shows a comparison of the fit indices obtained using ML in AMOS versus the fit indices obtained using Robust ML in EQS.

Table 5.41: Comparison of ML estimation versus Robust ML estimation fit indices

Fit index	ML estimation	*df*	Robust ML estimation
χ^2	1348.101	161	966.610*
χ^2/df	8.373	161	6.004
Comparative Fit Index (CFI)	0.941		0.952
Tucker Lewis Index (TLI)	0.930		0.943**
Root Mean Square Error of Approximation (RMSEA)	0.085		0.070
RMSEA – 90% Confidence Interval (CI)	[0.081; 0.089]		[0.066; 0.074]

*Satorra-Bentler scaled chi-square (S-Bχ^2)
**Nonnormed Fit Index (NNFI) ie: Tucker Lewis Index (TLI)

Since no previous switching intention models comprising relational switching costs, perceived value and alternative attractiveness exist, the above model lays the foundation for future switching intention research (Whitten & Wakefield, 2006:239). The χ^2/df ratio of 6.004 does not indicate good fit. The RMSEA = 0.07 shows reasonable fit; but the confidence intervals are not ideal [0.066 0.074]. The CFI = 0.952 indicates good fit, and the NNFI = 0.943 shows good fit. Researchers are encouraged to consider the full 'bouquet' of fit indices (Iacobucci, 2010:90; Whitten & Wakefield, 2006:234). Yet no guidelines could be found in the literature regarding how mixed results should be dealt with to determine the model's overall goodness-of-fit. To conclude the fit for the switching intention model, it can be said that the model fits the data with an adequate degree of confidence.

Once the first objective (testing a conceptual switching intention model) was investigated, the second main research objective was pursued. The second objective was: to compare switching intention and switching behaviour by fitting the switching behaviour data to the switching intention model. In the following section the switching behaviour data is fitted to the final switching intention model to compare switching behaviour and switching intention. The procedure used for the comparison is explained in the section to follow.

5.7 RO2: COMPARISON OF SWITCHING INTENTION AND SWITCHING BEHAVIOUR

The purpose of the second main research objective was to use the switching intention model that was tested and refined in research objective one, and fit the switching behaviour data to the switching intention model. Most data available focus on intention (Ahn *et al*., 2006:553). Thus the purpose was to investigate actual behaviour to determine whether persons that had already switched would react in a similar manner to the intention sample.

After testing and refinement, the final switching intention model had 49 parameters – the 46 original parameters plus the three (3) covariances that were added to the relational switching costs scale. Thus, were the switching behaviour data to be fitted to the switching intention model, 49 parameters would need to be estimated for the switching behaviour model. Since the number of cases for the switching behaviour sample (N_2 = 135) were far less than the number of cases needed for the parameters to be estimated (49 x 10 = 490), statistical power was a concern when testing the switching behaviour model. Nevertheless, a decision was made to conduct a SEM analysis on the behaviour data. The iteration limit for the switching behaviour model was reached without convergence, due to the small number of available cases. In order to be as accurate as possible, the computer programme continues to analyse the data until convergence. However, sometimes the programme is unable to converge due to a too small sample size. In such cases it is said that the iteration limit has been reached. Increasing the number of iterations programmatically did not help. Consequently the switching behaviour SEM model could not be estimated. Since RO2 was one of the main objectives of the study, and since the statistical comparison could not be made as originally intended, various alternatives were considered to find another way in which to compare switching intention and switching behaviour.

In an attempt to decrease the number of parameters to be estimated, only the measurement part of the SEM model was considered instead of using the full SEM (which includes both the measurement model and the structural model). In other words, instead of a full SEM, only a CFA was considered. Deleting the structural paths, namely the 3Y (gamma) relationships and the 6 covariances (ϕ), decreased the number of parameter estimates from 49 to 40. According to the general rule of thumb, the number of cases should be 10 times more than the number of parameters to be estimated (Schreiber, 2008:85). The number of parameters multiplied by 10 (40 x 10 = 400) were still far greater than the number of cases (400 > 135). Therefore the tests would still not have sufficient statistical power if estimated using only the CFA (measurement model).

In a third attempt to compare switching intention and switching behaviour, a path analysis was considered. Path analysis is a multivariate data analysis technique that graphically presents causal relationships among variables (Babbie, 2010:488). Kline (2011:103) describes a path analysis as “a structural model for observed variables”. Not only does path analysis graphically depict a network of relationships among variables, path analysis also depicts the strength of the relationships between pairs of variables via path coefficients, derived from a regression analysis (Babbie, 2010:488). Path analysis is a causal model which assumes one variable has an impact on another variable. Therefore a path analysis indicates distinct dependent and independent relationships. The causal order of the variables and the structure of the relationships is pre-determined by the researcher, and not by the actual analysis (Babbie, 2010:489).

To calculate the number of parameter estimates for a path analysis, the error terms and manifest variables of the exogenous latent variables are not included. To calculate the total number of parameters to be estimated, all regression coefficients (parameter factor loadings), variances (error variances and factor variances) and factor covariances are added together and fixed parameters are deducted from the calculation (Byrne, 2010:33). For the path model, the total regression coefficients included the 3Y (gamma) relationships between the exogenous and endogenous variables and the 3 covariances (ϕ) between the exogenous latent variables. There are 5 parameter factor loadings for the endogenous latent variable (λ_y). One fixed parameter was deducted, leaving 4 parameter factor loadings. There are 5 error variances (Ɛ) for the endogenous manifest variable. Furthermore, there are a total of 4 factor variances, 3 for the exogenous latent variables (ξ) and one for the endogenous latent variable (η). Thus the total parameter estimates calculated amounted to 19.

The general rule-of-thumb is that the sample size should be ten times greater than the number of parameter estimates. Due to the small number of cases obtained for the switching behaviour sample (*n* = 135), the requirements for parameters estimation were not met (19 x 10 = 190), and the analysis could not be executed.

A final attempt to compare switching intention and switching behaviour resulted in a multiple regression to compare frameworks. Using only the framework for the comparison meant that the number of parameters that needed to be estimated would no longer be an influencing factor. Multiple regression is a data analysis technique that is used to investigate the relationship between a dependent variable and many independent variables (Pallant, 2011:148). Multiple regression is based on correlation, since relationships between variables are investigated. Therefore the correlations between the independent and dependent variables of the switching intention model were compared to the same relationships in the switching behaviour model.

The results of a multiple regression show the combined influence that the independent variables have on the dependent variable (Hair *et al*., 2014:16). Thus it was decided to use multiple regression, specifically stepwise regression, to determine how well each individual independent variable can predict the dependent variable while controlling for the other independent variables. When using stepwise regression, predictor variables are entered into the regression model according to their anticipated contribution toward improving model fit (Boslaugh, 2013:262). All the predictors in the model are re-evaluated each time the next predictor is added to the model. If a predictor already in the model does not contribute toward an improved model fit, the predictor may be removed (Boslaugh, 2013:262).

The section to follow discusses how the stepwise regression was applied to compare switching intention and switching behaviour. Before performing the stepwise regression, the assumptions for linearity were tested. Next, a stepwise regression was conducted on the switching intention sample, followed by a stepwise regression conducted on the switching behaviour sample.

5.7.1 Stepwise regression – Switching intention sample (N_1)

All linear equations assume that a dependent variable is the function of two or more independent variables (Allen & Bennett, 2010:177; Boslaugh, 2013:193). Therefore, since stepwise regression is a type of linear regression (Pallant, 2011:148), the assumptions for linear regression should be met before continuing with the stepwise regression.

Regarding sample size, for stepwise regression specifically, Pallant (2011:150) recommends a ratio of 40 cases for every independent variable. Therefore an ideal number of cases for three (3) independent variables is 120 (40*3). Also, using the generally accepted formula to calculate an acceptable sample size for linear regression: $N > 50 + 8m$, where m = the number of independent variables (Tabachnick & Fidell, 2013:159), the result is as follows: $N > 50 + 8(3)$; $N > 50 + 24$; $N > 74$, since there are three (3) independent variables. Since the number of cases in the switching intention sample is $n = 1{,}025$, using either of the aforementioned calculations, the sample size of $N_1 = 1{,}025$ meets the minimum requirements.

Multicollinearity should not be present when conducting multiple regression (Pallant, 2011:151). The variance inflation factor (VIF) and tolerance values were measured to assess mutlicollinearity. All the VIF values were below the cut-off point of 10 (Pallant, 2011:183). Similarly, all of the variables had tolerance values above the 0.1 cut-off point (Pallant, 2011:188), indicating that the assumption of multicollinearity was not violated. Furthermore, all correlations were less than 0.90. The VIF and tolerance results are presented in Table 7.2 in Appendix F.

Outliers must be identified and should be removed, since multiple regression is sensitive to outliers (Allen & Bennett, 2010:180). Univariate outliers are detected using scatterplots, and multivariate outliers are detected by using Mahalanobis distance and Cook's distance (Allen & Bennett, 2010:180; Pallant, 2011:159-160). The scatterplot revealed univariate outliers (see Figure 7.2, Appendix F). Cook's distance (0.048) is below 1.00, which does not reveal any outliers. Inspection of Mahalanobis distances (22.873) identified outliers. Thus further inspection of the outliers was required before the analysis could continue. The critical value for three independent variables for a Mahalanobis distance test is 16.27 (Pallant, 2011:159). Four cases were above the Mahalanobis distance critical value and were deleted. After deleting the four cases, the Mahalanobis distance value was 16.899, suggesting that more outliers needed to be removed. Therefore a further three cases with values above the critical value of 16.27 were removed. Once removed, the Mahalanobis distance value decreased to 15.377, which is below the critical value. Therefore N_1 = 1018 for the remainder of the analysis of RO2 for the switching intention sample.

Further analyses were conducted to investigate whether the assumptions for homoscedasticity, linearity and normality were met. See Figure 7.2 in Appendix F for the scatterplot and Normal Probability Plot (P-P Plot).

Since all of the assumptions of linear regression were met, the stepwise regression analysis could continue. All three of the independent variables were included in the stepwise regression. The Adjusted R^2 indicates how much variance in the dependent variable is accounted for by the model. All three of the independent variables together explained 52% of variance (Adjusted R^2 = 0.520). Alternative attractiveness alone explained 47.0% of variance (Adjusted R^2 = 0.470). Alternative attractiveness and relational switching costs together explained 51.8% of variance (Adjusted R^2 = 0.518), meaning that perceived value only explained a further 0.2% of variance. Thus the influence of perceived value on switching intention is negligible.

The standardised coefficients (beta) show the unique contributions made by each independent variable in predicting the dependent variable (Allen & Bennett, 2010:189; Pallant, 2011:161-162). All three independent variables were significant, which conforms with the SEM results (see Section 5.6.3). The results show that alternative attractiveness has the largest contribution toward predicting switching intention, followed by relational switching costs. The results suggest that perceived value does not contribute toward the prediction of switching intention, in the presence of the previous two antecedents. The results are summarised in Table 5.42 below.

Table 5.42: Summary of the stepwise regression for the switching intention sample (N_1)

Switching intention (N_1 = 1018)		Standardised coefficients Beta	t	p-value	R^2	Adjusted R^2
Model 1	**(Constant)**		6.830	< 0.001	0.471	0.470
	Alternative attractiveness	0.686	30.074	< 0.001		
Model 2	**(Constant)**		12.312	< 0.001	0.519	0.518
	Alternative attractiveness	0.576	23.644	< 0.001		
	Relational switching costs	-0.244	-10.020	< 0.001		
Model 3	**(Constant)**		10.946	< 0.001	0.521	0.520
	Alternative attractiveness	0.549	20.229	< 0.001		
	Relational switching costs	-0.212	-7.538	< 0.001		
	Perceived value	-0.072	-2.310	0.021		

A stepwise regression was also performed for the switching behaviour sample (N_2).

5.7.2 Stepwise regression – Switching behaviour sample (N_2)

Prior to conducting the stepwise regression for the switching behaviour sample (N_2), the assumptions for linear regression were tested. As previously mentioned, when using stepwise regression, Pallant (2011:150) recommends a ratio of 40 cases for every independent variable. Consequently, a minimum of 120 cases are recommended for three (3) independent variables. Therefore the switching behaviour sample, N_2 = 135, meets the minimum recommended requirements.

Multicollinearity was assessed by measuring the variance inflation factor (VIF) and tolerance values. The VIF values were below the cut-off point of 10 (Pallant, 2011:183). Similarly, all of the variables had tolerance values above the 0.1 cut-off (Pallant, 2011:188). Thus the assumption on multicollinearity was not violated (Pallant, 2011:158). The VIF and tolerance results is presented in Table 7.3 in Appendix F.

The scatterplots (see Figure 7.4, Appendix F) revealed possible outliers. However, inspection of Mahalanobis distances (9.837) and Cook's distance (0.105) did not reveal any outliers. Further analyses were conducted to investigate whether the assumptions for homoscedasticity, linearity and normality were met. The scatterplot showed a "classic data cloud" (Boslaugh, 2013:204), thus the assumption of homoscedasticity was met. The scatterplot also indicated a horizontal line, therefore the assumption of linearity was not violated. The Normal Probability Plot (P-P Plot) in Figure 7.5 of Appendix also confirmed the assumption of normality.

Since all of the assumptions of linear regression were met, the stepwise regression analysis for the switching behaviour sample could continue. All three of the independent variables were included in the stepwise regression. As mentioned, during stepwise regression antecedents are entered in to the regression model according to their anticipated contribution toward improving model fit (Boslaugh, 2013:262). Each time an antecedent is added, all antecedents in the model are re-evaluated. Should an antecedent in the model not contribute toward improving model fit, that antecedent may be removed (Boslaugh, 2013:262). During the switching behaviour stepwise regression, perceived value did not enter the model, implying that perceived value did not contribute toward improving model fit. Thus in the current study, perceived value does not explain switching behaviour. Together, alternative attractiveness and relational switching costs explained only 12.3% of variance (Adjusted R^2 = 0.123). On its own, alternative attractiveness explained 8.9% of variance (Adjusted R^2 = 0.089).

The standardised coefficients (beta) show the relative contribution of the variables toward the prediction of the dependent variable (Pallant, 2011:161-162). The results show that alternative attractiveness is the strongest predictor of switching behaviour (beta = 0.225), followed by relational switching costs (beta = -0.219). Perceived value did not meet the criteria for inclusion in the stepwise regression. The results are summarised in Table 5.43 below.

Table 5.43: Summary of the stepwise regression for the switching behaviour sample (N_2)

Switching behaviour (N_2 = 135)		Standardised coefficients Beta	t	p-value	R^2	Adjusted R^2
Model 1	**(Constant)**		7.206	< 0.001	0.095	0.089
	Alternative attractiveness	0.309	3.746	< 0.001		
Model 2	**(Constant)**		6.731	< 0.001	0.136	0.123
	Alternative attractiveness	0.225	2.570	0.011		
	Relational switching costs	-0.219	-2.499	0.014		

Since the three predictors explain 52% of variance for switching intention, but only 12.3% of variance for switching behaviour, the conclusion can be drawn that switching intention and switching behaviour are essentially different.

Up until this point of investigating RO2, the comparison was considered from a switching intention perspective. Due to the large difference between switching intention and switching behaviour, revealed by the stepwise regression, the decision was made to use switching behaviour as the starting point of the comparison. In so doing, switching behaviour would be compared with switching intention, instead of switching intention being compared with switching behaviour, as is the case in the preceding section. Using switching behaviour as the driver of the comparison firstly allows switching behaviour to be explored further by conducting an EFA on the switching behaviour scales, followed by a comparison with switching intention.

Therefore the next section explains the switching intention and switching behaviour comparison from a switching behaviour perspective. To facilitate the exploration, the switching behaviour scales are first examined, using EFA, followed by the comparison of switching behaviour with switching intention using stepwise regression.

5.7.3 <u>Switching behaviour perspective</u>

To commence the investigation of the antecedents from a behaviour perspective, construct validity of the switching behaviour scales was established.

5.7.3.1 Validation of the switching behaviour scale

To investigate construct validity of the switching behaviour scale, an EFA was conducted for the same reasons provided earlier. Five generally accepted steps are required to conduct an EFA (Hair *et al*., 2014:95; Mooi & Sarstedt, 2011:206; Pallant, 2011:182). Firstly, data suitability is determined by investigating sample size and item intercorrelation strength (Pallant, 2011:182).

The sample size should be 150 cases or more, ideally more than 300 cases. Furthermore the ratio of cases to each item to be factor analysed should be at least 5:1, but preferably 10:1 (Pallant, 2011:187). For the current study, the switching behaviour sample realised was N = 135, thus the sample size is slightly below the requirement. In terms of the ratio of cases to items to be factor analysed, all four of the measurement scales together have 15 items (RSC = 7; PV = 3; AA = 5). For the sample size, the ratio of cases to factors is 9:1 (135/15). On the whole, the inter-item correlations were greater than 0.3 (see Table 7.4 in Appendix F). Bartlett's (1954) test of sphericity was statistically significant ($p < 0.05$) and the KMO value was 0.835, exceeding the minimum suggested threshold of 0.60 (Tabachnick & Fidell, 2013:620). Therefore the factorability of the correlation matrix was supported and the first assumption for the EFA was met.

During the second stage of the EFA the 15 items in the three switching behaviour measurement scales were subjected to PAF. The third step of the EFA entailed considering the number of factors to retain (Pallant, 2011:184). The PAF revealed the presence of three components with eigenvalues greater than one. The three factors accounted for 71.22% of the total variance. The first factor emerged with an eigenvalue of 5.798 and explained 38.65% of variance. The second factor emerged with an eigenvalue of 3.311 and explained an additional 22.08% of variance. In total, the two factors accounted for 60.73% of the total variance. The third factor emerged with an eigenvalue of 1.574 and explained 10.49% of variance. An inspection of the scree plot (Figure 7.6, Appendix F) showed a change after the third factor. Thus using Catell's (1966) scree test, all three factors were retained.

The fourth step of the EFA entailed using Direct Quartimin Oblique rotation with Kaiser Normalisation as the rotation method. Both rotated matrices – the pattern matrix and the structure matrix – were investigated. Finally, the fifth step of the EFA involves interpreting the factors by considering the factor loadings (Byrne, 2010:5-6). Upon investigation of the pattern matrix (see Table 5.44), two items loaded highly onto an unexpected component in the pattern matrix. The two items were B7_2 *(I am more comfortable interacting with the staff working for my current mobile network than I was interacting with the staff at my previous mobile network)* and B8_3 *(My current mobile network offers better value for money than what I paid for the same service at my previous mobile network)*. Similarly, all but the same two variables (B7_2 and B8_3) showed strong correlations to specific factors (components) in the structure matrix. Furthermore, B8_3 cross-loaded onto factor 3 in both the pattern and structure matrices. Table 5.44 shows both the pattern and structure matrices.

Table 5.44: Pattern matrix and structure matrix of the switching behaviour (N_2) measurement scales

PATTERN MATRIX				STRUCTURE MATRIX			
	FACTORS				FACTORS		
	Alternative attractiveness	Relational switching costs	Perceived value		Alternative attractiveness	Relational switching costs	Perceived value
B9_3	-0.946	-0.041	0.073	**B9_3**	-0.937	-0.180	-0.140
B9_4	-0.915	-0.124	0.122	**B9_5**	-0.919	-0.323	-0.119
B9_5	-0.912	-0.202	0.124	**B9_4**	-0.910	-0.246	-0.105
B9_2	-0.785	0.083	-0.240	**B9_2**	-0.823	-0.103	-0.389
B9_1	-0.646	0.125	-0.494	**B9_1**	-0.732	-0.099	-0.603
B7_2	0.628	0.068	-0.116	**B7_2**	0.614	0.144	0.035
B8_3	0.516	-0.198	0.445	**B8_3**	0.579	-0.007	0.509
B7_4	-0.003	0.880	-0.083	**B7_4**	0.125	0.860	0.125
B7_3	0.012	0.866	-0.049	**B7_3**	0.145	0.857	0.159
B7_5	0.022	0.702	0.116	**B7_5**	0.163	0.734	0.288
B7_1	0.158	0.679	-0.077	**B7_7**	0.168	0.703	0.485
B7_6	0.024	0.631	0.244	**B7_6**	0.181	0.693	0.399
B7_7	-0.008	0.624	0.339	**B7_1**	0.254	0.687	0.118
B8_2	0.017	0.215	0.691	**B8_2**	0.201	0.381	0.746
B8_1	-0.097	0.208	0.517	**B8_1**	0.048	0.315	0.546

Extraction Method: Principal Axis Factoring
Rotation Method: Direct Quartimin Oblique with Kaiser Normalization

Extraction Method: Principal Axis Factoring
Rotation Method: Direct Quartimin Oblique with Kaiser Normalization

Therefore the decision was made to delete the two items (B7_2 and B8_3), since the two items did not provide conceptual support for the alternative attractiveness factor (Hair *et al.*, 2014:118). A second PAF was conducted to investigate the remaining items. The second PAF revealed the presence of three components with eigenvalues greater than one. Together the three factors accounted for 74.66% of the total variance. The first factor emerged with an eigenvalue of 5.312 and explained 40.87% of variance. The second factor emerged with an eigenvalue of 2.974 and explained an additional 22.88% of variance. In total, the two factors accounted for 63.74% of the total variance. The third factor emerged with an eigenvalue of 1.42 and explained 10.92% of variance.

Catell's (1966) scree test (see Figure 7.7, Appendix F) showed a change after the third factor. Thus all three factors were retained. Again, Direct Quartimin Oblique rotation with Kaiser Normalisation was used as the rotation method. Both rotated matrices – the pattern matrix and the structure matrix – showed satisfactory loadings and there were no cross-loadings. Table 5.45 shows the pattern and structure matrices.

Table 5.45: Pattern matrix and structure matrix the switching behaviour (N_2) measurement scales

PATTERN MATRIX				STRUCTURE MATRIX			
	FACTORS				FACTORS		
	Relational switching costs	Alternative attractiveness	Perceived value		Relational switching costs	Alternative attractiveness	Perceived value
B7_4	0.926	0.041	-0.074	**B7_4**	0.892	-0.141	0.236
B7_3	0.894	0.012	-0.035	**B7_3**	0.879	-0.172	0.270
B7_1	0.689	-0.130	-0.053	**B7_5**	0.704	-0.185	0.447
B7_5	0.623	-0.005	0.232	**B7_1**	0.699	-0.266	0.211
B7_6	0.544	-0.026	0.333	**B7_7**	0.667	-0.207	0.621
B7_7	0.512	-0.008	0.443	**B7_6**	0.665	-0.210	0.526
B9_3	-0.028	0.940	0.090	**B9_3**	-0.197	0.928	-0.109
B9_4	-0.132	0.923	0.164	**B9_4**	-0.272	0.918	-0.068
B9_5	-0.204	0.896	0.144	**B9_5**	-0.345	0.910	-0.107
B9_2	0.125	0.826	-0.176	**B9_2**	-0.112	0.835	-0.300
B9_1	0.161	0.690	-0.364	**B9_1**	-0.112	0.729	-0.448
B8_2	0.074	-0.093	0.708	**B8_2**	0.337	-0.251	0.752
B8_1	0.072	0.046	0.598	**B8_1**	0.268	-0.090	0.613

Extraction Method: Principal Axis Factoring
Rotation Method: Direct Quartimin Oblique with Kaiser Normalization

Extraction Method: Principal Axis Factoring
Rotation Method: Direct Quartimin Oblique with Kaiser Normalization

From the PAF the conclusion can be drawn that the factors loaded onto the expected components, thereby validating the measurement scales. Since the EFA indicated construct validity, a reliability assessment was conducted for the switching behaviour scales using Cronbach's alpha.

5.7.3.2 Switching behaviour scale reliability

The Cronbach's alpha values for the three independent and the dependent variable were examined. The commonly accepted cut-off criterion for Cronbach's alpha is 0.70 (Peterson, 1994:381). Alternative attractiveness (α = 0.933) and relational switching costs (α = 0.844) met the recommended cut-off. Cronbach's alpha values for perceived value (α = 0.645) and switching intention (α = 0.540) were below the recommended cut-off. Peterson (1994:381) mentions that a cut-off of 0.5 is acceptable. Thus the analysis was continued. The results for the reliability analysis for the four switching behaviour measurement scales are shown in Table 5.46 below.

Table 5.46: Cronbach's alpha reliability values for the switching behaviour (N_2) measurement scales

Construct	Scale reliability for the switching behaviour sample (N_2)
Switching behaviour	α = 0.540
Relational switching costs	α = 0.844
Perceived value	α = 0.645
Alternative attractiveness	α = 0.933

Due to acceptable measurement scale reliability, the stepwise regression for the switching behaviour sample could be conducted. The section to follow explains how stepwise regressions were used to examine how well each individual independent variable predicts the dependent variable, while controlling for the other independent variables. A stepwise regression is first conducted on the switching intention sample (N_1), followed by the switching behaviour sample's (N_2) stepwise regression results, in order to compare switching behaviour and switching intention.

5.7.4 Second stepwise regression – Switching intention sample (N_1)

In order to make a valid comparison of switching intention and switching behaviour from a switching behaviour perspective, the same two items removed from the switching behaviour measurement scales were removed from the switching intention measurement scales. The items were: A6_2 *(I am more comfortable interacting with the staff working for my current mobile network than I would be if I switched to another mobile network)* and A7_3 *(My current mobile network offers better value for money than what I would pay for the same service at another mobile network)*. Table 5.47 shows the reliability values for all of the scales after the aforementioned items were deleted. All of the scales exceeded the recommended 0.70 threshold for Cronbach's alpha (Peterson, 1994:381).

Table 5.47: Cronbach's alpha reliability values for the switching intention (N_1) measurement scales after deleting item A6_2 and item A7_3

Construct	Switching intention scale reliability after deleting A6_2 and A7_3
Switching intention	α = 0.873
Relational switching costs	α = 0.938
Perceived value	α = 0.927
Alternative attractiveness	α = 0.948

The assumptions for linear regression for the switching intention sample (N_1) were evaluated and confirmed in Section 5.7.1, therefore the stepwise regression could continue. All three of the independent variables were included in the stepwise regression. All three of the independent variables together explained 52.0% of variance (Adjusted R^2 = 0.520). Alternative attractiveness alone explained 47.0% of variance (Adjusted R^2 = 0.470). Alternative attractiveness and relational switching costs together explained 51.7% of variance (Adjusted R^2 = 0.517), meaning that perceived value only explained 0.3% of variance. Thus the influence of perceived value on switching intention is negligible. The above results are very similar to the results obtained for the previous stepwise regression for switching intention.

The standardised coefficients (beta) show which of the variables contributed toward the prediction of the dependent variable (Pallant, 2011:161-162). All three independent variables were significant. The results show that alternative attractiveness is the strongest predictor of switching intention, followed by relational switching costs. The results suggest that perceived value does not contribute toward predicting switching intention, given the other two predictors.

The above results are very similar to the results obtained for the previous stepwise regression for switching intention. The results are summarised in Table 5.48 below.

Table 5.48: Summary of the stepwise regression for the switching intention sample (N_1) after deleting items from the two measurement scales

Switching intention (N_1 = 1018)		Standardised coefficients Beta	t	p-value	R^2	Adjusted R^2
Model 1	**(Constant)**		6.830	< 0.001	0.471	0.470
	Alternative attractiveness	0.686	30.074	< 0.001		
Model 2	**(Constant)**		12.274	< 0.001	0.518	0.517
	Alternative attractiveness	0.575	23.507	< 0.001		
	Relational switching costs	-0.244	-9.977	< 0.001		
Model 3	**(Constant)**		11.391	< 0.001	0.522	0.520
	Alternative attractiveness	0.546	20.496	< 0.001		
	Relational switching costs	-0.210	-7.687	< 0.001		
	Perceived value	-0.080	-2.723	0.007		

5.7.5 Second stepwise regression – Switching behaviour sample (N_2)

Certain assumptions should be met prior to conducting a linear regression. Since the assumptions for linear regression were met for the switching behaviour sample (N_2) in the previous section (see Section 5.7.2) the stepwise regression analysis could continue.

All three of the independent variables were included in the stepwise regression. Antecedents in the model that do not contribute toward improving model fit are excluded from the model during the stepwise regression process (Boslaugh, 2013:262). During the second switching behaviour stepwise regression, relational switching costs did not enter the model, implying that relational switching costs did not contribute toward improving model fit. Together, alternative attractiveness and perceived value explained 10.9% of variance (Adjusted R^2 = 0.109). Alternative attractiveness alone explained 8.9% of variance (Adjusted R^2 = 0.089).

The standardised coefficients (beta) show which of the variables contributed toward the prediction of the dependent variable (Pallant, 2011:161-162). The results show that alternative attractiveness is the strongest predictor of switching behaviour (beta = 0.274), followed by perceived value (beta = -0.168). As mentioned, relational switching costs did not meet the criteria for inclusion in the stepwise regression. The results are summarised in Table 5.49 below.

Table 5.49: Summary of the stepwise regression for the switching behaviour sample (N_2) after deleting items from the two measurement scales

Switching behaviour (N_2 = 135)		Standardised coefficients Beta	t	p-value	R^2	Adjusted R^2
Model 1	**(Constant)**		7.206	< 0.001	0.095	0.089
	Alternative attractiveness	0.309	3.746	< 0.001		
Model 2	**(Constant)**		6.804	< 0.001	0.122	0.109
	Alternative attractiveness	0.274	3.294	0.001		
	Perceived value	-0.168	-2.015	0.046		

Overall the results show that together the three antecedents explain at least half of switching intention. Surprisingly these same three antecedents explain very little regarding switching behaviour. The fact that the antecedents do not explain switching behaviour as well as switching intention suggests that different predictors influence switching behaviour. Consequently switching behaviour should be further investigated to determine which predictors influence switching behaviour. The possibility exists that the antecedents may have non-linear relationships with switching behaviour. Since SEM was not possible with the switching behaviour sample, these relationships could not be investigated.

Once the comparison was complete, the role of relationship length, depth and breadth in switching intention and switching behaviour was investigated. The relationship characteristics' role in switching intention and switching behaviour was the third main objective of the study.

5.8 RO3: THE ROLE OF RELATIONSHIP CHARACTERISTICS IN SWITCHING INTENTION AND SWITCHING BEHAVIOUR

The third main research objective was to determine whether relationship characteristics had any influence on switching intention and/or switching behaviour. The influence of relationship length, depth and breadth on switching intention is first examined, followed by the influence of these relationship characteristics on switching behaviour, using multiple regression analysis.

5.8.1 Multiple regression – Switching intention sample (N_1)

Certain assumptions should be met prior to conducting linear regression. The assumption of sample size for the switching intention sample (N_1 = 1,025) was met in Section 5.7.1. Mutlicollinearity was assessed by inspecting VIF and tolerance values. As per Pallant's (2011:183) guidelines, none of the tolerance values were below 0.10 and none of the variables had VIF values above 10 (Pallant, 2011:158), indicating that the assumption of multicollinearity was not violated. Furthermore, all correlations were less than 0.9. The VIF and tolerance results is presented in Table 7.6, Appendix F.

The scatterplot revealed outliers (see Figure 7.8 in Appendix F). Inspection of Mahalanobis distances (41.393) identified outliers that should be removed. Cook's distance (0.025) was below 1.00, thereby not revealing any outliers.

Further inspection of the outliers suggested that 15 cases should be deleted. After the analysis, the Mahalanobis distance value was 22.159, suggesting that more outliers needed to be removed. The procedure was repeated until the Mahalanobis distance value decreased to 15.4. The sample size decreased to N_1 = 985.

Assumptions for homoscedasticity, linearity and normality were examined. The scatterplot (Figure 7.8, Appendix F) revealed that the assumption of linearity was met. The P-P Plots (Figure 7.9, Appendix F) indicated that the assumptions of normality were met.

Since all of the assumptions of linear regression were met, the multiple regression analysis could continue. The Adjusted R^2 indicates the variance explained. The three relationship characteristics together explain 1.3% of variance (Adjusted R^2 = 0.013). In other words, relationship length, depth and breadth weakly explain switching intention and together account for only 1.3% of variance.

The standardised coefficients (beta) show which of the variables contributed toward the prediction of the dependent variable (Pallant, 2011:161-162). Of the three relationship characteristics, although weak, relationship depth was the greatest predictor of switching intention (beta = 0.127) and the contribution was statistically significant. The contributions by relationship length (beta = -0.061) and relationship breadth (beta = -0.003) were not statistically significant. Table 5.50 presents a summary of the results.

Table 5.50: Summary of the multiple regression for the switching intention sample (N_1)

Switching intention (N_1 = 985)		Standardised coefficients	t	p-value	R^2	Adjusted R^2
		Beta				
Model 1	(Constant)		16.315	< 0.001	0.016	0.013
	Relationship length	-0.061	-1.882	0.060		
	Relationship depth	0.127	3.817	< 0.001		
	Relationship breadth	-0.003	-0.097	0.923		

5.8.2 Multiple regression – Switching behaviour sample (N_2)

The assumption of sample size for switching behaviour was previously met – see Section 5.7.2. All correlations were less than 0.9. None of the tolerance values were below 0.10 and none of the variables had VIF values above 10 – see Table 7.7 in Appendix F (Pallant, 2011:158). Thus the assumption of multicollinearity was not violated.

The scatterplot (Figure 7.10, see Appendix F) revealed outliers. Inspection of Mahalanobis distances (30.310) identified outliers that should be removed. Cook's distance (0.230) was below 1.00, thereby not revealing any outliers.

Two cases were found to be above the critical value of 16.27. After the two cases were deleted, the Mahalanobis distance value was 25.237, suggesting that further investigation was required. The procedure was repeated until the Mahalanobis distance value decreased to 11.313. The sample size decreased to $N_2 = 128$.

The following three assumptions are examined using scatterplots, namely: homoscedasticity, linearity and normality (Pallant, 2011:151). Scatterplots revealed a horizontal line, therefore the assumption of linearity was met. The P-P Plots (see Figure 7.11 in Appendix F) met the assumptions as stipulated by Pallant (2011:158).

Since all of the assumptions of linear regression were met, the multiple regression analysis could continue. The three relationship characteristics together explain 2.9% of variance (Adjusted $R^2 = 0.029$). So, relatively speaking, relationship length, depth and breadth explain switching behaviour slightly better than switching intention.

The standardised coefficients (beta) show which of the variables contributed toward the prediction of the dependent variable (Pallant, 2011:161-162). Of the three relationship characteristics, relationship depth was the greatest contributor toward switching behaviour (beta = 0.230), however, the contribution was not statistically significant. The contributions by relationship length (beta = -0.142) and relationship breadth (beta = -0.091) were also not statistically significant. The results are summarised in Table 5.51 below.

Table 5.51: Summary of the multiple regression for the switching behaviour sample (N_2)

Switching behaviour ($N_2 = 128$)		Standardised coefficients Beta	t	p-value	R^2	Adjusted R^2
Model 1	**(Constant)**		11.969	< 0.001	0.052	0.029
	Relationship length	-0.142	-1.539	0.126		
	Relationship depth	0.230	2.385	0.019		
	Relationship breadth	-0.091	-0.972	0.333		

Overall, the relationship characteristics did not influence switching behaviour nor switching intention as expected. However, relationship depth had a significant influence on both switching intention and switching behaviour.

The secondary objectives were investigated using hypothesis testing. Secondary objectives included examining the interrelationships, that is, the correlations between the constructs in the switching intention model (H_{1a} to H_{6a}); the constructs in the switching behaviour model (H_{1b} to H_{6b}); the influence of relationship characteristics on switching intention (H_{7a} to H_{9a}); and the influence of relationship characteristics on switching behaviour (H_{7b} to H_{9b}).

5.9 HYPOTHESIS TESTING OF SECONDARY OBJECTIVES

All of the secondary research objectives were converted into corresponding hypothesis statements regarding bivariate correlations. The results of the hypothesis tests are provided in the paragraphs to follow. All hypothesis tests were conducted to evaluate Pearson's product moment correlations. Hypotheses were tested at a 5% level of significance ($\alpha = 0.05$).

5.9.1 Hypothesis 1

$H_{1a(null)}$: There is no relationship between relational switching costs and switching intention.
$H_{1a(alt)}$: There is a negative relationship between relational switching costs and switching intention.

There is a statistically significant negative relationship between relational switching costs and switching intention ($p < 0.001$) within a switching intention context. Therefore $H_{1a(null)}$ can be rejected, in support of $H_{1a(alt)}$. The *p*-value of $p < 0.001$ is highly significant. The correlation coefficient ($r = -0.503$) indicates a moderate negative correlation between relational switching costs and switching intention.

$H_{1b(null)}$: There is no relationship between relational switching costs and switching behaviour.
$H_{1b(alt)}$: There is a negative relationship between relational switching costs and switching behaviour.

The correlation coefficient (r = -0.305) indicates a low correlation between relational switching costs and switching behaviour. There is a statistically significant negative relationship between relational switching costs and switching behaviour ($p < 0.001$) within a switching behaviour context. Therefore $H_{1b(null)}$ can be rejected, in support of $H_{1b(alt)}$.

5.9.2 <u>Hypothesis 2</u>

$H_{2a(null)}$: There is no relationship between perceived value and switching intention.
$H_{2a(alt)}$: There is a negative relationship between perceived value and switching intention.

$H_{2a(null)}$ can be rejected, in support of $H_{2a(alt)}$, since $p < 0.001$. Therefore there is a statistically significant negative relationship between perceived value and switching intention within a switching intention context. The correlation coefficient (r = -0.528) indicates a moderate correlation between perceived value and switching intention.

$H_{2b(null)}$: There is no relationship between perceived value and switching behaviour.
$H_{2b(alt)}$: There is a negative relationship between perceived value and switching behaviour.

There is a statistically significant negative relationship between perceived value and switching behaviour ($p = 0.004$) within a switching behaviour context. Therefore $H_{2b(null)}$ can be rejected in support of $H_{2b(alt)}$. The correlation coefficient (r = -0.231) indicates a weak correlation between perceived value and switching behaviour.

5.9.3 Hypothesis 3

$H_{3a(null)}$: There is no relationship between alternative attractiveness and switching intention.
$H_{3a(alt)}$: There is a positive relationship between alternative attractiveness and switching intention.

The correlation coefficient (r = 0.686) indicates a moderate correlation between alternative attractiveness and switching intention. There is a statistically significant positive relationship between alternative attractiveness and switching intention ($p < 0.001$) within a switching intention context. Therefore $H_{3a(null)}$ can be rejected, in support of $H_{3a(alt)}$.

$H_{3b(null)}$: There is no relationship between alternative attractiveness and switching behaviour.
$H_{3b(alt)}$: There is a positive relationship between alternative attractiveness and switching behaviour.

The result is highly significant since $p < 0.001$. Therefore there is a statistically significant positive relationship between alternative attractiveness and switching behaviour within a switching behaviour context and $H_{3b(null)}$ can be rejected in support of $H_{3b(alt)}$. The correlation coefficient (r = 0.309) indicates a weak correlation between alternative attractiveness and switching behaviour.

Table 5.52 provides a summary of the hypothesis testing results for switching intention, switching behaviour, and the three antecedents.

Table 5.52: Summary of the hypothesis testing results for the three antecedents in the switching intention (H_{1a} to H_{3a}) and switching behaviour (H_{1b} to H_{3b}) contexts

		Switching intention (N_1 = 1018)	Sig. (1-tailed)	Switching behaviour (N_2 = 135)	Sig. (1-tailed)
Pearson correlation	**Relational switching costs**	-0.503	< 0.001	-0.305	< 0.001
	Perceived value	-0.528	< 0.001	-0.231	0.004
	Alternative attractiveness	0.686	< 0.001	0.309	< 0.001

5.9.4 Hypothesis 4

$H_{4a(null)}$: There is no relationship between relational switching costs and perceived value.
$H_{4a(alt)}$: There is a relationship between relational switching costs and perceived value in a switching intention context.

There is a statistically significant positive relationship between relational switching costs and perceived value (p < 0.001) within a switching intention context. Therefore $H_{4a(null)}$ can be rejected, in support of $H_{4a(alt)}$. The correlation coefficient (r = 0.626) indicates a moderate correlation between relational switching costs and perceived value within a switching intention context.

$H_{4b(null)}$: There is no relationship between relational switching costs and perceived value.
$H_{4b(alt)}$: There is a relationship between relational switching costs and perceived value in a switching behaviour context.

$H_{4b(null)}$ can be rejected in support of $H_{4b(alt)}$. Hence there is a statistically significant positive relationship between relational switching costs and perceived value within a switching behaviour context. The correlation coefficient (r = 0.364) indicates a weak correlation between relational switching costs and perceived value within a switching behaviour context.

5.9.5 Hypothesis 5

$H_{5a(null)}$: There is no relationship between relational switching costs and alternative attractiveness.
$H_{5a(alt)}$: There is a relationship between relational switching costs and alternative attractiveness in a switching intention context.

$H_{5a(null)}$ can be rejected, in support of $H_{5a(alt)}$. There is a statistically significant negative relationship between relational switching costs and alternative attractiveness within a switching intention context. The correlation coefficient ($r = -0.450$) indicates a low correlation between relational switching costs and alternative attractiveness within a switching intention context.

$H_{5b(null)}$: There is no relationship between relational switching costs and alternative attractiveness.
$H_{5b(alt)}$: There is a relationship between relational switching costs and alternative attractiveness in a switching behaviour context.

There is a statistically significant negative relationship between relational switching costs and alternative attractiveness ($p < 0.001$) within a switching behaviour context. Therefore $H_{5b(null)}$ can be rejected, in support of $H_{5b(alt)}$. The correlation coefficient ($r = -0.383$) indicates a weak correlation between relational switching costs and alternative attractiveness within a switching behaviour context.

5.9.6 Hypothesis 6

$H_{6a(null)}$: There is no relationship between perceived value and alternative attractiveness.
$H_{6a(alt)}$: There is a relationship between perceived value and alternative attractiveness in a switching intention context.

Perceived value and alternative attractiveness were found to have a statistically significant negative relationship ($p < 0.001$) within a switching intention context. Therefore $H_{6a(null)}$ can be rejected in support of $H_{6a(alt)}$. The correlation coefficient (r = -0.590) indicates a moderate correlation between perceived value and alternative attractiveness within a switching intention context.

$H_{6b(null)}$: There is no relationship between perceived value and alternative attractiveness.
$H_{6b(alt)}$: There is a relationship between perceived value and alternative attractiveness in a switching behaviour context.

There is a statistically significant negative relationship between perceived value and alternative attractiveness within a switching behaviour context. Therefore $H_{6b(null)}$ can be rejected in support of $H_{6b(alt)}$. The correlation coefficient (r = -0.420) indicates a low correlation between perceived value and alternative attractiveness within a switching behaviour context.

Table 5.53 is a summary of the hypothesis testing results for the interrelationships between the three switching intention antecedents.

Table 5.53: Summary of the hypothesis testing results of the interrelationships between the three antecedents in the switching intention context (H_{4a} to H_{6a})

Switching intention context (N_1 = 1018)		Relational switching costs	Perceived value	Alternative attractiveness
Pearson correlation	**Relational switching costs**	1.000		
	Perceived value	0.626	1.000	
	Alternative attractiveness	-0.450	-0.590	1.000
Sig. (2-tailed)	**Relational switching costs**	.		
	Perceived value	< 0.002	.	
	Alternative attractiveness	< 0.002	< 0.002	.

Table 5.54 provides a summary of the hypothesis testing results for the interrelationships between the three switching behaviour antecedents.

Table 5.54: Summary of the hypothesis testing results of the interrelationships between the three antecedents in the switching behaviour context (H_{4b} to H_{6b})

Switching behaviour context (N_2 = 135)		Relational switching costs	Perceived value	Alternative attractiveness
Pearson correlation	**Relational switching costs**	1.000		
	Perceived value	0.364	1.000	
	Alternative attractiveness	-0.383	-0.420	1.000
Sig. (2-tailed)	**Relational switching costs**	.		
	Perceived value	< 0.002	.	
	Alternative attractiveness	< 0.002	< 0.002	.

5.9.7 Hypothesis 7

$H_{7a(null)}$: There is no relationship between relationship length and switching intention.
$H_{7a(alt)}$: There is a negative relationship between relationship length and switching intention.

The relationship between relationship length and switching intention is not statistically significant (*p* > 0.001; p = 0.143). Therefore $H_{7a(null)}$ can not be rejected. The correlation coefficient (r = -0.034) indicates an extremely weak correlation between relationship length and switching intention, which is clear from the rejection of the alternative hypothesis.

$H_{7b(null)}$: There is no relationship between relationship length and switching behaviour.
$H_{7b(alt)}$: There is a negative relationship between relationship length and switching behaviour.

$H_{7b(null)}$ can not be rejected since the relationship between relationship length and switching behaviour is not statistically significant (*p* > 0.001; *p* = 0.156). The correlation coefficient (r = -0.090) indicates an extremely weak correlation between relationship length and switching intention, which is clear from the rejection of the alternative hypothesis.

5.9.8 Hypothesis 8

$H_{8a(null)}$: There is no relationship between relationship depth and switching intention.
$H_{8a(alt)}$: There is a negative relationship between relationship depth and switching intention.

Despite a statistically significant positive relationship between relationship depth and switching intention ($p < 0.001$), $H_{8a(null)}$ can not be rejected. The relationship was expected to be negative, but the result was positive. The correlation coefficient ($r = 0.112$) indicates an extremely weak correlation between relationship depth and switching intention.

$H_{8b(null)}$: There is no relationship between relationship depth and switching behaviour.
$H_{8b(alt)}$: There is a negative relationship between relationship depth and switching behaviour.

$H_{8b(null)}$ can not be rejected since the relationship was expected to be negative, but the result was positive. Despite the fact that there is a statistically significant positive relationship between relationship depth and switching behaviour ($p = 0.040$). The correlation coefficient ($r = 0.156$) indicates an extremely weak correlation between relationship depth and switching behaviour.

5.9.9 Hypothesis 9

$H_{9a(null)}$: There is no relationship between relationship breadth and switching intention.
$H_{9a(alt)}$: There is a negative relationship between relationship breadth and switching intention.

The positive relationship between relationship breadth and switching intention is not statistically significant ($p = 0.295$). Therefore $H_{9a(null)}$ can not be rejected. The correlation coefficient ($r = 0.017$) indicates an extremely weak correlation between relationship breadth and switching intention.

$H_{9b(null)}$: There is no relationship between relationship breadth and switching behaviour.

$H_{9b(alt)}$: There is a negative relationship between relationship breadth and switching behaviour.

$H_{9b(null)}$ can not be rejected since the negative relationship between relationship breadth and switching behaviour is not statistically significant ($p > 0.001$; $p = 0.331$). The correlation coefficient (r = -0.039) indicates an extremely weak correlation between relationship breadth and switching behaviour.

Table 5.55 is a summary of the hypothesis testing results of relationship characteristics in the switching intention and switching behaviour contexts.

Table 5.55: Summary of the hypothesis testing results for relationship characteristics in the switching intention (H_{7a} to H_{9a}) and switching behaviour (H_{7b} to H_{9b}) contexts

		Switching intention (N_1 = 985)	Sig. (1-tailed)	Switching behaviour (N_2 = 128)	Sig. (1-tailed)
Pearson correlation	**Relationship length**	-0.034	0.143	-0.090	0.156
	Relationship depth	0.112	0.000	0.156	0.040
	Relationship breadth	0.017	0.295	-0.039	0.331

Table 5.56 provides a summary of the results of the hypothesis tests.

Table 5.56: Hypothesis testing summary

Alternative hypotheses	Supported or not supported
H_{1a}: There is a negative relationship between relational switching costs and switching intention.	Supported
H_{1b}: There is a negative relationship between relational switching costs and switching behaviour.	Supported
H_{2a}: There is a negative relationship between perceived value and switching intention.	Supported
H_{2b}: There is a negative relationship between perceived value and switching behaviour.	Supported
H_{3a}: There is a positive relationship between alternative attractiveness and switching intention.	Supported
H_{3b}: There is a positive relationship between alternative attractiveness and switching behaviour.	Supported

Alternative hypotheses	Supported or not supported
H_{4a}: There is a relationship between relational switching costs and perceived value in a switching intention context.	Supported
H_{4b}: There is a relationship between relational switching costs and perceived value in a switching behaviour context.	Supported
H_{5a}: There is a relationship between relational switching costs and alternative attractiveness in a switching intention context.	Supported
H_{5b}: There is a relationship between relational switching costs and alternative attractiveness in a switching behaviour context.	Supported
H_{6a}: There is a relationship between perceived value and alternative attractiveness in a switching intention context.	Supported
H_{6b}: There is a relationship between perceived value and alternative attractiveness in a switching behaviour context.	Supported
H_{7a}: There is a negative relationship between relationship length and switching intention.	Not supported
H_{7b}: There is a negative relationship between relationship length and switching behaviour.	Not supported
H_{8a}: There is a negative relationship between relationship depth and switching intention.	Not supported
H_{8b}: There is a negative relationship between relationship depth and switching behaviour.	Not supported
H_{9a}: There is a negative relationship between relationship breadth and switching intention.	Not supported
H_{9b}: There is a negative relationship between relationship breadth and switching behaviour.	Not supported

5.10 CONCLUSION

The chapter began with a sample profile of both the switching intention and switching behaviour samples, which included demographic information and information regarding relationship length, depth and breadth. Next, an overview of information regarding the MNOs with whom respondents have a contract (the switching intention sample) and the MNOs with whom respondents previously had a contract (the switching behaviour sample) was presented. The descriptive statistical results for each scale were interpreted in the ensuing section, followed by an investigation of the validity and reliability of each measurement scale.

Thereafter the switching intention model was built and refined, followed by an analysis to fit the switching behaviour sample data to the final switching intention model. SEM, CFA and path analysis were attempted. However, due to a high number of parameter estimates and sample size restrictions, model fitting could not be pursued. Consequently switching intention and behaviour were compared using stepwise regression. Following the initial comparison, the antecedents of switching intention and switching behaviour revealed differences. Subsequently a comparison was made from a switching behaviour perspective.

The switching behaviour scales were first validated using PAF, with the aid of Direct Quartimin Oblique rotation with Kaiser Normalisation. Reliability testing using Cronbach's alpha followed. Next, two items were deleted, thus a second EFA was conducted. After acceptable EFA results, the switching behaviour stepwise regression was conducted. Then the same items deleted from the switching behaviour scales were deleted from the switching intention scales. Cronbach's alpha revealed acceptable reliability, thus the stepwise regression continued. Results showed that from a switching behaviour perspective, the three antecedents still explained switching intention well, but not switching behaviour. The third main research objective regarding the role of relationship characteristics in switching was examined next. Finally, hypothesis testing was conducted to evaluate Pearson's product moment correlations to assess the secondary objectives of the study.

CHAPTER 6

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

6.1 INTRODUCTION

The concluding chapter presents a summary of the empirical results arising from the study. The chapter begins with a synopsis of the study, followed by a discussion of the findings. Additionally, the results of the current study are likened to previous research to ascertain in what way the current study's results reflect or build upon previous research. Subsequently, the contribution of the study and managerial implications are discussed. Finally, limitations of the study are noted, followed by suggests for future research.

6.2 SYNOPSIS OF THE STUDY

To date, most switching studies have focussed on the predictive accuracy of switching intention only, neglecting actual switching behaviour. Furthermore, researchers have conflicting opinions regarding switching predictors. Hence, the primary objectives were threefold. Firstly, to develop a conceptual switching intention model; secondly to compare the conceptual switching intention model to actual switching behaviour data; and thirdly, to investigate the role of relationship characteristics in both a switching intention and switching behaviour context. Secondary objectives were to further investigate switching predictors and to investigate the interrelationships between the antecedents in both the conceptual model and in a switching behaviour context.

The primary data were collected via a structured questionnaire in the form of an online self-administered survey using the Survey Workbench programme. The data were collected from Consulta Research's cross-sectional online panel. All participants were required to have a contract with a South African MNO. The switching intention sub-sample and the switching behaviour sub-sample answered separate questionnaires. Pre-testing was conducted online, in three phases. Firstly by the researcher; secondly by

43 colleagues, family and friends (after which minor alterations were made); lastly, the pre-test survey was sent to 300 Consulta Research online panel members. Once all three pre-tests were complete, the survey was sent to 54,924 panel members. A total of 1,668 surveys were returned. The observations were separated into the switching intention observations (N = 1,483) and the switching behaviour observations (N = 185). Cases with incomplete demographic information were not discarded, because the demographic data were not incorporated into the SEM model and were also not the focus of the study. However, all cases with incomplete construct questions were deleted, as those missing cases would affect model building. After discarding incomplete and erroneous cases, a usable sample of switching intention (N_1 = 1,025) and switching behaviour (N_2 = 135) were analysed.

To answer the three main research objectives, different data analysis techniques were performed. The purpose of research objective one (RO1) was to empirically test the conceptual switching intention model. Parameter estimates were obtained by means of SEM using maximum likelihood (ML) in the AMOS package. Bootstrapping confirmed that the parameter estimates attained through ML could be reported with confidence. A switching intention model with adequate fit was found after three covariances were added to the relational switching cost scale. Due to nonnormality of the data, the final switching intention model was tested using the EQS package to obtain robust ML fit indices. The final fit indices obtained were: χ^2/df = 6.004 (χ^2 = 966.61; df = 161; $p < 0.000$); RMSEA = 0.070 [0.066; 0.074]; NNFI = 0.943; CFI = 0.952.

Due to the low number of cases obtained from the switching behaviour sample (N_2 = 135) and the high number of parameters to be estimated (49 parameters), the switching behaviour data could not be fitted to the switching intention model (RO2). However, to allow some form of comparison, stepwise regression was used to compare the frameworks of both switching behaviour and switching intention, since fewer parameters are required for estimation. In the switching behaviour context, two of the three antecedents (alternative attractiveness and relational switching costs) explained 12.3% of variance, while in the switching intention context, all three antecedents explained 52% of variance. Thus the conclusion was drawn that switching intention and switching behaviour are intrinsically different. Since the comparison revealed a relatively large difference between switching intention and switching behaviour, a decision was made to consider a second comparison from a switching behaviour angle (as opposed to the switching intention focus applied to the first comparison). In so doing, switching behaviour could be compared with switching intention, instead of comparing switching intention with switching behaviour, as was the case in the preceding section.

Using switching behaviour as the driver of the comparison firstly allowed switching behaviour to be further explored by conducting an EFA on the switching behaviour scales, followed by a comparison with switching intention. Consequently, the switching intention and switching behaviour comparison was explained from a switching behaviour perspective. To facilitate the exploration, the switching behaviour scales were first examined, using EFA (principal axis factoring in particular), followed by the comparison of switching behaviour with switching intention.

As part of the evaluation, the reliability and validity of the switching behaviour measurement scales were examined. The 15 items in the three measurement scales were subjected to principal axis factoring (PAF), which revealed the presence of three factors. The Direct Quartimin Oblique Rotation with Kaiser Normalisation revealed that two items loaded onto unrelated components in the pattern matrix. In the structure matrix, all but the same two variables showed strong correlations to specific components. The two items were removed from the measurement scales since these two items did not provide conceptual support for the alternative attractiveness factor. A second round of PAF showed satisfactory factor loadings. Also, factor loadings were above the minimum requirement of 0.4 (Hair *et al*., 2014:136). To facilitate the comparison with switching intention, the same two items were removed from the switching intention measurement scales. Measurement scale reliability for the switching intention scales was recalculated, and acceptable reliability values were obtained. Next, both switching behaviour and switching intention were subjected to stepwise regression. In the switching behaviour context, two of the three antecedents (alternative attractiveness and perceived value) explained 10.9% of variance, whereas all three switching intention antecedents again explained 52% of variance. The low percentage of variance accounted for in switching behaviour once again suggested that switching intention and switching behaviour are different and that factors other than the antecedents investigated drive switching behaviour.

Secondary objectives related to the first two main research objectives were to investigate the direct relationship between the antecedents and the dependent variable, and the construct interrelationships in both the switching intention and switching behaviour contexts. The aforementioned relationships were investigated using Pearson's product moment correlation hypothesis testing. All direct relationships between the antecedents and the dependent variable in both switching intention and switching behaviour were supported, as well as all interrelationships between the antecedents.

Regarding the third main research objective (RO3), the role of relationship characteristics in both switching intention and switching behaviour was investigated using multiple regression. The results of the multiple regression showed that relationship depth was a weak predictor of switching intention, while relationship length and breadth did not contribute toward predicting switching intention.

The relationship between each individual relationship characteristic and switching intention, and separately with switching behaviour, was investigated by evaluating Pearson's product moment correlations. None of the relationship characteristic hypotheses, neither in the switching intention nor the switching behaviour context, were supported.

Following from the manner in which the research was conducted and the data analysed, the empirical findings are summarised in the next section.

6.3 SUMMARY OF THE EMPIRICAL RESULTS AND CONCLUSIONS

The main findings of the research are summarised in the paragraphs to follow. Where relevant, comparisons of the findings in the study are made to findings in previous research mentioned in the literature review. Comparisons are also made between findings obtained from the switching intention sample and those attained from the switching behaviour sample. Some notable descriptive findings are first discussed, followed by the findings pertaining to the three primary objectives of the study.

6.3.1 Mobile network operators

The majority of the switching intention sample had a contract with Vodacom, followed by MTN and then Cell C. Most switching behaviour respondents had a contract with Cell C, followed by Vodacom and then MTN subscribers. Of the respondents that had switched, overall Vodacom lost the most subscribers while Cell C gained the most subscribers. Both Cell C and Telkom Mobile gained more subscribers than they lost, while Vodacom, MTN and Virgin Mobile lost more subscribers than they gained.

The results suggest that most respondents seem to switch between Vodacom and Cell C, since the majority Vodacom switchers moved to Cell C and the majority Cell C switchers moved to Vodacom. Interestingly, most MTN, Telkom Mobile and Virgin Mobile subscribers switched to Vodacom, which may explain why Vodacom gained back almost as many subscribers as they lost.

The results are somewhat in line with current events. Deloitte Digital SA (2013) estimated market shares for the South African MNOs for September 2012 as: Vodacom (47%), MTN (37%), Cell C (14%) and Telkom Mobile (2%). Figures for August 2013 were as follows: Vodacom (43%), MTN (36.8%), Cell C (17.1%) and Telkom Mobile (2.3%). Virgin Mobile's estimated market share is 0.7% (Bronkhorst, 2013). Cell C is steadily gaining market share, while both Vodacom and MTN are losing market share (Bronkhorst, 2013).

6.3.2 Demographics

The highest age grouping for the switching intention respondents (N_1) was 50-59 years, whereas the highest age grouping in the switching behaviour sample (N_2) was the

30-39 year age category. The results suggest that older subscribers have a higher intention to switch, but that younger subscribers are more likely to switch.

6.3.3 Switching intention and switching behaviour

Most switching intention respondents demonstrated a high intention to switch since they did not expect to remain with their current MNO for the foreseeable future. However, when asked whether their intention was to switch to another MNO as soon as their contract with their current MNO expired, respondents were hesitant to switch. The respondents' reaction clearly demonstrates the paradox between switching intention and behaviour. Persons readily intend to switch, however, when asked to commit to actually switching, for example, committing to switching when their contract ends, hesitation sets in.

The switching behaviour respondents demonstrated very similar results as they too did not expect to stay with their MNO for long when originally subscribing to their previous MNO. But they had also not intended to switch to another MNO once their contract with their previous MNO expired.

Interestingly, switching intention subscribers were unlikely to switch as a result of experiencing problems with their current MNO and were also unsure whether they would switch to a MNO that offered better services. This begs the questions as to what else, apart from experiencing problems, may cause switching. Overall, the switching behaviour respondents switched because they wanted a MNO that offered better services, but not necessarily because they had experienced problems with their previous MNO on a regular basis. Once again the results allude to the fact that the switching intention and switching behaviour samples differ and that more insight is needed regarding actual behaviour.

6.3.4 Relational switching costs

The results suggest that the switching intention respondents had a rather neutral opinion regarding the MNO's brand. These results are surprising, considering the fact that relational switching costs refer to customers suffering brand relationship loss following the termination of the customer–service provider relationship (Antón *et al.*, 2007b:141; Burnham *et al*., 2003:112; Chuang, 2011:131; Hu & Hwang, 2006:80). Therefore it may be useful to increase the strength of customers bonds with the service provider's brand to increase customers' likelihood of remaining with that service provider (Burnham *et al*., 2003:120). To build stronger brand relationship bonds between customers and service providers, Burnham *et al*. (2003:114) recommend multiple B2C interactions, since the more customers interact with their service provider, the more emotionally dependent they become, which decreases the likelihood of switching (Hu & Hwang, 2006:84; Jones *et al.*, 2007:338). Respondents showed a slight preference toward liking their MNO's public image and supporting their MNO as a firm. These results are in line with Gerpott *et al*.'s (2001:265) findings – if customers have a positive of their MNO they are likely to remain with that service provider. Lastly, respondents were neutral regarding caring about their MNO's brand/company name.

In contrast, the switching behaviour respondents were not concerned about their previous MNO's brand/company name and did not like their previous MNO's public image. The result is in line with Burnham *et al*.'s (2003:114) opinion that customers who have switched may not have developed brand and personal relationship bonds with that service provider. Furthermore, Chuang (2011:131) suggests that when customers no longer receive the services of their original service providers, they lose the brand relationship built with that service provider.

Neither group of respondents felt very strongly about having a relationship with the MNO staff. Both the switching intention and switching behaviour respondents seemed apathetic to any questions related to personal relational switching costs. Even after switching, respondents did not attach high value to the staff relationships. The possibility that subscribers seldom interact with the staff could be a contributing factor to the result, since there is not as much interaction with staff at a MNO as one would have with staff at, for example, a hairdresser or restaurant. The above results suggest that relational switching costs in mobile telecommunications are very low. Burnham *et al.* (2003:p120) recommend that increasing the strength of customers' relational bonds increases the likelihood that customers will remain with the service provider, even in industries with little or no face-to-face contact.

6.3.5 Perceived value

Even though the switching intention respondents seemed to have a rather neutral opinion regarding perceived value in general, most respondents seem to agree that the total monthly bill from their current MNO was acceptable and that their current MNO offered good value-for-money. When compared to other MNOs, respondents also agreed that their current MNO offered better value-for-money than what they would pay for the same service at another MNO. Antón *et al.* (2007b:148) found that customers with more knowledge about alternatives are more inclined to switch service providers, especially when customers perceive prices to be unfair. Whereas customers with less knowledge about alternatives are less likely to switch. Perhaps the switching intention sample had less knowledge about prices offered by other service providers, or found that the value-for-money comparison of various MNO packages difficult.

The switching behaviour sample were of the opinion that their previous MNO did not offer good value-for-money. Surprisingly, after switching, the switching behaviour sample still felt that their new MNO did not offer good value-for-money. Therefore obtaining a package that offers good value-for-money seems to remain an issue for switchers, and was certainly not solved by switching. Receiving value-for-money could possibly be an issue for mobile subscribers in general. The result begs the question as to what exactly customers regard to be value-for-money in the mobile telecommunications context and certainly requires further investigation.

6.3.6 Alternative attractiveness

The switching intention respondents were of the opinion that they would be much more satisfied with another MNO than they are with their current MNO. The results imply that respondents would prefer to do business with, and would be more satisfied with an alternate MNO. This finding is in line with that of Chuang (2011:138) who verified s that the greater the attractiveness of competing alternatives, the stronger customers' switching intentions become.

Overall, the majority of respondents held the view that their current MNO was not as fair as other MNOs. Burnham *et al.*, (2003:119) found that individuals with more knowledge about alternatives were more inclined to switch if they perceived unfairness, while those with less knowledge are more inhibited to change (Antón *et al.*, 2007b:148). Thus, as Antón *et al.* (2007b:148) suggest, firms should get to know their customers better by assessing their degree of knowledge about alternatives, since customers who have less experience with other providers appear to perceive stronger ties to their existing providers (Burnham *et al.*, 2003:119).

Overall, the results show that the switching behaviour respondents are much happier with their current MNO than they were with their previous MNO, implying that they are happy that they switched. The switching behaviour respondents have more knowledge about alternatives and are thus able to more accurately compare alternatives. In general, switching behaviour respondents were much more satisfied with their current MNO than they were with their previous MNO. Respondents felt that their current MNO was more fair than their previous MNO. Furthermore, the switching behaviour respondents were much more satisfied with the service available from their current MNO than the service provided by their previous MNO.

In conclusion, the switching intention sample has a high intention to switch while the switching behaviour sample is pleased that they made the switch. The switching behaviour sample appear to be content with their current service provider and do not currently wish to switch to another service provider again.

6.3.7 RO1: Testing the switching intention model

To test the conceptual switching intention model, parameter estimates were obtained by means of SEM using maximum likelihood (ML) in the AMOS package. After three covariances were added to the relational switching costs scale, acceptable fit was achieved. Bootstrapping confirmed that the estimates could be reported with confidence. Furthermore, the EQS package was used to obtain robust ML fit indices, despite nonnormality of the data. As reported earlier, the final fit indices obtained were: χ^2/df = 6.004 (χ^2 = 966.61; df = 161; $p < 0.000$); RMSEA = 0.070 [0.066; 0.074]; NNFI = 0.943; CFI = 0.952. Due to the better fit of the fourth switching intention model, researchers using the same relational switching costs scale in future could consider deleting one of the items that were correlated or combine items that were correlated to improve fit. The improved fit indicates that including both questions that were correlated is possibly unnecessary. Another option may be to treat the relational switching costs scale as a multidimensional scale with personal relationship costs and brand relationship costs as separate sub-scales.

6.3.8 RO2: Comparison of the conceptual switching intention model to the switching behaviour data

When comparing switching intention to switching behaviour, all three antecedents explained 52% of variance in the switching intention context, while only two of the three antecedents, namely alternative attractiveness and relational switching costs explained 12.3% of variance in the switching behaviour context. The results implied that switching intention and behaviour are intrinsically different.

When making the same comparison from a switching behaviour point of view, it was found that two of the three antecedents, namely alternative attractiveness and perceived value, explained 10.9% of variance in the context of switching behaviour. These two antecedents were not the same as the two that explained the 12.3% of variance in switching behaviour from the switching intention perspective. Nonetheless, all three switching intention antecedents still explained 52% of variance.

The low percentage of variance accounted for in switching behaviour suggests that factors other than the antecedents investigated drive switching behaviour. Thus marketing practitioners should not assume that intention acts as a proxy for behaviour, since the results clearly indicate that intention and behaviour are different.

Of interest is the fact that a different antecedent was removed during each stepwise regression for switching behaviour. The stepwise regression first removed perceived value. Consequently alternative attractiveness and relational switching costs together explained 12.3% of variance. In the second stepwise regression relational switching costs was removed. As a result alternative attractiveness and perceived value together explained 10.9% of variance. Alternative attractiveness was certainly constant in predicting switching behaviour, as 8.9% of variance was explained by alternative attractiveness in both cases. Thus the results suggest that alternative attractiveness explains switching behaviour to a small degree, however further investigation is necessary to determine other predictors of switching behaviour.

6.3.9 <u>RO1 and RO2: Secondary objectives</u>

Secondary objectives investigated both the direct influence of switching antecedents on switching intention and switching behaviour and interrelationships between the antecedents.

6.3.9.1 Direct relationships

Hypothesis testing confirmed a statistically significant negative relationship between relational switching costs and switching. The results are in line with studies conducted by Burnham *et al*. (2003:118) and Hu and Hwang (2006:83) who also found a significant negative relationship between relational switching costs and switching intention.

A statistically significant negative relationship between perceived value and switching were also confirmed. Bansal and Taylor (1999a:78), and Turel *et al*. (2007:69) also found a significant negative relationship between perceived value and switching intention.

Furthermore, the hypothesis testing revealed a statistically significant positive relationship between alternative attractiveness and switching in both the switching intention and switching behaviour contexts. Similarly, studies conducted by Chuang (2011:135), Bansal and Taylor (1999a:77) and Bansal *et al*. (2005:105) also found a significant positive influence of alternative attractiveness on customer switching intention.

In general, the strength of the relationships between the dependent variable and the antecedent variable were stronger in the switching intention context than in the switching behaviour context. In both contexts, alternative attractiveness was more highly correlated with the dependent variables, namely switching intention and switching behaviour than the other antecedents, namely relational switching costs and perceived value.

6.3.9.2 Antecedent interrelationships

The interrelationships between the antecedents, relational switching costs and perceived value showed a relatively strong positive correlation in the switching intention context, similar to results attained by Edward and Shadev (2011:338). Perceived value and relational switching costs were both negatively correlated to alternative attractiveness. The correlation between perceived value and alternative attractiveness was slightly stronger than the correlation between relational switching costs and alternative attractiveness. In the switching behaviour context the overall strength of the correlations were comparatively weaker, but the direction of the correlations remained the same. Perceived value and alternative attractiveness had the strongest correlation. Although relational switching costs and perceived value had the strongest correlation in the switching intention context, these antecedents had the weakest correlation in the switching behaviour context, again alluding that switching intention and switching behaviour are, in essence, different.

6.3.10 RO3: The role of relationship characteristics in switching intention and switching behaviour

Overall, the relationship characteristics did not influence switching behaviour nor switching intention as expected. In terms of the influence of relationship characteristics on switching intention, the three relationship characteristics together explained 1.3% of the variance, meaning that relationship length, depth and breadth do not explain switching intention well. The multiple regression showed that relationship depth was the greatest contributor toward switching intention and that the contribution was statistically significant. The results suggest that customers may perceive the cost of their monthly bill to cause them to switch. The finding is in line with findings by Ranganathan *et al*.'s (2006:274) study which revealed that relationship depth was the strongest switching antecedent and was also statistically significant. The contributions by relationship length and breadth were negligible and not statistically significant. Ranganathan *et al*.'s (2006:274) study found that relationship breadth and length had a negligible effect but were statistically significant.

In the context of switching behaviour, the three relationship characteristics together explained 2.9% of variance. Thus, in comparison, relationship length, depth and breadth explain switching behaviour a fraction better than switching intention. The multiple regression showed that relationship depth was the greatest contributor toward switching behaviour, however the contribution was not statistically significant in the switching behaviour context, neither were the contributions by relationship length nor relationship breadth. Customers may perceive the cost of their monthly bill to cause them to switch, however when actually switching, other factors seemed to play a role in customers' switching decisions.

The results of the hypothesis tests indicated that relationship length and breadth do not have a statistically significant relationship with switching intention nor switching behaviour; while relationship depth has a statistically significant relationship with both switching intention and switching behaviour.

The results of the hypothesis tests indicated a negative relationship between switching intention and relationship length, as well as switching behaviour and relationship length, albeit that both relationships were not significant. The results are in line with research in mobile telecommunications, which have shown that the longer the customer has subscribed to a service provider, the lower the switching intention (Kim & Yoon, 2004:762; Malhotra & Malhotra, 2013:19; Ranganathan *et al*., 2006:273). The findings dispute the counterintuitive results attained by researchers that found a positive correlation between relationship length and switching intention (Keramati & Ardabili, 2011:352; Maicas *et al*., 2009b:168), implying that the probability that the customer will switch to another service provider increases the longer the customer remains with the service provider.

Relationship depth showed a statistically significant relationship with switching intention and switching behaviour, however, the correlations were extremely weak. The correlations were expected to be negative, but counterintuitively, the result was positive. Some researchers have found similar counterintuitive results. Ahn *et al*. (2006:564) and Madden *et al*. (1999:205) found that heavy users are more likely to switch, since heavy users are more price-sensitive because of their high expenditures and thus constantly search for the best value-for-money.

The hypothesis testing results indicated a positive relationship between switching intention and relationship breadth, but a negative relationship between switching behaviour and relationship breadth. Neither relationship was significant. Ranganathan *et al*. (2006:274) and Lopez *et al.* (2006:564) found that relationship breadth is negatively correlated to switching intention. However, Ahn *et al*. (2006:564) and Maicas *et al*. (2009b:169) found a positive relationship between relationship breadth and switching intention. Thus the incongruent results obtained for relationship breadth are not surprising.

Taking the results into consideration, a discussion of the contribution of the study are discussed in the section to follow.

6.4 CONTRIBUTION OF THE STUDY

Social exchange theory evaluates benefits compared to costs of remaining in a relationship (Edward & Sahadev, 2011:329; Roberts, 1989:20). As explained in the literature review, in the context of the study, social exchange theory applies to relational switching costs. Limited interaction occurs between customers and staff at a MNO compared to staff at, for example, a restaurant or hairdresser. The limited interactions possibly led to the finding that both groups of respondents were apathetic to any questions related to personal relational switching costs. Even after switching, respondents did not attach high value to relationships with the staff. The above results suggest that relational switching costs in mobile telecommunications are very low. These results contribute toward marketing literature and specifically social exchange theory, since it was found that relational switching costs did not play as important a role as expected, particularly not in the mobile telecommunications context. By implication, the results suggest that other costs may play a larger role. Thus other costs could be explored in future research.

A second contribution of the study was the comparison of intention versus actual behaviour. Most consumer studies investigate what customers intend to do. However, this study has shown that intention and behaviour are different. By implication, one cannot assume that intention serves as a proxy for behaviour, at least not in the mobile context. This may suggest that even though customers may have a particular intention, they may actually behave in an often totally different manner.

Another contribution is the development of the switching intention model. Research combining relational switching costs, perceived value and alternative attractiveness into one switching model has not previously been conducted. Furthermore, exploring the interrelationships between the antecedents is a contribution, as such relationships have also not been tested previously. Moreover, the direct relationships and interrelationships were explored in both the switching intention and switching behaviour contexts, which also adds to the body of knowledge on consumer behaviour.

A further contribution is that the study investigated constructs that had been neglected in the literature. Alternative attractiveness and perceived value are constructs that have not been well-researched. Furthermore, research regarding relational switching costs as a separate switching cost has also not received much attention in the literature, nor previous studies.

Finally, the study was able to dispute the counterintuitive results regarding relationship length. However, counterintuitive results concerning relationship depth and breadth require further investigation.

The research conducted in this study not only contributes toward adding more understanding of consumer behaviour, but also may assist managers in industry. Managerial implications for marketing practitioners and MNOs (where applicable) are discussed in the next section.

6.5 MANAGERIAL IMPLICATIONS

Development and testing of the conceptual switching intention model contributes toward an understanding of switching behaviour. In an effort to better understand the antecedents of switching, new insight is gained for industry. Knowledge of types of switching antecedents informs marketing practitioners what to monitor to prevent customer switching. The results showed that alternative attractiveness had an extremely strong influence on switching intention. This strong influence reminds managers to be vigilant and anticipate competitor activity, or at least ensure that they remain more attractive than the competition.

In the switching behaviour situation, neither relational switching costs, perceived value nor alternative attractiveness had a meaningful influence on switching behaviour. Thus it seems that once customers have switched, alternative attractiveness strategies will not attract customers back to their ‘original’ MNO. MNOs already know that the only way to gain customers in a saturated market is to attract the competitor’s customers. But how will they get their customers back once they have switched if alternative attractiveness does not have a meaningful influence on switching behaviour? Marketing practitioners and MNOs will have to find other ways to entice customers to return. Acquisition of previous customers may become an essential strategy to implement in mobile telecommunications in the future. It should be emphasised, however, that customers should not be lost to begin with. However, in the unfortunate situation that the customer has in fact switched, the above may be applicable.

Findings surprisingly indicated that relationship length and relationship breadth do not influence switching intention, nor switching behaviour. Therefore monitoring relationship length and relationship breadth will not assist organisations to determine which customers are likely to switch. Organisations could possibly keep track of relationship depth (customer spend). The results show that customers are more likely to switch if the service becomes too expensive.

In the mobile telecommunications industry, monitoring competitors is of particular importance, especially in current times. French telecommunications giant Orange launched their South African subsidiary Orange Horizons coinciding with the Africa Cup of Nations football tournament hosted in South Africa in January 2013 (BusinessTech, 2013; Wright & Blin, 2013). Orange plan to be a full MVNO in the future (McLeod, 2013). Orange has already established an online presence and a network of WiFi hotspots in Cape Town and Johannesburg (Tubbs, 2014). Moreover, Orange opened their first brick-and-mortar store in Claremont (Western Cape) in December 2014 (Alfreds, D, 2014; McLeod, 2014b). Since Orange only launched in January 2013 and has already implemented an innovative strategy to capture all inbound tourists by providing WiFi in conjunction with African Eagle, a major inbound tour operator (Tubbs, 2014), further switching studies between MNOs in South Africa will be necessary as competition in the South African market will undoubtedly intensify in the near future.

All research that is conducted has certain restrictions. The limitations of the study are discussed in the section to follow.

6.6 LIMITATIONS

Since most studies use a sample and not a census, the nature of the sample is usually a limitation. For the current study, the target population was adults that have a contract with a mobile network operator (MNO), have the ability to independently choose the MNO with whom they had a contract, and reside in South Africa. To collect information regarding the target population, Consulta Research's online panel was surveyed. Since the online panel was as convenience sample, the results cannot be generalised. Furthermore, the sample comprised 79% white respondents with a monthly income of between R16,001-R20,000. Thus it is acknowledged that the sample may be skewed.

A limitation of the study was the small sample size of the switching behaviour sample (N_2 = 135). Due to the small sample, the switching behaviour data could not be fitted to the switching intention model as originally planned. Results were nonetheless obtained using stepwise regression, by comparing frameworks. However using the full model may have given more comprehensive insight as to the difference between switching intention and switching behaviour.

As with all models, as more constructs are added, model complexity increases and sample size needs requirements become larger to make provision for the increased number of parameters that need to be estimated. It would have been ideal to add more constructs to the model, however parameter estimates and the related required sample sizes always place restrictions on model building.

6.7 RECOMMENDATIONS FOR FUTURE RESEARCH

Future research should certainly continue to explore switching behaviour. Perceived value and relational switching costs did not explain switching behaviour well. Alternative attractiveness only marginally explained switching behaviour. However, three aforementioned antecedents explained switching intention reasonably well. The fact that the antecedents explained switching intention, but not switching behaviour should be investigated further.

To measure switching behaviour, the wording of the switching intention measurement scale was changed to the past tense, so that respondents that had already switched would be asked the same questions as the switching intention respondents. However, in effect, the measurement scale used for the switching behaviour sample literally measured 'past switching intention' and not switching behaviour as such. Thus exploring a way in which to measure switching behaviour is another avenue for future research. Future studies could consider an experimental design to measure actual behaviour.

Should researchers consider investigating relational switching costs, it is suggested that the relational switching costs measurement scale be refined in future studies. As mentioned before, the relational switching cost scale is part of Burnham, Frels and Mahajan's (2003) multidimensional switching cost scale. The aforementioned switching costs scale measures switching costs using three dimensions, namely procedural, financial and relational switching costs (Burnham *et al*., 2003:112). Subsequent research used the relational switching cost scale independently as a unidimensional scale (Vasudevan *et al*., 2006). However, when the modification indices were inspected, the suggested correlations supported those researchers who indicated two sub-scales within the relational switching costs scale. Future researchers should thus either improve the unidimensional relational switching costs scale or treat the scale as multidimensional.

The researcher acknowledges that perceived value may include many sub-dimensions. After considering many measurement scales for perceived value, the 'monetary value' sub-dimension of Pihlström and Brush's (2008) scale was chosen for this study. The complete scale consists of nine sub-dimensions (31 items), including emotional value and social value. However, since perceived value was not the sole focus of the current study, only one monetary value dimension was included. Future researchers may consider simplifying the Pihlström and Brush (2008) scale, or developing an alternative perceived value scale.

Brand value is a major asset for service providers, especially since services are intangible (Sweeney & Soutar, 2201:217). Perceived value is a key driver of customer loyalty and also significantly influences customer satisfaction (Chen & Cheng, 2012:814; Yang &

Peterson, 2004:815). Since customer loyalty is associated with higher profits (Sweeney & Soutar, 2201:217) incorporating brand value into the perceived value construct may provide useful insight.

Research should continue to determine which antecedents influence switching intention. Alternative attractiveness should most certainly be further explored as a switching intention antecedent, since it was the antecedent that was the strongest driver of switching intention. However, since perceived value and relational switching costs had a negligible influence, perhaps other antecedents should be explored in the conceptual switching intention model instead. A construct such as trust may be necessary from a relationship marketing perspective. However, since respondents did not attach much value to relational switching costs, constructs that are not relationship-orientated, for example, satisfaction or service quality, may be more advisable constructs to explore.

Lastly, Burnham *et al*., (2003:121) suggest that a longitudinal study could offer further insights regarding switching perceptions and experiences. Thus investigating switching intention and behaviour over a period of time may prove useful.

Switching intention research has been conducted in various industries, including the banking industry (Bansal & Taylor, 1999b; Ganesh *et al*., 2000:68; Kaur *et al*., 2012), higher education (Shah & Shaefer, 2006), Internet service providers (Keaveney & Parthasarathy, 2001; Madden *et al*., 1999) and vehicle insurance (Antón *et al.*, 2007b). Thus applying the switching intention model developed in this study to various industries may assist to gain insight as to whether the same antecedents influence switching in all service industries, or have a stronger influence in particular service industries.

With regard to MNOs, the South African Customer Satisfaction index (SAcsi) indicated that none of the current MNOs in South Africa were prominent leaders in the market in terms of customer satisfaction. In 2013, MTN was the clear industry leader, however, in 2014, all of the MNOs were on par, except Cell C, who scored below par. Such results are worrying, considering the recent entrance of Orange. Professor Adré Schreuder, founder and chair of SAcsi, commented that lower loyalty levels and no clear differentiation between the MNOs will contribute to the ease of switching (mybroadband, 2014a).

Lastly, the advent of smart phones is shifting the paradigm of the mobile telecommunications industry from being voice-driven to data-driven (Malhotra & Malhotra, 2013:13). Currently there is an increased demand for data services and faster internet services (Govan-Vassen, 2014). Internet analysts predict that data usage and internet access via mobile devices will increase tremendously in the near future (Malhotra & Malhotra, 2013:13).

Vodacom's financial results for the year ended 31 March 2014 showed strong growth in data usage (mybroadband, 2014b). Most data subscribers are post-paid subscribers (Deloitte Digital SA, 2013) and are thus an important market to capture and retain. Furthermore, the data market is largely untapped as 63% of the South African market is not yet online (Bizcommunity.com, 2014). As data costs decrease, competition will become more intense. The Managing Director of Orange Horizons, Sébastian Crozier, is of the opinion that due to a decrease in data costs, South Africa will follow current European trends of consuming radio and television broadcasting via mobile phone or fixed broadband instead of using traditional broadcasting networks. Thus future studies could explore the influence that the increase in data usage and the decrease in data costs has on switching, and also what effect the decrease in data costs has on cross-industry switching.

REFERENCES

Ackerman, R. & Schibrowsky, J. 2007. A business marketing strategy applied to student retention: a higher education initiative. *Journal of College Student Retention*, *9*(*3*):307-336.

African Telecoms News. Not dated. *Major African mobile markets: South Africa*. [Online] Available from: http://www.africantelecomsnews.com/resources/AfricaOpp_South_Africa.shtml#Mobile [Accessed: 2012-09-27].

Ahn, J.-H., Han, S.-P. & Lee, Y.-S. 2006. Customer churn analysis: churn determinants and mediation effects of partial defection in the Korean mobile telecommunications service industry. *Telecommunications Policy*, 30(10-11):552-568.

Ajzen, I. 1991. The theory of planned behaviour. *Organizational Behavior and Human Decision Processes*, 50(2):179-211.

Alam, S.M. 2011. Telecommunication scenario. *Economic Review*, 5(5):6-9.

Albright, S.C., Winston, W.L. & Zappe, C.J. 2009. *Data analysis and decision making with Microsoft Excel*. United States: South-Western Cengage Learning.

Alfreds, D. 2014. *Orange aims disrupting SA mobile market with store*. [Online] Available from: http://www.fin24.com/Tech/Mobile/Orange-aims-disrupting-SA-mobile-market-with-store-20141210 [Accessed: 2015-04-28].

Allen, P. & Bennett, K. 2010. *PASW statistics by SPSS: a practical guide, version 18.0*. Australia: Cengage Learning.

Altuna, O.K. & Konuk, F.A. 2009. Understanding consumer attitudes toward mobile advertising & its impact on consumer's behavioural intentions: a cross-market comparison of United States and Turkish consumers. *International Journal of Mobile Marketing*, 4(2):43-51.

Anderson, J.C. & Gerbing, D.W. 1988. Structural equation modeling in practice: a review and recommended two-step approach. *Psychological Bulletin*, 103(3):411-423.

Antón, C., Camarero, C. & Carrero, M. 2007a. The mediating effect of satisfaction on consumers' switching intention. *Psychology & Marketing*, 24(6):511-538.

Antón, C., Camarero, C. & Carrero, M. 2007b. Analysing firms' failures as determinants of consumer switching intentions: the effect of moderating factors. *European Journal of Marketing*, 41(1/2):135-158.

Araujo, L. 2007. Markets, market-making and marketing. *Marketing Theory*, 7(3):211-216.

Armstrong, J.S. & Overton, T.S. 1977. Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, 14(3):396-402.

Athanassopoulos, A., Gounaris, S. & Stathakopoulos, V. 2001. Behavioural responses to customer satisfaction: an empirical study. *European Journal of Marketing*, 35(5/6):687-707.

Aydin, S. & Özer, G. 2005. How switching costs affect subscriber loyalty in the Turkish mobile phone market: an exploratory study. *Journal of Targeting, Measurement and Analysis for Marketing*, 14(2):141-155.

Aydin, S., Özer, G. & Arasil, Ö. 2005. Customer loyalty and the effect of switching costs as a moderator variable: a case in the Turkish mobile phone market. *Marketing Intelligence & Planning*, 23(1):89-103.

Babbie, E. 2010. *The practice of social research*.12th ed. Belmont, CA: Wadsworth Cengage Learning.

Babin, B.J & Harris, E.G. 2013. *CB4*. Mason, Ohio: South-Western.

Bagozzi, R.P. 1975. Marketing as exchange. *Journal of Marketing*, 39(4):32-39.

Ballantyne, D., Christopher, M. & Payne, A. 2003. Relationship marketing: looking back, looking forward. *Marketing Theory*, 3(1):159-166.

Banerjee, A. & Dippon, C.M. 2009. Voluntary relationships among mobile network operators and mobile virtual network operators: an economic explanation. *Information Economics & Policy*, 21(1):72-84.

Bansal, H.S. & Taylor, S.F. 1999a. *Beyond service quality and customer satisfaction: investigating additional antecedents of service provider switching intentions*. Proceedings of the Academy of Marketing Science (AMS) Annual Conference, p75-82. Springer International Publishing.

Bansal, H.S. & Taylor, S.F. 1999b. The service provider switching model (SPSM): a model of consumer switching behaviour in the services industry. *Journal of Service Research*, 2(2):200-218.

Bansal, H.S., Irving, P.G. & Taylor, S.F. 2004. A three-component model of customer to service providers. *Journal of the Academy of Marketing Science*, 32(3):234-250.

Bansal, H.S., Taylor, S.F. & St. James, Y. 2005. “Migrating” to new service providers: toward a unifying framework of consumers’ switching behaviours. *Journal of the Academy of Marketing Science*, 33(1):96-115.

Baron, S., Conway, T. & Warnaby, G. 2010. *Relationship marketing: a consumer experience approach*. London; Sage.

Baron, R.M. & Kenny, D.A. 1986. The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *Journal of Personality & Social Psychology*, 51(6):1173-1182.

Barrett, P. 2007. Structural equation modelling: Adjudging model fit. *Personality and Individual Differences*, 42(5):815-824.

Beneke, J., Cumming, G., Stevens, A. & Versfeld, M. 2010. Influences on attitude toward mobile text message advertisements: an investigation of South Africa youth. *International Journal of Mobile Marketing*, 5(1):77-97.

Belleau, B.D., Summers, T.A., Xu, Y. & Pinel, R. 2007. Theory of Reasoned Action: purchase intention of young consumers. *Clothing & Textiles Research Journal*, 25(3):244-257.

Berndt, A. & Petzer, D. 2011. *Marketing research*. Cape Town: Pearson Education South Africa.

Berry, L.L. 2002. Relationship marketing of service perspectives from 1983 and 2000. *Journal of Relationship Marketing,* 1(1):59-65.

Bitner, M.J., 1992, Servicescapes: the impact of physical surroundings on customers and employees. *Journal of Marketing*, 56(2), 57−71.

Bizcommunity.com. 2014. *South Africa not online – 63% have no access*. [Online] Available from: http://www.bizcommunity.com/Article/196/19/114948.html [Accessed: 2014-06-19].

Blery, E., Batistatos, N., Papastratou, E., Perifanos, I., Remoundaki, G. & Retsina, M. 2009. Service quality and customer retention in mobile telephony. *Journal of Targeting, Measurement and Analysis for Marketing*, 17(1):27-37.

Blythe, J. 2006. *Principles and practice of marketing*. London: Thomson Learning.

Bodet, G. 2008. Customer satisfaction and loyalty in service: two concepts, four constructs, several relationships. *Journal of Retailing and Consumer Services*, 15(3):156-162.

Bollen, K.A. 1995. Foreword. In: Hoyle, R.H. (ed.) *Structural equation modelling: concepts, issues, and applications*. Thousand Oaks, California: Sage.

Bolton, R.N. 1998. A dynamic model of the duration of the customer's relationship with a continuous service provider: the role of satisfaction. *Marketing Science*, 17(1):45-65.

Bolton, R.N. & Drew, J.H. 1991. A multistage model of customers' assessments of service quality and value. *Journal of Consumer Research*, 17(4):375-384.

Bolton, R.N. & Lemon, K.N. 1999. A dynamic model of customers' usage of services: usage as an antecedent and consequence of satisfaction. *Journal of Marketing Research*, 36(2):171-186.

Bolton, R.N., Lemon, K.N. & Verhoef, P.C. 2004. The theoretical underpinnings of customer asset management: a framework and propositions for future research. *Journal of the Academy of Marketing Science*, 32(3):271-292.

Boshoff, C. 2007. Understanding service recovery satisfaction from a service encounter perspective: a pilot study. *South African Journal of Business Management*, 38(2):41-51.

Boslaugh, S. 2013. *Statistics in a nutshell*. 2nd ed. Beijing:O'Reilly Media.

Bradley, N. 2013. *Marketing research: tools & techniques*. 3rd ed. Oxford, United Kingdom: Oxford University Press.

Bronkhorst, Q. 2013. *Mobile subscribers in SA: who's eating whose lunch?* [Online] Available from: http://businesstech.co.za/news/mobile/44164/mobile-subscribers-in-sa-whos-eating-whose-lunch/ [Accessed: 2015-01-26].

Brown, K. 2004. Holding onto customers. *Wireless Week*, 15 February:6-9.

Brown, I., Cajee, Z., Davies, D. & Stroebel, S. 2003. Cell phone banking: predictors of adoption in South Africa – an exploratory study. *International Journal of Information Management*, 23(5):381-394.

Bruhn, M. 2003. *Relationship marketing: management of customer relationships*. Harlow, England: Pearson Education.

Buehler, S., Dewenter, R. & Haucap, J. 2006. Mobile number portability in Europe. *Telecommunications Policy*, 30(7):385-399.

Burnham, T.A., Frels, J.K. & Mahajan, V. 2003. Consumer switching costs: a typology, antecedents, and consequences. *Journal of the Academy of Marketing Science*, 31(2):109-126.

Büschken, J. 2004. *Higher profits through customer lock-in: a roadmap*. United States of America: Phoenix Color.

BusinessTech. 2013. *French telecom's Orange set for SA launch*. [Online] Available from: http://businesstech.co.za/news/mobile/29903/france-telecoms-orange-set-for-sa-launch/ [Accessed: 2014-06-19].

Byrne, B.M. 2010. *Structural equation modeling with AMOS*. 2nd ed. New York: Routledge.

Cell C. n.d. *Vision and Mission*. [Online] Available from: http://www.cellc.co.za/explore/additionalinfo/vision-and-mission [Accessed: 2014-10-26].

Cellular-news, 2008. *South Africa bans long contracts and SIM locking of handsets. 20 June 2008*. [Online] Available from: http://www.cellular-news.com/story/31939.php [Accessed: 2012-09-07].

Central Intelligence Agency (CIA). 2014. *The World Factbook: South Africa.* [Online] Available from: https://www.cia.gov/library/publications/the-world-factbook/geos/sf.html [Accessed: 2014-10-15].

Chang, T.-Z. & Wildt, A.R. 1994. Price, product information, and purchase intention: an empirical study. *Journal of the Academy of Marketing Science*, 22(1):16-27.

Chen, C.-F. & Chao, W.-H. 2011. Habitual or reasoned? Using the theory of planned behavior, technology acceptance model, and habit to examine switching intentions toward public transit. *Transportation Research Part F*, 14:128-137.

Chen, C.-F. & Cheng, L.-T. 2012. A study on mobile phone service loyalty in Taiwan. *Total Quality Management & Business Excellence*, 23(7):807-819.

Chen, J.V., Yen, D.C. & Chen, K. 2009. The acceptance and diffusion of the innovative smart phone use: a case study of a delivery service company in logistics. *Information & Management*, 46(4):241-248.

Chiao, Y.-C., Chiu, Y.-K. & Guan, J.-L. 2008. Does the length of a customer–provider relationship really matter? *The Service Industries Journal*, 28(5):649-667.

Choi, K.-S., Cho, W.-H., Lee, S., Lee, H. & Kim, C. 2004. The relationships among quality, value, satisfaction and behavioural intention in health care provider choice: a South Korean study. *Journal of Business Research*, 57(8):913-921.

Chou, C.-P. & Bentler, P.M. 1995. Estimates and testing in structural equation modelling. In: Hoyle, R.H. (ed.) *Structural equation modelling: concepts, issues, and applications*. Thousand Oaks, California: Sage.

Chuang, Y.-F. 2011. Pull-and-suck effects in Taiwan mobile phone subscribers switching intentions. *Telecommunications Policy*, 35(2):128-140.

Colgate, M. & Lang, B. 2001. Switching barriers in consumer markets: an investigation of the financial services industry. *Journal of Consumer Marketing*, 18(4):332-347.

Cooper, D.R. & Schindler, P.S. 2014. *Business research methods*. 12th ed. New York, NY: McGraw-Hill.

Corrocher, N. & Zirulia, L. 2005. Switching costs, consumers' heterogeneity and price discrimination in the mobile communications industry. *Centro di Ricerca sui Processi di Innovazione e Internazionalizzazione (CESPRI)*, March:1-19.

Costello, A.B. & Osborne, J.W. 2005. Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation*, 10(7):1-9.

Coulter, K.S. & Coulter, R.A. 2002. Determinants of trust in a service provider: the moderating role of length of relationship. *Journal of Services Marketing*, 16(1):35-50.

Cricelli, Grimaldi & Ghiron, 2012 – The impact of regulating mobile termination rates and MNO-MVNO relationships on retail prices. *Telecommunications Policy*, 36(1):1-12.

Cronin, J.J. (Jr.), Brady, M.K. & Hult, G.T.M. 2000. Assessing the effects of quality, value, and customer satisfaction on consumer behavioural intentions in service environments. *Journal of Retailing*, 76(2):193-218.

Curran, P.J., West, S.G. & Finch, J.F. 1996. The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological Methods*, 1(1):16-29.

Dass, R. & Jain, R. 2011. *An Analysis on the factors causing telecom churn: first findings*. Proceedings of the Seventeenth Americas Conference on Information Systems (AMCIS), Detroit, Michigan, 4-7 August, Paper 2, http://aisel.aisnet.org/amcis2011_submissions/2.

Dedrick, J. Kraemer, K.L. & Linden, G. 2011. The distribution of value in the mobile phone supply chain. *Telecommunications Policy*, 35(6):505-521.

Deloitte Digital SA. 2013. *2013 Forecast for the South African telecoms market*. [Online] Available from: http://www.deloittedigital.co.za/blog/author/1 [Accessed: 2014-06-24].

De Matos, C.A., Henrique, J.L. & de Rosa, F. 2009. The different roles of switching costs on the satisfaction-loyalty relationship. *International Journal of Bank Marketing*, 27(7):506-523.

De Ruyter, K.,& Wetzels, M. & Bloemer, J. 1998. On the relationship between perceived service quality, service loyalty and switching costs. *International Journal of Service Industry Management*, 9(5):436-453.

Deng, Z., Lu, Y., Wei, K.K. & Zhang, J. 2010. Understanding customer satisfaction and loyalty: an empirical study of mobile instant messages in China. *International Journal of Information Management*, 30(4):289-300.

Diamantopoulos, A. & Schlegelmilch, B.B. 2000. *Taking the fear out of data analysis: a step-by-step approach*. London: Business Press, Thomson Learning.

Dick, A.S. & Basu, K. 1994. Customer loyalty: toward an integrated conceptual framework. *Journal of the Academy of Marketing Science*, 22(2):99-113.

Dodds, W.B. & Monroe, K.B. & Grewal, D. 1991. Effects of price, brand, and store information on buyers' product evaluations. *Journal of Marketing Research*, 28(3):307-319.

Doney, P.M. & Cannon, J.P. 1997. An examination of the nature of trust in buyer-seller relationships. *Journal of Marketing*, 61(2):35-51.

Dowling, G.R. & Uncles, M. 1997. Do customer loyalty programmes really work? *Sloan Management Review,* 38(4):71-82.

Dwyer, F.R., Schurr, P.H. & Oh, S. 1987. Developing buyer-seller relationships. *Journal of Marketing*, 51(2):11-27.

East, R., Wright, M. & Vanhuele, M. 2008: *Consumer behaviour: applications in marketing*. Los Angeles: Sage.

Edward, M. & Sahadev, S. 2011. Role of switching costs in the service quality, perceived value, customer satisfaction and customer retention linkage. *Asia Pacific Journal of Marketing & Logistics*, 23(3):327-345.

Edward, M., George, B.P. & Sarkar, S.K. 2010. The impact of switching costs upon the service quality-perceived value-customer satisfaction-service loyalty chain: a study in the context of cellular services in India. *Services Marketing Quarterly*, 31(2):151-173.

Erickson, G.M. & Johansson, J.K. 1985. The role of price in multi-attribute product evaluations. *Journal of Consumer Research*, 12(2):195-199.

Eshghi, A., Haughton, D., Teebagy, N. & Topi, H. 2006. Determinants of customer churn behaviour: the case of the local telephone service. *The Marketing Management Journal*, 16(2):179-187.

Fahy, J. & Jobber, D. 2012. *Foundations of marketing*. 4th ed. London: McGraw-Hill.

Ferreira, T. 2013. *Optimising the online customer experience*. [Online] Available from: http://www.sablog.kpmg.co.za/2013/09/optimising-the-online-customer-experience/ [Accessed: 2014-10-26].

Fornell, C. 1992. A national customer satisfaction barometer: the Swedish experience. *Journal of Marketing*, 56(1):6-21.

Fornell, C. & Larcker, D.F. 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.

Fullerton, G. & Taylor, S. 2002. Mediating, interactive, and non-linear effects in service quality and satisfaction with services research. *Canadian Journal of Administrative Sciences*, 19(2):124-136.

Ganesh, J., Arnold, M.J. & Reynolds, K.E. 2000. Understanding the customer base of service providers: an examination of the differences between switchers and stayers. *Journal of Marketing*, 64(3):65-87.

Gao, T., Rohm, A.J., Sultan, F. & Huang, S. 2012. Antecedents of consumer attitudes toward mobile marketing: a comparative study of youth markets in the United States and China. *Thunderbird International Business Review*, 54(2):211-224.

Gerpott, T.J., Rams, W. & Schindler, A. 2001. Customer retention, loyalty, and satisfaction in the German mobile cellular telecommunications market. *Telecommunications Policy*, 25(4):249:269.

Gillwald, A. 2005. Good intentions, poor outcomes: telecommunications reform in South Africa. *Telecommunications Policy*, 29(7):469-491.

Glass, R.S. & Wood, W.A. 1996. Situational determinants of software piracy: an equity theory perspective. *Journal of Business Ethics*, 15(11):1189-1198.

Glotz, P., Bertschi, S. & Locke, C. 2006. Introduction: mobile phones and mass communications. *Knowledge, Technology, & Policy*, 19(2):3-6.

Gonçalves, H.M. & Sampaio, P. 2012. The customer satisfaction-customer loyalty relationship: reassessing customer and relational characteristics moderating effects. *Management Decision*, 50(9):1509-1526.

Gould-Williams, J. 1999. The impact of employee performance cues on guest loyalty, perceived value and service quality. *The Service Industries Journal*, 19(3):97-118.

Govan-Vassen, N. 2014. *Africa: Communications forecast to 2018*. [Online] Available from: http://www.bizcommunity.com/Article/410/78/122424.html [Accessed: 2015-01-26].

Gravetter, F.J & Wallnau, L.B. 2013. *Statistics for the behavioural sciences*. 9th ed. Belmont, CA: Wadsworth Cengage Learning.

Grönroos, C. 2002. Quo vadis marketing? Toward a relationship marketing paradigm. *The Marketing Review*, 3(2):129-146.

Grönroos, C. 2004. The relationship marketing process: communication, interaction, dialogue, value. *Journal of Business & Industrial Marketing*, 19(2):99-113.

Gummesson, E. 2000. *Total relationship marketing: rethinking marketing management: from 4Ps to 30Rs*. Boston, Mass: Butterworth-Heinemann.

Gundlach, G.T. & Murphy, P.E. 1993. Ethical and legal foundations of relational marketing exchanges. *Journal of Marketing*, 57(4):35-46.

Gustafsson, A., Johnson, M.D. & Roos, I. 2005. The effects of customer satisfaction, relationship commitment dimensions, and triggers on customer retention. *Journal of Marketing*, 69(4):210-218.

Gwinner, K.P., Gremler, D.D. & Bitner, M.J. 1998. Relational benefits in services industries: the customer's perspective. *Journal of the Academy of Marketing Science*, 26(2):101-114.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. & Tatham, R.L. 2014. *Multivariate data analysis*. 7th ed. Upper Saddle River, New Jersey: Pearson Prentice Hall.

Han, H., Kim, W. & Hyun, S.S. 2011. Switching intention model development: role of service performances, customer satisfaction, and switching barriers in the hotel industry. *International Journal of Hospitality Management*, 30(3):619-629.

Harrison, M.P., Beatty, S.E., Reynolds, K.E. & Noble, S.M. 2012. Why customers feel locked into relationships: using qualitative research to uncover the lock-in factors. *Journal of Marketing Theory & Practice*, 20(4):391-406.

Heide, J.B. & Weiss, A.M. 1995. Vendor consideration and switching behaviour for buyers in high-technology markets. *Journal of Marketing*, 59(3):30-43.

Hellier, P.K., Geursen, G.M., Carr, R.A. & Rickard, J.A. 2003. Customer repurchase intention: a general structural equation model. *European Journal of Marketing*, 37(11):1762-1800.

Hodge, J. 2005. Tariff structures and access substitution of mobile cellular for fixed line in South Africa. *Telecommunications Policy*, 29(7):493-505.

Hoffman, K.D., Bateson, J.E.G., Wood E.H. & Kenyon, A.J. 2009. *Services marketing: concepts, strategies & cases*. Australia: South-Western.

Holmbeck, G.N. 1997. Toward terminological, conceptual, and statistical clarity in the study of mediators and moderators: examples from the child-clinical and pediatric psychology literatures. *Journal of Consulting and Clinical Psychology*, 6(4):599-610.

Homburg, C., Giering, A. & Menon, A. 2003. Relationship characteristics as moderators of the satisfaction–loyalty link: findings in a business-to-business context. *Journal of Business-to-Business Marketing*, 10(3):35-62.

Hooper, D., Coughlan, J. & Mullen, M. R. 2008. Structural equation modelling: guidelines for determining model fit. *The Electronic Journal of Business Research Methods,* 6(1):53-60.

Hopwood, C.J. 2007. Moderation and mediation in structural equation modeling: applications for early intervention research. *Journal of Early Intervention*, 29(3):262-272.

Horovitz, J. 2000. *Seven secrets of service strategy*. London: Financial Times Management.

Horrocks, M. 2013. *The internet: South Africa vs. the rest of the world.* [Online] Available from: http://www.surveycompare.co.za/blog/internet-south-africa-vs-rest-world-infographic [Accessed: 2014-06-19].

Houston, F.S. & Gassenheimer, J.B. 1987. Marketing and exchange. *Journal of Marketing*, 51(4):3-18.

Howard, J.A. & Sheth, J.N. 1969. *A theory of buyer behaviour*. New York: John Wiley & Sons.

Hoyle, R.H. 1995. *Structural equation modelling: concepts, issues, and applications*. Thousand Oaks, California: Sage.

Hsu, J.L. & Chang, W.-H. 2003. The role of advertising played in brand switching. *Journal of American Academy of Business, Cambridge*, 2(2):322-328.

Hu, L. & Bentler, P.M. 1999. Cut-off criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Structural Equation Modeling: a Multidisciplinary Journal*, 6(1):1-55.

Huang, L.-Y. & Hsieh, Y.-J. 2012. Consumer electronics acceptance based on innovation attributes and switching costs: the case of e-book readers. *Electronic Commerce Research & Applications*, 11(3):218-228.

Hu, A.W.-L. & Hwang, I.-S. 2006. Measuring the effects of consumer switching costs on switching intention in Taiwan mobile telecommunication services. *The Journal of American Academy of Business, Cambridge*, 9(1):75-85.

Hughes, A.M. 2008. Churn away: how to prevent high-turnover telecom customers from leaving. *Direct*, 20(3):17-18.

Hunt, S.D. 1997. Competing through relationships: grounding relationship marketing in resource-advantage theory. *Journal of Marketing Management*, 13(5):431-445.

Hunt, S.D. 2010. *Marketing theory: foundations, controversy, strategy, resource-advantage theory*. Armonk, N.Y.: M.E. Sharpe.

Hunt, S.D., Arnett, D.B. & Madhavaram, S. 2006. The explanatory foundations of relationship marketing theory. *Journal of Business & Industrial Marketing*, 21(2):72-87.

Huppertz, J.W., Arenson, S.J. & Evans, R.H. 1978. An application of equity theory to buyer-seller exchange situations. *Journal of Marketing Research*, 15(2):250-260.

Iacobucci, D. 2009. Everything you always wanted to know about SEM (structural equations modeling) but were afraid to ask. *Journal of Consumer Psychology*, 19:673-680.

Iacobucci, D. 2010. Structural equations modeling: fit Indices, sample size, and advanced topics. *Journal of Consumer Psychology*, 20(1):90-98.

Ivens, B.J. & Blois, K.J. 1994. Relational exchange norms in marketing: a critical review of Macneil's contribution. *Marketing theory*, 4(3):239-263.

Jahanzeb, S., Fatima, T. & Khan, M.B. 2011. An empirical analysis of customer loyalty in Pakistan ' s telecommunication industry. *Database Marketing & Customer Strategy Management*, 18(1):5-15.

Johnson, M.D., Hermann, A. & Huber, F. 2006. The evolution of loyalty intentions. *Journal of Marketing*, 70(2):122-132.

Jones, M.A., Mothersbaugh, D.L. & Beatty, S.E. 2000. Switching barriers and repurchase intentions in services. *Journal of Retailing*, 76(2):259-274.

Jones, M.A., Mothersbaugh, D.L. & Beatty, S.E. 2002. Why customers stay: measuring the underlying dimensions of services switching costs and managing their differential strategic outcomes. *Journal of Business Research*, 55(6):441-450.

Jones, M.A., Reynolds, K.E., Mothersbaugh, D.L. & Beatty, S.E. 2007. The positive and negative effects of switching costs on relational outcomes. *Journal of Service Research*, 9(4):335-355.

Joshi. A.W. & Stump, R.L. 1999. Determinants of commitment and opportunism: integrating and extending insights from transaction cost analysis and relational exchange theory. *Canadian Journal of Administrative Sciences*, 16(4):334-352.

Kardes, F.R., Cline, T.W. & Cronley, M.L. 2011. *Consumer behaviour: science and practice*. Australia: South-Western Cengage Learning.

Kasper, H., van Helsdingen, P. & Gabbott, M. 2006. *Services marketing management: a strategic perspective*. 2nd ed. Chichester, England: John Wiley & Sons.

Kaur, G., Sharma, R.D. & Mahajan, N. 2012. Exploring customer switching intentions through relationship marketing paradigm. *International Journal of Bank Marketing*, 30(4):280-302.

Keaveney, S.M. 1995. Customer switching behaviour in service industries: an exploratory study. *Journal of Marketing*, 59(2):71-82.

Keaveney, S.M. & Parthasarathy, M. 2001. Customer switching behaviour in online services: an exploratory study of the role of selected attitudinal, behavioural and demographic factors. *Journal of the Academy of Marketing Science*, 29(4):374-390.

Kenny, D.A. 2014. *Measuring model fit.* [Online] Available from http://davidakenny.net/cm/fit.htm [Accessed: 2014-08-13].

Keramati, A. & Ardabili, S.M.S. 2011. Churn analysis for an Iranian mobile operator. *Telecommunications Policy*, 35(4):344-356.

Ketola, P. & Röykkee, M. 2001. *The three facets of usability in mobile handsets*. Presented at the CHI 2001 Workshop: Mobile Communication: Understanding User, Adoption & Design, Seattle, WA: 31 March – 5 April.

Kim, H.-S. & Yoon, C.-H. 2004. Determinants of subscriber churn and customer loyalty in the Korean mobile telephony market. *Telecommunications Policy*, 28(9-10):751-765.

Kim, M.-K., Park, M.-C. & Jeong, D.-H. 2004. The effects of customer satisfaction and switching barrier on customer loyalty in Korean mobile telecommunication services. *Telecommunications Policy*, 28(2):145-159.

Klem, L. 2000. Structural equation modeling. In: Grim, L.G. & Yarnold, P.R. (eds.) *Reading and understanding more multivariate statistics*. Washington, DC: American Psychological Association.

Klemperer, P. 1987a. The competitiveness of marketing with switching costs. *Rand Journal of Economics*, 18(1):138-150.

Klemperer, P. 1987b. Markets with consumer switching costs. *The Quarterly Journal of Economics*, 102(2):375-394.

Klemperer, P. 1995. Competition when consumers have switching costs: an overview with applications to industrial organization, macroeconomics, and international trade. *Review of Economic Studies*, 62(4):515-539.

Kline, R.B. 2011. *Principles and practice of structural equation modeling*. 3rd ed. New YorkL Guildford Press.

Kotler, P. & Keller, K.L. 2006. *Marketing management*. 12th ed. Upper Saddle River, New Jersey: Pearson Prentice Hall.

Kruger, L. & Mostert, P.G. 2012. Young adults' relationship intentions towards their cell phone network operators. *South African Journal of Business Management*, 43(2):41-49.

Kuo, Y.-F., Wu, C.-M. & Deng, W.-J. 2009. The relationships among service quality, perceived value, customer satisfaction, and post-purchase intention in mobile value-added services. *Computers in Human Behavior*, 25(4):887-896.

Kuusik, A. & Varblane, U. 2009. How to avoid customers leaving: the case of the Estonian telecommunication industry. *Baltic Journal of Management*, 4(1):66-79.

Lamb, C.W., Hair, J.F., McDaniel, C., Boshoff, C., Terblanche, N.S., Elliott, R. & Klopper, H.B. 2010. *Marketing*. 4th ed. Cape Town: Oxford University Press.

Lapidus, R.S. & Pinkerton, L. 1995. Customer complaint situations: an equity theory perspective. *Psychology & Marketing*, 12(2):105-122.

Lee, H.-S. 2010. Factors influencing customer loyalty of mobile phone service: empirical evidence from Koreans. *Journal of Internet Banking & Commerce*, 15(2):1-14.

Lee, J., Kim, Y., Lee, J.-D. & Park, Y. 2006b. Estimating the extent of potential competition in the Korean mobile telecommunications market: switching costs and number portability. *International Journal of Industrial Organization*, 24(1):107-124.

Lee, J., Lee, J. & Feick, L. 2001. The impact of switching costs on the customer satisfaction-loyalty link: mobile phone service in France. *Journal of Services Marketing*, 15(1):35-48.

Lee, R., Murphy, J. & Dickinger, A. 2006a. *Investigating the loyalty of prepaid and postpaid mobile customer*. Unpublished paper. Australia: University of Western Australia.

Leedy, P.D. & Ormrod, J.E. 2010. *Practical research: Planning and design.* 9th ed. Upper Saddle River, NJ: Pearson.

Levitt, T. 1981. Marketing intangible products and product intangibles. *Harvard Business Review*, 59(3):94-102.

Liang, C.-J. & Chen, H.-J. 2009. How to lengthen, deepen and broaden customer-firm relationships with online financial services? *Journal of Financial Services Marketing*, 14(3):218-231.

Lim, H., Widdows, R. & Park, J. 2006. M-loyalty: winning strategies for mobile carriers. *Journal of Consumer Marketing*, 23(4):208-218.

Lindquist, J.D. & Sirgy, M.J. 2006. *Shopper, buyer, and consumer behaviour: theory, marketing applications, and public policy implications*. 3rd ed. Cincinnati, Ohio: Atomic Dog.

Liu, C.-T., Guo, Y.M. & Lee, C.-H. 2011. The effects of relationship quality and switching barriers on customer loyalty. *International Journal of Information Management*, 31(1):71-79.

Liu, C., Marchewka, J.T., Lu, J. & Yu, C.-S. 2005. Beyond concern: a privacy-trust-behavioural intention model of electronic commerce. *Information & Management*, 42(2):289-304.

Lopez, J.P.M., Redondo, Y.P. & Olivan, F.J.S. 2006. The impact of customer relationship characteristics on customer switching behaviour: differences between switchers and stayers. *Managing Service Quality*, 16(6):556-574.

Lovelock, C.H. 1996. *Services marketing*. 3rd ed. Upper Saddle River, N.J.: Prentice Hall.

Lovelock, C. & Wright, L. 2002. *Principles of service marketing and management*. 2nd international ed. Upper Saddle River, New Jersey: Prentice Hall.

Lovelock. C. & Wirtz, J. 2011. *Services marketing: people, technology, strategy*. 7th global ed. Boston: Prentice Hall.

Lu, T., Tu, R. & Jen, W. 2011. The role of service value and switching barriers in an integrated model of behavioural intentions. *Total Quality Management & Business Excellence*, 22(10):1071-1089.

Luo, X. 2002. Trust production and privacy concerns on the Internet: a framework based on relationship marketing and social exchange theory. *Industrial Marketing Management*, 31(2):111-118.

MacCallum, R.C. 1995. Model specification: procedures, strategies, and related issues. In: Hoyle, R.H. (ed.) *Structural equation modelling: concepts, issues, and applications*. Thousand Oaks, California: Sage.

MacCallum, R.C., Browne, M.W. & Sugawara, H.M. 1996. Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods,* 1(2):130-149.

Mackay, N. 2012. *The interrelationship between selected customer relationship management initiatives, customer satisfaction and behavioural intention*. Unpublished doctoral thesis. Potchefstroom: North-West University.

Macneil, I.R. 1987. Relational contract theory as sociology: a reply to Professors Lindenberg and de Vos. *Journal of Institutional & Theoretical Economics*, 143(2):272-290.

Madden, G., Savage, S.J. & Coble-Neal, G. 1999. Subscriber churn in the Australian ISP market. *Information Economics & Policy*, 11(2):195-207.

Maicas, J.P., Polo, Y. & Sese, F.J. 2009a. The role of (personal) network effects and switching costs in determining mobile users' choice. *Journal of Information Technology*, 24(2):160-171.

Maicas, J.P., Polo, Y. & Sese, F.J. 2009b. Reducing the level of switching costs in mobile telecommunications: the case of mobile number portability. *Telecommunications Policy*, 33(9):544-554.

Malhotra, N.K. 2009. *Basic marketing research: a decision-making approach*. 3rd ed. Upper Saddle River, NJ: Pearson.

Malhotra, A. & Malhotra, C.K. 2013. Exploring switching behavior of US mobile service customers. *Journal of Services Marketing*, 27(1):13–24.

Mathieson, R. 2005. *Branding unbound: the future of advertising, sales and the brand experience in the wireless age.* New York: Amacom.

McColl, R., Callaghan, B. & Palmer, A. 1998. *Services marketing: a managerial perspective*. Sydney, Australia: McGraw-Hill.

McDaniel, C. & Gates, R. 2013. *Marketing research*. 9th international student version ed. Hoboken, N.J.: Wiley.

McDonald, R.P. & Ho, M-H.R. 2002. Principles and practice in reporting structural equation analyses. *Psychological Methods*, 7(1):64-82.

McDougall, G.H.G & Levesque, T. 2000. Customer satisfaction with services: putting perceived value into the equation. *Journal of Services Marketing*, 14(5):392-410.

McLeod, D. 2013. *Inside Orange's SA expansion plans*. [Online] Available from: http://www.techcentral.co.za/insideorangessaexpansionplans/37539/ [Accessed: 2014-12-17].

McLeod, D. 2014a. *SA to get second MVNO*. [Online] Available from: http://www.techcentral.co.za/sa-to-get-second-mvno/48501/ [Accessed: 2014-10-26].

McLeod, D. 2014b. *France's Orange to open first SA store*. [Online] Available from: http://www.techcentral.co.za/francesorangetoopenfirstsastore/53275/ [Accessed: 2014-12-17].

Min, D. & Wan, L. 2009. Switching factors of mobile consumers in Korea. *Journal of Service Science*, 1(1):105-120.

Minges, M. 1999. Mobile cellular communications in the Southern African region. *Telecommunications Policy*, 23(7-8):585-593.

Mitchell, V.-W. & Boustani, P. 1994. A preliminary investigation into pre- and post-purchase risk perception and reduction. *European Journal of Marketing*, 28(1):56-71.

Mittal, B. & Lassar, W.M. 1998. Why do customers switch? The dynamics of satisfaction versus loyalty. *The Journal of Services Marketing*, 12(3):177-194.

Möller, K. & Halinen, A. 2000. Relationship marketing theory: its roots and direction. *Journal of Marketing Management*, 16(1-3):29-54.

Mooi, E. & Sarstedt, M. 2011. *A concise guide to market research: the process, data, and methods using IBM SPSS statistics*. Berlin: Springer.

Morgan, R.M. & Hunt, S.D. 1994. The commitment-trust theory of relationship marketing. *Journal of Marketing*, 58(3):20-38.

Muller, R. 2010. *Internet demographics in South Africa*. [Online] Available from: http://mybroadband.co.za/news/internet/17347-internet-demographics-in-south-africa .html [Accessed: 2014-06-19].

Mybroadband. 2014b. *Lower data prices and more users for Vodacom*. [Online] Available from: http://mybroadband.co.za/news/cellular/102441-lower-data-prices-and-more-users-for-vodacom.html [Accessed: 2014-06-19].

Mybroadband. 2014a. *Surprising loser in cellular satisfaction.* [Online] Available from: http://mybroadband.co.za/news/general/103575-suprising-loser-in-cellular-satis faction.html [Accessed: 2014-06-19].

Nakamura, A. 2010. Estimating switching costs involved in changing mobile phone carriers in Japan: evaluation of lock-in factors related to Japan's SIM card locks. *Telecommunications Policy*, 34(11):736-746.

Negi, R. 2009. Determining customer satisfaction through perceived service quality: a study of Ethiopian mobile users. *International Journal of Mobile Marketing*, 4(1):31-38.

Newsom, J. 2012. *Some clarifications and recommendations on fit indices*. [Online] Available from: http://www.upa.pdx.edu/IOA/newsom/semclass/ho_fit.pdf [Accessed, 2014-03-20].

Nikbin, D., Ismail, I., Marimuthu, M. & Armesh, H. 2012. Perceived justice in service recovery and switching intention: evidence from Malaysian mobile telecommunication industry. *Management Research Review*, 35(3/4):309-325.

Nysveen, H., Pedersen, P.E. & Thorbjørnsen, H. 2005. Intentions to use mobile services: antecedents and cross-service comparisons. *Journal of the Academy of Marketing Science*, 33(3):330-346.

O'Malley, L. 1998. Can loyalty schemes really build loyalty? *Marketing Intelligence & Planning*, 16(1):47-55.

Oliver, R.L. 1999. Whence consumer loyalty? *Journal of Marketing*, 63(4) Special issue:33-44.

Pallant, J. 2011. *SPSS survival manual: a step by step guide to data analysis using SPSS.* 4th ed. Crows Nest, Australia: Allen & Unwin.

Palmer, A. 2008. *Principles of services marketing*. 5th ed. Maidenhead: McGraw-Hill Education.

Pan, Y., Sheng, S. & Xie, F.T. 2012. Antecedents of customer loyalty: an empirical synthesis and re-examination. *Journal of Retailing & Consumer Services*, 19(1):150-158.

Parasuraman, A., Zeithaml, V.A. & Berry, L.L. 1985. A conceptual model of service quality and its implications for future research. *Journal of Marketing*, 49(4):41-50.

Parasuraman, A., Zeithaml, V.A. & Berry, L.L. 1988. SERVQUAL: a multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing*, 64(1):12-40.

Paret, M. 2012. *Alphas, p-values, and confidence intervals, oh my!* [Online] Available from http://blog.minitab.com/blog/michelle-paret/alphas-p-values-confidence-intervals-oh-my [Accessed: 2014-02-26].

Patterson, P.G. 2004. A contingency model of behavioural intentions in a services context. *European Journal of Marketing*, 38(9/10):1304-1315.

Patterson, P.G. & Smith, T. 2003. A cross-cultural study of switching barriers and propensity to stay with service providers. *Journal of Retailing*, 79(2):107-120.

Patterson, P.G. & Spreng, R.A. 1997. Modelling the relationship between perceived value, satisfaction and repurchase intentions in a business-to-business, services context: an empirical examination. *International Journal of Service Industry Management*, 8(5):414-434.

Patterson, P.G., "A", R.M. & Smith, T. 2001. Switching costs as a moderator of service satisfaction processes in Thailand. *Journal of International Consumer Marketing*, 14(1):1-21.

Perreault, W.D. & McCarthy, E.J. 2006. *Essentials of marketing: a global-managerial approach.* 10th ed. New York, NY: McGraw-Hill Irwin.

Peterson, R.A. 1994. A meta-analysis of Cronbach's coefficient alpha. *Journal of Consumer Research*, 21(2):381-391.

Petzer, D.J. 2011. Investigating mobile marketing acceptance of urban South Africans residing in Gauteng. *Journal of Contemporary Management*, 8:384-407.

Petzer, D., Mostert, P., Kruger, L.M. & Kuhn, S. 2014. The dimensions of brand romance as predictors of brand loyalty among cell phone users. *South African Journal of Economic & Management Sciences*, 17(4):457-470.

Pihlström, M. & Brush, G.J. 2008. Comparing the perceived value of information and entertainment mobile services. *Psychology & Marketing*, 25(8):732-755.

Polo, Y. & Sesé, F.J. 2009. How to make switching costly: the role of marketing and relationship characteristics. *Journal of Service Research*, 12(2):119-137.

Pride, W.M. & Ferrell, O.C. 2010. *Marketing*. 15th ed. Canada: South-Western Cengage Learning.

Ranganathan, C., Seo, D.B. & Babad, Y. 2006. Switching behaviour of mobile users: do users' relational investments and demographics matter? *European Journal of Information Systems*, 15(3):269-276.

Rathmell, J.M. 1966. What is meant by services? *Journal of Marketing,* 30(4):32-36.

Reichheld, F.F. 1996. Learning from customer defections. *Harvard Business Review*, 74(2):56-69.

Reicheld, F.F. & Sasser, W.E. (Jr.). 1990. Zero defections: quality comes to services. *Harvard Business Review*, 68(5):105-111.

Rigdon, E.E. 1994. Calculating degrees of freedom for a structural equation model. *Structural Equation Modeling: a Multidisciplinary Journal*, 1(3):274-278.

Rigdon, E.E. 1996. *The form of structural equation models*. [Online] Available from: http://www.gsu.edu/~mkteer/sem2.html [Accessed: 2012-11-12].

Rigdon, E.E. 1998. Structural equation modeling. In Marcoulides, G.A. (ed.) *Modern methods for business research*. New York, N.Y.: Psychology Press.

Roberts, W.A. 1989. *Towards an understanding of relationship commitment: an empirical test of several models*. Unpublished doctoral thesis. Arizona: Arizona State University.

Roos, I. & Gustafsson, A. 2007. Understanding frequent switching patterns. *Journal of Service Research*, 10(1):93-108.

Rust, R.T. & Zahorik, A.J. 1993. Customer satisfaction, customer retention, and market share. *Journal of Retailing*, 69(2):193-215.

Satorra, A. & Bentler, P.M. 2001. A scaled difference chi-square test statistic for moment structure analysis. *Psychometrika*, 6(4):507-514.

Scanlan, L. & McPhail, J. 2000. Forming service relationships with hotel business travelers: the critical attributes to improve retention. *Journal of Hospitality & Tourism Research*, 24(4):491-513.

Schermelleh-Engel, K. Moosbrugger, H. & Műller, H. 2003. Evaluating the fit of structural equation models: tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research Online*, 8(2):23-74.

Schakett, T.J. 2009. *The impact of social bonding on the buyers loyalty, trust, satisfaction and service quality towards the seller in a B2B relationship*. Unpublished doctoral thesis. California: TUI University.

Schreiber, J.B. 2008. Core reporting practices in structural equation modelling. *Research in Social & Administrative Pharmacy*, 4(2):83-97.

Schreiber, J.B., Nora, A., Stage, F.K., Barlow E.A. & King, J. 2006. Reporting structural equation modelling and confirmatory factor analysis results: a review. *The Journal of Educational Research*, 99(6):323-338.

Schumacker, R.E. & Lomax, R.G. 2010. *A beginner's guide to structural equation modeling*. 3rd ed. New York, N.Y.: Routledge.

Seo, D.B., Ranganathan, C. & Babad, Y. 2008. Two-level model of customer retention in the US mobile telecommunications service market. *Telecommunications Policy*, 32(3-4):182-196.

Shah, A. & Schaefer, A.D. 2006. Switching service providers. *Services Marketing Quarterly*, 27(1):73-91.

Sharma, N. 2003. The role of pure and quasi-moderators in services: an empirical investigation of ongoing customer – service-provider relationships. *Journal of Retailing & Consumer Services*, 10(4):253-262.

Sharma, P.N. & Kim, K. H. 2013. A comparison of PLS and ML bootstrapping techniques in SEM: a Monte Carlo study. *New perspectives in partial least squares and related methods*. Springer: New York: Springer. [Online] Available from http://0-www2.pitt.edu.innopac.up.ac.za/~pns9/Sharma%20and%20Kim.pdf [Accessed: 2014-03-11].

Sharma, N. & Ojha, S. 2004. Measuring service performance in mobile communications. *Service Industries Journal*, 24(6):109-128.

Sharma, N. & Patterson, P.G. 2000. Switching costs, alterative attractiveness and experience as moderators of relationship commitment in professional, consumer services. *International Journal of Service Industry Management*, 11(5):470-490.

Shi, M., Chiang, J. & Rhee, B.-D. 2006. Price competition with reduced consumer switching costs: the case of "wireless number portability" in the cellular phone industry. *Management Science*, 52(1):27-38.

Shin, D.H. 2007. A study of mobile number portability effects in the United States. *Telematics & Informatics*, 24(1):1-14.

Shin, D.H. & Kim, W.Y. 2007. Mobile number portability on customer switching behaviour: in the case of the Korean mobile market. *info*, 9(4):38-54.

Shin, D.-H. & Kim, W.-Y. 2008. Forecasting customer switching intention in mobile service: an exploratory study of predictive factors in mobile number portability. *Technological Forecasting & Social Change*, 75(6):854-874.

Shostack, G.L. 1977. Breaking free from product marketing. *Journal of Marketing*, 41(2):73-80.

Shrivastava, S. & Kale, S.H. 2003. Philosophising on the elusiveness of relationship marketing theory in consumer markets: a case for reassessing ontological and epistemological assumptions. *Australian Marketing Journal*, 11(3):61-71.

Shukla, P. 2010. Effects of perceived sacrifice, quality, value, and satisfaction on behavioural intentions in the service environment. *Services Marketing Quarterly*, 31(4):466-484.

Shy, O. 2002. A quick-and-easy method for estimating switching costs. *International Journal of Industrial Organization*, 20(1):71-87.

Soureli, M., Lewis, B.R. & Karantinou, K.M. 2008. Factors that affect consumer's cross-buying intention: a model for financial services. *Journal of Financial Services Marketing*, 13(1):5-16.

SouthAfricaInfo. Not dated. *South Africa's telecommunications*. [Online] Available from: http://www.southafrica.info/business/economy/infrastructure/telecoms.htm#.UGKzbI3ib0M [Accessed: 2012-09-26].

South Africa Yearbook 2013/14. 2013. *Economy*. [Online] Available from: http://www.gcis.gov.za/sites/www.gcis.gov.za/files/docs/resourcecentre/yearbook/2012/Economy.pdf [Accessed: 2014-10-23]

Southern African Development Community. 2012. *South Africa*. [Online] Available from: http://www.sadc.int/member-states/south-africa/ [Accessed: 2014-10-15].

Srinuan, P., Bohlin, E. & Madden, G. 2012. The determinants of mobile subscriber retention in Sweden. *Applied Economics Letters*, 19(5):453-457.

Stevens, L. 2000. Shop at home creates a 'mom-and-pop' feel. *InternetWeek*, 833:58.

Steyn, T.F.J., Mostert, P.G. & De Jager, J.N.W. 2008. The influence of length of relationship, gender and age on the relationship intention of short-term insurance clients: an exploratory study. *South African Journal of Economic & Management Sciences*, 11(2):139-156.

Strasheim, A., Pitt, L. & Caruana, A. 2007. Psychometric properties of the Schlinger Viewer Response Profile (VRP): evidence from a large sample. *Journal of Advertising*, 36(4):101-114.

Sultan, F., Rohm, A.J. & Gao, T. 2009. Factors influencing consumer acceptance of mobile marketing: a two-country study of youth markets. *Journal of Interactive Marketing*, 23(4):308-320.

Sutherland, E. 2007. Mobile number portability. *The Journal of Policy, Regulation & Strategy for Telecommunications*, 9(4):10-24.

Sweeney, J.C. & Soutar, G.N. 2001. Consumer perceived value: the development of a multiple item scale. *Journal of Retailing*, 77(2):203-220.

Tabachnick, B.G. & Fidell, L.S. 2013. *Using multivariate statistics*. 6th ed. Boston: Pearson.

Tähtinen, J. & Halinen, A. 2002. Research on ending exchange relationships: a categorization, assessment and outlook. *Marketing Theory*, 2(2):165-188.

Telkom. 2013. *8ta to be rebranded to Telkom Mobile.* [Online] Available from: http://www.telkommobile.co.za/news/detail/8ta-to-be-rebranded-to-telkom-mobile [Accessed: 2014-10-15].

Theron, E., Terblanche, N.S. & Boshoff, C. 2008. The antecedents of relationship commitment in the management of relationships in business-to-business (B2B) financial services. *Journal of Marketing Management*, 24(9/10):997-1010.

Thomson, B. 2000. Ten commandments of structural equation modeling. In: Grim, L.G. & Yarnold, P.R. (eds.) *Reading and understanding more multivariate statistics*. Washington, DC: American Psychological Association.

Thong, B.Q. 2007. Antecendents of intention to use mobile music services: a study among Swedish consumers. Unpublished doctoral thesis. Sweden: Luleå University of Technology.

Totten, J.W., Lipscomb, T.J., Cook, R.A. & Lesch, W. 2005. General patterns of cell phone usage among college students: a four-state study. *Services Marketing Quarterly*, 26(3):13-39.

Tubbs, B. 2014. *Orange quietly launches WiFi foray*. [Online]. Available from: http://www.itweb.co.za/index.php?option=com_content&view=article&id=72452 [Accessed: 2014-12-17].

Turel, O. & Serenko, A. 2006. Satisfaction with mobile services in Canada: an empirical investigation. *Telecommunications Policy*, 30(5-6):314-331.

Turel, O., Serenko, A. & Bontis, N. 2007. User acceptance of wireless short messaging services: deconstructing perceived value. *Information & Management*, 44(1):63-73.

Ultsch, 2002. Emergent self-organising feature maps used for prediction and prevention of churn in mobile phone markets. *Journal of Targeting, Measurement & Analysis for Marketing*, 10(4):314-324.

Van der Wal, R.W.E., Pampallis, A. & Bond, C. 2002. Service quality in a cellular telecommunications company: a South African experience. *Managing Service Quality*, 12(5):323-355.

Van der Waldt, D.L.R., Rebello, T.M. & Brown, W.J. 2009. Attitudes of young consumers towards SMS advertising. *African Journal of Business Management*, 3(9):444-452.

Varnali, K. & Toker, A. 2010. Mobile marketing research: the-state-of-the-art. *International Journal of Information Management*, 30(2):144-151.

Vargo, S.L. & Lusch, R.F. 2004. Evolving to a new dominant logic for marketing. *Journal of Marketing*, 68(1):1-17.

Vasudevan, H., Gaur, S.S. & Shinde, R.K. 2006. Relational switching costs, satisfaction and commitment: a study in the Indian manufacturing context. *Asia Pacific Journal of Marketing & Logistics*, 18(4):342-353.

Vermeulen, J. 2015. *SA mobile operators can lock your phone to their network*. [Online] Available from: http://mybroadband.co.za/news/cellular/125972-sa-mobile-operators-can-lock-your-phone-to-their-network.html [Accessed: 2015-11-09].

Vlachos, P.A. & Vrechopoulos, A.P. 2008. Determinants of behavioural intentions in the mobile internet services market. *Journal of Services Marketing*, 22(4):280-291.

Vovici Corporation. 2010. *Welcome to Survey Workbench*. [Online] Available from: http://www.vovici.com/help/community/5.0/whnjs.htm [Accessed: 2014-02-04].

Wallace, B. 2006. *30 countries passed 100% mobile phone penetration in Q1: Informa Telecoms and Media Report Predicts Number to Reach 40 by Year's End*. [Online] Available from: http://www.telecommagazine.com/newsglobe /article.asp?HH_ID=AR_2148 [Accessed: 2007-10-15].

Walters, D. & Lancaster, G. 1999. Value-based marketing and its usefulness to customers. *Management Decision*, 37(9):697-708.

Wang, C.-Y. 2009. Investigating antecedents of consumers' recommend intentions and the moderating effect of switching barriers. *The Service Industries Journal*, 29(9):1231-1241.

Wang, C.-Y. 2010. Service quality, perceived value, corporate image, and customer loyalty in the context of varying levels of switching costs. *Psychology & Marketing*, 27(3):252-262.

Wang, Y.-S., Lin, H.-H. & Luarn, P. 2006. Predicting consumer intention to use mobile service. *Information Systems Journal*, 16(2):157-179.

Wang, C.-Y. & Wu, L.-W. 2012. Customer loyalty and the role of relationship length. *Managing Service Quality*, 22(1):58-74.

Weston, R. & Gore, P.A. 2006. A brief guide to structural equation modelling. *The Counseling Psychologist*, 34(5):719-751.

Wheaton. Not dated. *Structural equation modelling.* [Online] Available from: http://www.stat.purdue.edu/~bacraig/SCS/Structural%20Equation%20Modeling.doc. [Accessed: 2014-06-02].

Whitten, D. & Wakefield, R.L. 2006. Measuring switching costs in IT outsourcing services. *Journal of Strategic Information Systems*, 15(3):219-248.

Wieringa, J.E. & Verhoef, P.C. 2007. Understanding customer switching behavior in a liberalizing service market. *Journal of Service Research*, 10(2):174-86.

Williams, B., Onsman, A. & Brown, T. 2010. Exploratory factor analysis: a five-step guide for novices. *Journal of Emergency Primary Health Care (JEPHC)*, 8(3): article 990399.

Woisetschläger, D.M., Lentz, P. & Evanshitzky, H. 2011. How habits, social ties, and economic switching barriers affect customer loyalty in contractual settings. *Journal of Business Research*, 64(8):800-808.

Wong, K.K.-K. 2011. Using Cox regression to model customer time to churn in the wireless telecommunications industry. *Journal of Targeting, Measurement & Analysis for Marketing*, 19(1):37-43.

Woo, K.-S. & Fock, H.K.Y. 1999. Customer satisfaction in the Hong Kong mobile phone industry. *The Service Industries Journal*, 19(3):162-174.

Wright, T. & Blin, M. 2013. *Orange launches Orange Horizons to seek out new business opportunities outside its operator footprint*. [Online] Available from: http://www.orange.com/en/press/press-releases/press-releases-2013/orange-launches-orange-horizons-to-seek-out-new-business-opportunities-outside-its-operator-footprint [Accessed: 2014-12-17].

Wu, L.-W. 2011. Satisfaction, inertia, and customer loyalty in the varying levels of the zone of tolerance and alternative attractiveness. *Journal of Services Marketing*, 25(5):310-322.

Xavier, P. & Ypsilanti, D. 2008. Switching costs and consumer behaviour: implications for telecommunications regulation. *Journal of Policy, Regulation & Strategy for Telecommunications*, 10(4):13-29.

Yang, Z. & Peterson, R.T. 2004. Customer perceived value, satisfaction, and loyalty: the role of switching costs. *Psychology & Marketing*, 21(10):799-822.

Zeithaml, V.A. 1988. Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *Journal of Marketing*, 52(3):2-22.

Zeithaml, V.A. 2000. Service quality, profitability and the economic worth of customers: what we know and what we need to learn. *Journal of the Academy of Marketing Science*, 28(1):67-85.

Zeithaml, V.A., Berry, L.L. & Parasuraman, A. 1996. The behavioural consequences of service quality. *Journal of Marketing*, 60(2):31-46.

Zikmund, W.G. & Babin, B.J. 2013. *Essentials of marketing research*. 5th international ed. Australia: South-Western.

Zikmund, W.G., Babin, B.J., Carr, J.C. & Griffin, M. 2009. *Business research methods*. 8th ed. Mason, Ohio: South-Western.

Zins, A.H. 2001. Relative attitudes and commitment in customer loyalty models: some experiences in the commercial airline industry. *International Journal of Service Industry Management*, 12(3):269:294.

APPENDIX A

- Letter of permission -

UNIVERSITEIT VAN PRETORIA
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YUNIBESITHI YA PRETORIA

Faculty of Economic and Management Sciences
Fakulteit Ekonomiese en Bestuurswetenskappe
Lefapha la Disaense tša Ekonomi le Taolo

CONSULTA
DISCOVER SCIENTIFIC RESEARCH

6 September 2013

To whom it may concern

USE OF CONSULTA RESEARCH (PTY) LTD ONLINE COMMUNITY

Consulta hereby gives Ms MC van der Merwe permission to use our full online panel as part of the data collection for her Doctoral thesis.

The online panel consists of a database of panel members that regularly complete a variety of surveys for Consulta. Panel members are not offered an incentive to complete surveys and their participation is strictly voluntary.

Upon registration, panel members give consent to participate in the surveys. The potential panel member goes through a double opt-in process, which means that the respondent agrees twice that they are prepared to answer surveys and have the option to withdraw from the panel before being added to the database.

The opt-in procedure clearly explains that participation in the surveys is voluntary and that panel members have the option to withdraw from the panel at any time. Details of the terms and conditions can be found by clicking on the following link:
http://www.consultapanel.co.za/TermsAndConditions.aspx

Thus, panel members give "overall" consent to participate in all surveys, which implies that consent has already been given by all panel members to participate in Ms van der Merwe's study. In addition, respondents will be given the option to unsubscribe from the particular study, should they wish to do so.

Yours faithfully,

Ingrid Olivier
COMMUNITY MANAGER

Olivier
....
Signature

12/09/2013
....
Date

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APPENDIX B

- Data collection instruments -

- Questionnaire A:

Switching intention measurement instrument -

SECTION 1: Screening questions	
A1 Are you able to independently choose which mobile network you use?	
Yes	
No	
A2 Which mobile network service do you currently use? If you currently make use of both contract and pre-paid, kindly select the one you consider to be your primary service.	
Contract	
Prepaid	
SECTION 2: Categorisation question	
A3 Which one of the following mobile networks do you consider to be your main provider?	
Cell C	
MTN	
Telkom Mobile (8ta)	
Virgin Mobile	
Vodacom	
SECTION 3: Branching question	
A4 Have you switched from another mobile network within the past 6 months?	
Yes	
No	

SECTION 4: Construct questions

A5	**Please indicate the extent to which you agree or disagree that the statements below describe how you feel about switching from your current mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
A5.1	I expect to stay with my current mobile network for the foreseeable future	0	1	2	3	4	5	6	7	8	9	10
A5.2	When my contract with my current mobile network expires, I am likely to switch to another mobile network	0	1	2	3	4	5	6	7	8	9	10
A5.3	I have often considered changing from my current mobile network to another mobile network	0	1	2	3	4	5	6	7	8	9	10
A5.4	I am likely to switch to a mobile network that offers better services	0	1	2	3	4	5	6	7	8	9	10
A5.5	I am likely to switch to another mobile network because I have experienced problems with my current mobile network	0	1	2	3	4	5	6	7	8	9	10
A6	**Please indicate the extent to which you agree or disagree that the statements describe how you feel about the relationship that you have with your current mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
A6.1	I would miss dealing with the staff at my current mobile network if I switched to another mobile network	0	1	2	3	4	5	6	7	8	9	10
A6.2	I am more comfortable interacting with the staff working for my current mobile network	0	1	2	3	4	5	6	7	8	9	10

	than I would be if I switched to another mobile network											
A6.3	The staff at my current mobile network matter to me	0	1	2	3	4	5	6	7	8	9	10
A6.4	I like talking to the staff at my current mobile network	0	1	2	3	4	5	6	7	8	9	10
A6.5	I like the public image that my current mobile network has	0	1	2	3	4	5	6	7	8	9	10
A6.6	I support my current mobile network as a firm	0	1	2	3	4	5	6	7	8	9	10
A6.7	I care about my current mobile network's brand / company name	0	1	2	3	4	5	6	7	8	9	10
A7	**Please indicate the extent to which you agree or disagree that the statements describe how you feel about the value that you receive from the services that you purchase from your mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
A7.1	My total monthly bill from my current mobile network is acceptable	0	1	2	3	4	5	6	7	8	9	10
A7.2	My current mobile network offers good value for money	0	1	2	3	4	5	6	7	8	9	10
A7.3	My current mobile network offers better value for money than what I would pay for the same service at another mobile network	0	1	2	3	4	5	6	7	8	9	10
A8	**Please indicate the extent to which you agree or disagree with the following statements about the difference between your current mobile network and other mobile networks.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
A8.1	All in all, other mobile networks would be more fair than my current mobile network	0	1	2	3	4	5	6	7	8	9	10
A8.2	Overall, other mobile networks' policies would benefit me much more than my current mobile network's policies	0	1	2	3	4	5	6	7	8	9	10
A8.3	I would be much more satisfied with the service available from other mobile networks than the service provided by my current mobile network	0	1	2	3	4	5	6	7	8	9	10
A8.4	In general, I would be much more satisfied with other mobile networks than I am with my current mobile network	0	1	2	3	4	5	6	7	8	9	10
A8.5	Overall, other mobile networks would be better to do business with than my current mobile network	0	1	2	3	4	5	6	7	8	9	10

A9 How long have you been with your mobile network?	
Less than 6 months	
6 to 12 months	
12 to 18 months	
18 to 24 months	
2 - 5 years	
5 - 8 years	

8 - 12 years	
12 - 15 years	
Longer than 15 years	
A10 What is your average monthly bill with your mobile network?	
R0 – R200	
R201 – R400	
R401 – R600	
R601 – R800	
R801 – R1000	
R1001 – R1250	
R1251 – R1500	
R1501 – R1750	
R1751 – R2000	
R2001 – R2500	
R2501 – R3000	
R3001 – R3500	
R3501 – R4000	
R4001 – R4500	
R4501 – R5000	
Above R5001	
A11 Which of the following additional services have you purchased from your mobile network? Check ALL that apply.	
Data bundles	
Roaming	
SMS bundles	
Other (Please specify)	
None of the above	
SECTION 5: Demographic questions	
A12 Please specify your year of birth.	

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Lefapha la Disaense tša Ekonomi le Taolo

- Questionnaire B:

Switching behaviour measurement instrument -

SECTION 1: Screening questions	
B1 Are you able to independently choose which mobile network you use?	
Yes	
No	
B2 Which mobile network service do you currently use? If you currently make use of both contract and pre-paid, kindly select the one you consider to be your primary service.	
Contract	
Prepaid	
SECTION 2: Categorisation question	
B3 Which one of the following mobile networks do you consider to be your main provider?	
Cell C	
MTN	
Telkom Mobile (8ta)	
Virgin Mobile	
Vodacom	
SECTION 3: Branching question	
B4 Have you switched from another mobile network within the past 6 months?	
Yes	
No	
B5 From which mobile network did you switch in the last 6 months? In other words, with which mobile network were you previously? Please select the network that you most recently switched from.	
Cell C	
MTN	
Telkom Mobile (8ta)	
Virgin Mobile	
Vodacom	

SECTION 4: Construct questions												
B6	**Please indicate the extent to which you agree or disagree that the statements below describe how you feel about switching from your previous mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
B6.1	When I originally joined my previous mobile network, I expected to stay with them for long	0	1	2	3	4	5	6	7	8	9	10
B6.2	I intended to switch to another mobile network as soon as my contract with my previous mobile network expired	0	1	2	3	4	5	6	7	8	9	10
B6.3	I often considered changing networks when I was with my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B6.4	I intended to switch from my previous mobile network to a mobile network that offered better services	0	1	2	3	4	5	6	7	8	9	10
B6.5	I often had problems with my previous mobile network, which made me decide to switch to my current mobile network	0	1	2	3	4	5	6	7	8	9	10

B7	**Please indicate the extent to which you agree or disagree that the statements describe how you feel about the relationship that you had with your previous mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
B7.1	I miss dealing with the staff at my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B7.2	I am more comfortable interacting with the staff working for my current mobile network than I was interacting with the staff at my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B7.3	The staff at my previous mobile network mattered to me	0	1	2	3	4	5	6	7	8	9	10
B7.4	I liked talking to the staff at my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B7.5	I like the public image that my previous mobile network has	0	1	2	3	4	5	6	7	8	9	10
B7.6	I supported my previous mobile network as a firm	0	1	2	3	4	5	6	7	8	9	10
B7.7	I cared about my previous mobile network's brand / company name	0	1	2	3	4	5	6	7	8	9	10
B8	**Please indicate the extent to which you agree or disagree that the statements describe how you feel about the value that you received from the services that you purchased from your previous mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
B8.1	My total monthly bill from my previous mobile network was acceptable	0	1	2	3	4	5	6	7	8	9	10
B8.2	My previous mobile network offered good value for money	0	1	2	3	4	5	6	7	8	9	10
B8.3	My current mobile network offers better value for money than what I paid for the same service at my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B9	**Please indicate the extent to which you agree or disagree that the statements describe how you feel about the difference between your previous mobile network and other existing mobile networks.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
B9.1	All in all, my current mobile network is more fair than my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B9.2	Overall, my current mobile network's policies benefit me much more than my previous mobile network's policies	0	1	2	3	4	5	6	7	8	9	10
B9.3	I am much more satisfied with the service available from my current mobile network than the service provided by my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B9.4	In general, I am much more satisfied with my current mobile network than I was with	0	1	2	3	4	5	6	7	8	9	10

	my previous mobile network											
B9.5	Overall, my current mobile network is better to do business with than my previous mobile network	0	1	2	3	4	5	6	7	8	9	10

B10 How long were you with your previous mobile network?	
Less than 6 months	
6 to 12 months	
12 to 18 months	
18 to 24 months	
2 - 5 years	
5 - 8 years	
8 - 12 years	
12 - 15 years	
Longer than 15 years	
B11 What was your average monthly bill with your previous mobile network?	
R0 – R200	
R201 – R400	
R401 – R600	
R601 – R800	
R801 – R1000	
R1001 – R1250	
R1251 – R1500	
R1501 – R1750	
R1751 – R2000	
R2001 – R2500	
R2501 – R3000	
R3001 – R3500	
R3501 – R4000	
R4001 – R4500	
R4501 – R5000	
Above R5001	
B12 Did you purchase any of the following additional services from your previous mobile network? Check ALL that apply.	
Data bundles	
Roaming	
SMS bundles	
Other (Please specify)	
None of the above	
SECTION 5: Demographic questions	
B13 Please specify your year of birth.	

APPENDIX C

- Ethical clearance approval -

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FACULTY OF ECONOMIC AND MANAGEMENT SCIENCES

RESEARCH ETHICS COMMITTEE

Tel: +27 12 420 4102
E-mail: berendien.lubbe@up.ac.za

19 September 2013

Strictly confidential

Prof Y Jordaan
Department of Marketing Management

Dear Professor Jordaan

Project:	A comparison between switching intention and switching behaviour in the South African mobile telecommunication industry
Researcher:	MC van der Merwe
Student No:	04252071
Promoter:	Prof Y Jordaan
Department:	Marketing Management

Thank you for the application you submitted to the Committee for Research Ethics, Faculty of Economic and Management Sciences.

I have pleasure in informing you that the Committee formally approved the above study on 17 September 2013. The approval is subject to the candidate abiding by the principles and parameters set out in the application and research proposal in the actual execution of the research.

The approval does not imply that the researcher, student or lecturer is relieved of any accountability in terms of the Codes of Research Ethics of the University of Pretoria if action is taken beyond the approved proposal.

The Committee requests that you convey this approval to the researcher.

We wish you success with the project.

Sincerely

PROF BA LUBBE
CHAIR: COMMITTEE FOR RESEARCH ETHICS

cc: Student Administration

APPENDIX D

- Informed consent -

New Member Registration Form

Page 1

Community Research:

If you enjoyed this survey, you now have the opportunity to become part of a Research Community.

What is a Research Community?: A Research Community has regular discussions on various business and market practices. You can make a difference and improve service levels and product offerings by sharing your views on topics such as financial matters, media use, lifestyle and technology, through surveys and discussions.

By being part of a Research Community you are able to influence thinking and have early access to insights of what's to come, and be eligible for awards based on your participation when applicable.

Would you like to join in and participate in community research surveys?

- Yes
- No

Page 2

CLICK THE APPLICABLE BOXES TO INDICATE YOUR PREFERENCE. YOU MAY SELECT MULTIPLE OPTIONS. YOU MAY ALSO DESELECT OPTIONS YOU ARE NOT INTERESTED IN.

	Online surveys	Telephonic interviews
Research across all industries	☐	☐

Add

APPENDIX E

- Cover letter -

From: The ConsultaPanel Team [mailto:frontdesk@consultapanel.co.za]
Sent: 24 October 2013 02:06 PM
To: patterns@mweb.co.za
Subject: Have your say! Tell us why consumers switch network providers.

This email contains images. Please remember to enable images for it to display correctly.

Hi Ethel

New mobile telecommunications questionnaire!

ConsultaPanel – like the inquisitive busybody that we are – has partnered with a Doctoral student from the Department of Marketing Management at the University of Pretoria as part of our recently launched initiative to explore deeper into the mobile telecommunications industry. We present you with the latest questionnaire in our mobile telecommunications campaign.

This questionnaire aims to investigate **what influences consumers to switch mobile network service providers.**

Click here to have your say.

This questionnaire will close as soon as we have enough responses, so get started ASAP!

Remember that you can also complete the questionnaire on your ConsultaPanel Dash smartphone or tablet!

Ciao,

The ConsultaPanel Team

APPENDIX F

- Statistical assumptions -

7.1 VALIDATION OF THE SWITCHING INTENTION MEASUREMENT SCALES (N_1)

7.1.1 Inter-item correlations (switching intention sample, N_1)

Table 7.1 represents the correlation matrix for switching intention and the three predictor variables, namely: relational switching costs, perceived value and alternative attractiveness.

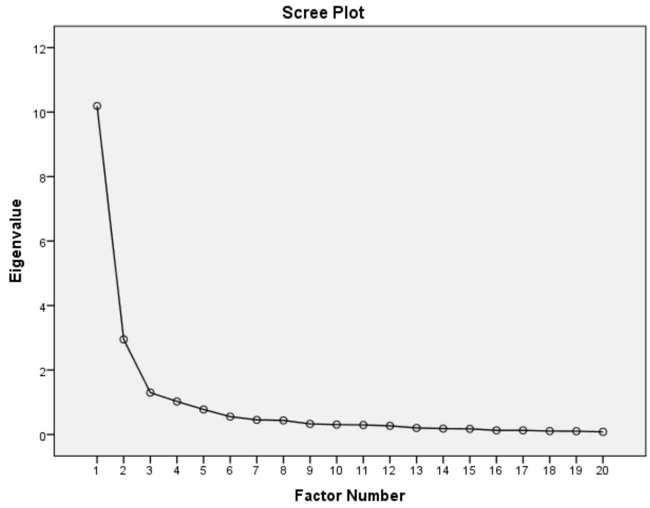
Table 7.1: Correlation matrix for switching intention and the three antecedents (switching intention sample, N_1)

Correlation Matrix																				
	A6_1	A6_2	A6_3	A6_4	A6_5	A7_1	A7_2	A7_3	A7_4	A7_5	A7_6	A7_7	A8_1	A8_2	A8_3	A9_1	A9_2	A9_3	A9_4	A9_5
A6_1	1.000																			
A6_2	.670	1.000																		
A6_3	.489	.610	1.000																	
A6_4	.454	.581	.549	1.000																
A6_5	.546	.662	.643	.598	1.000															
A7_1	-.358	-.302	-.316	-.323	-.335	1.000														
A7_2	-.349	-.305	-.327	-.333	-.347	.813	1.000													
A7_3	-.336	-.289	-.326	-.297	-.329	.736	.774	1.000												
A7_4	-.338	-.291	-.334	-.299	-.345	.771	.798	.868	1.000											
A7_5	-.408	-.345	-.372	-.302	-.404	.600	.624	.641	.653	1.000										
A7_6	-.459	-.378	-.387	-.339	-.454	.609	.630	.658	.667	.830	1.000									
A7_7	-.467	-.387	-.393	-.334	-.451	.642	.640	.692	.689	.807	.884	1.000								
A8_1	-.425	-.338	-.349	-.295	-.365	.418	.423	.435	.442	.433	.475	.501	1.000							
A8_2	-.492	-.421	-.429	-.370	-.459	.487	.491	.507	.513	.526	.567	.595	.865	1.000						
A8_3	-.468	-.389	-.365	-.324	-.383	.485	.497	.517	.503	.496	.544	.571	.681	.790	1.000					
A9_1	.452	.497	.431	.371	.429	-.264	-.272	-.294	-.289	-.300	-.331	-.357	-.445	-.500	-.509	1.000				
A9_2	.493	.517	.431	.431	.474	-.264	-.275	-.286	-.277	-.338	-.356	-.375	-.424	-.480	-.464	.784	1.000			
A9_3	.564	.583	.496	.455	.580	-.315	-.325	-.323	-.323	-.397	-.431	-.414	-.429	-.485	-.467	.702	.801	1.000		
A9_4	.583	.601	.535	.482	.599	-.303	-.324	-.321	-.320	-.404	-.444	-.436	-.438	-.514	-.483	.672	.776	.902	1.000	
A9_5	.586	.602	.512	.477	.588	-.330	-.342	-.335	-.339	-.399	-.431	-.433	-.435	-.502	-.473	.675	.770	.873	.902	1.000

7.1.2 Scree plot for factor identification (switching intention sample, N_1)

Figure 7.1 shows Catell's (1966) scree test, which was used to visually confirm whether the four factors should be retained in the EFA for switching intention.

Figure 7.1: Scree plot to determine the number of factors to retain for switching intention (switching intention sample, N_1)



7.2 TESTING ASSUMPTIONS FOR THE STEPWISE REGRESSIONS (SWITCHING INTENTION SAMPLE, N_1)

7.2.1 Assessment of multicollinearity (switching intention sample, N_1)

Table 7.2 represents the assessment multicollinearity by indicating the variance inflation factor (VIF) and tolerance values for the switching intention sample.

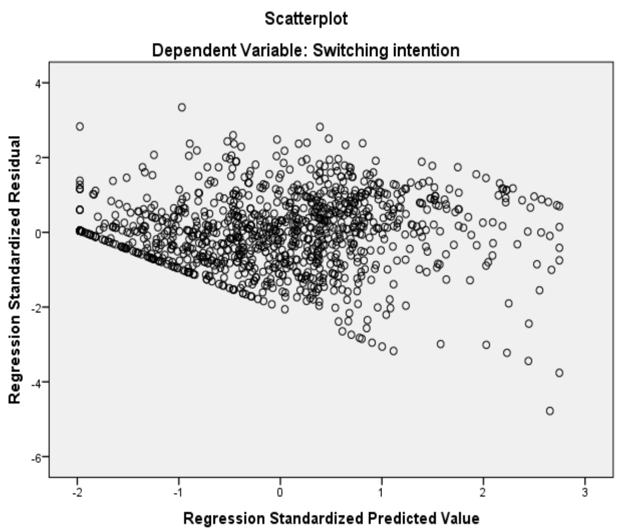
Table 7.2: Assessment of multicollinearity (switching intention sample, N_1)

Switching intention (N_1 = 1018)		Unstandardised coefficients	Standardised coefficients	t-value	p-value	Collinearity statistics	
		B	Beta-value			Tolerance	VIF
Model 1	(Constant)	3.968		7.147	0.000		
	Alternative attractiveness	0.755	0.685	30.044	0.000	1.000	1.000
Model 2	(Constant)	11.501		12.661	0.000		
	Alternative attractiveness	0.638	0.579	24.024	0.000	0.813	1.229
	Relational switching costs	-0.167	-0.246	-10.203	0.000	0.813	1.229
Model 3	(Constant)	13.368		11.532	0.000		
	Alternative attractiveness	0.607	0.550	20.883	0.000	0.675	1.481
	Relational switching costs	-0.143	-0.210	-7.534	0.000	0.607	1.648
	Perceived value	-0.126	-0.078	-2.581	0.010	0.512	1.951

7.2.2 Linear regression assumptions (switching intention sample, N_1)

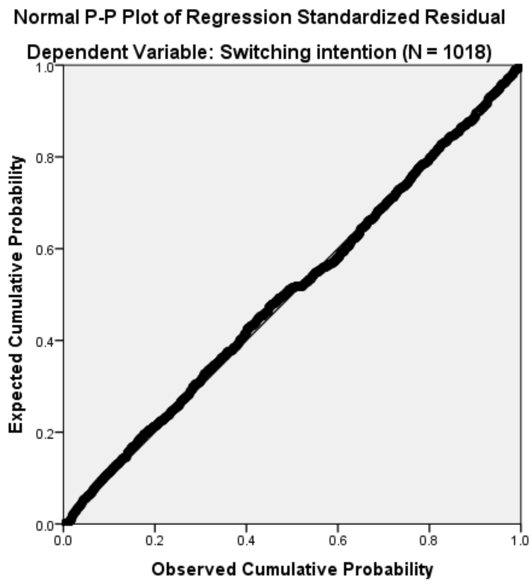
Figure 7.2 presents the scatterplot used to determine whether the assumption of homoscedasticity and linearity are met.

Figure 7.2: Scatterplot for the linear regression assumptions (switching intention sample, N_1)



P-P Plots (Figure 7.3) used to determine whether the assumption of normality was met.

Figure 7.3: Normality P-P Plot for the linear regression assumptions (switching intention sample, N_1)



7.3 TESTING ASSUMPTIONS FOR THE STEPWISE REGRESSIONS (SWITCHING BEHAVIOUR SAMPLE, N_2)

7.3.1 Assessment of multicollinearity (switching behaviour sample, N_2)

Table 7.3 represents the assessment multicollinearity by indicating the variance inflation factor (VIF) and tolerance values for the switching behaviour sample.

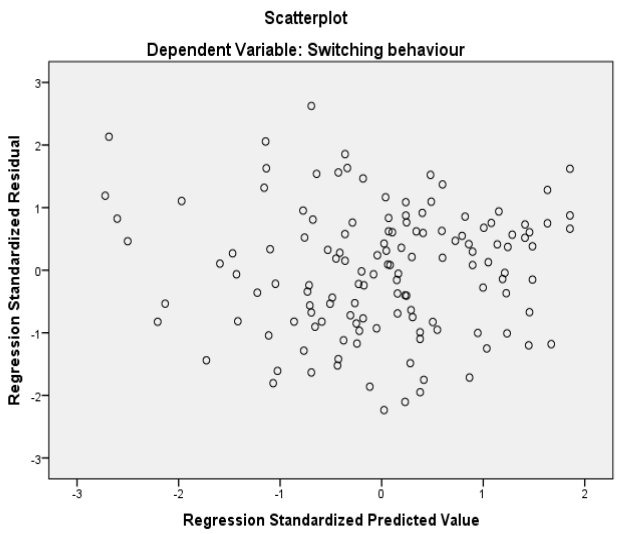
Table 7.3: Assessment of multicollinearity (switching behaviour sample, N_2)

Switching behaviour (N_2 = 135)		Unstandardised coefficients	Standardised coefficients	t-value	p-value	Collinearity statistics	
		B	Beta-value			Toler-ance	VIF
Model 1	(Constant)	14.840		7.206	0.000		
	Alternative attractiveness	0.225	0.309	3.746	0.000	1.000	1.000
Model 2	(Constant)	18.449		6.804	0.000		
	Alternative attractiveness	0.200	0.274	3.294	0.001	0.958	1.044
	Perceived value	-0.282	-0.168	-2.015	0.046	0.958	1.044

7.3.2 Linear regression assumptions (switching behaviour sample, N_2)

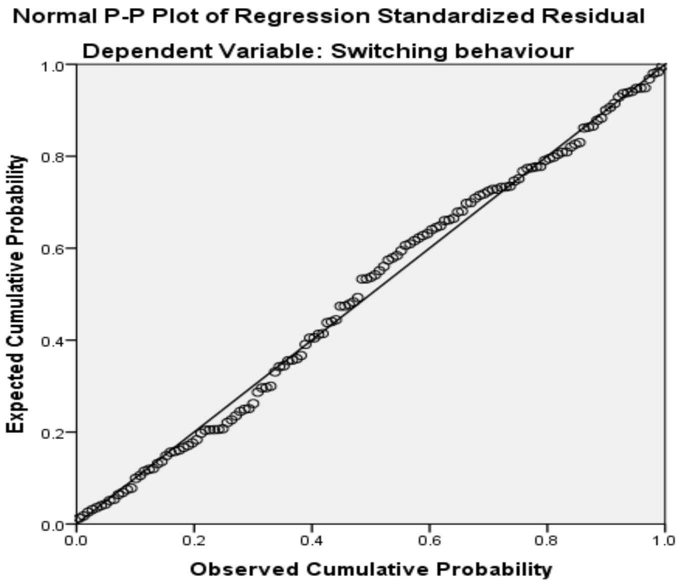
Figure 7.4 presents the scatterplot used to determine whether the assumption of homoscedasticity and linearity were met.

Figure 7.4: Scatterplot for the linear regression assumptions (switching behaviour sample, N_2)



P-P Plots used to determine whether the assumption of normality was met are shown in Figure 7.5.

Figure 7.5: Normality P-P Plot for the linear regression assumptions (switching behaviour sample, N_2)



7.4 VALIDATION OF THE SWITCHING BEHAVIOUR MEASUREMENT SCALES (N_2)

7.4.1 Inter-item correlations (switching behaviour sample, N_2)

Table 7.4 represents the correlation matrix for switching behaviour and the three predictor variables, namely: relational switching costs, perceived value and alternative attractiveness.

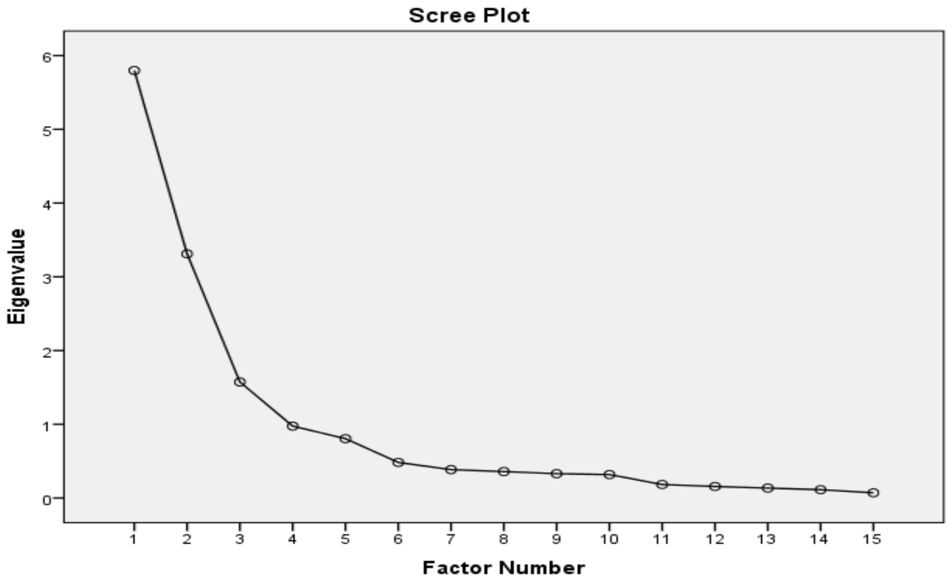
Table 7.4: Correlation matrix for switching behaviour and the three predictor variables (switching behaviour sample, N_2)

Correlation Matrix															
	B7_1	B7_2	B7_3	B7_4	B7_5	B7_6	B7_7	B8_1	B8_2	B8_3	B9_1	B9_2	B9_3	B9_4	B9_5
B7_1	1.000														
B7_2	.199	1.000													
B7_3	.644	.045	1.000												
B7_4	.702	.079	.853	1.000											
B7_5	.449	.194	.560	.549	1.000										
B7_6	.373	.131	.506	.494	.690	1.000									
B7_7	.373	.130	.551	.509	.629	.772	1.000								
B8_1	.227	.023	.238	.226	.270	.252	.330	1.000							
B8_2	.272	.058	.312	.289	.329	.344	.424	.627	1.000						
B8_3	.053	.253	.026	.010	.013	.134	.117	.142	.361	1.000					
B9_1	-.186	-.369	-.079	-.071	-.125	-.225	-.272	-.189	-.412	-.724	1.000				
B9_2	-.144	-.466	-.103	-.070	-.143	-.165	-.234	-.111	-.250	-.592	.771	1.000			
B9_3	-.238	-.638	-.156	-.117	-.147	-.196	-.170	-.062	-.160	-.476	.617	.749	1.000		
B9_4	-.295	-.550	-.231	-.187	-.210	-.200	-.155	-.024	-.192	-.455	.573	.698	.897	1.000	
B9_5	-.373	-.614	-.274	-.260	-.272	-.244	-.206	-.070	-.202	-.455	.582	.709	.860	.898	1.000

7.4.2 Scree plot for factor identification (switching behaviour sample, N_2)

Figure 7.6 shows Catell's (1966) scree test which was used to visually confirm whether the three factors should be retained for switching behaviour.

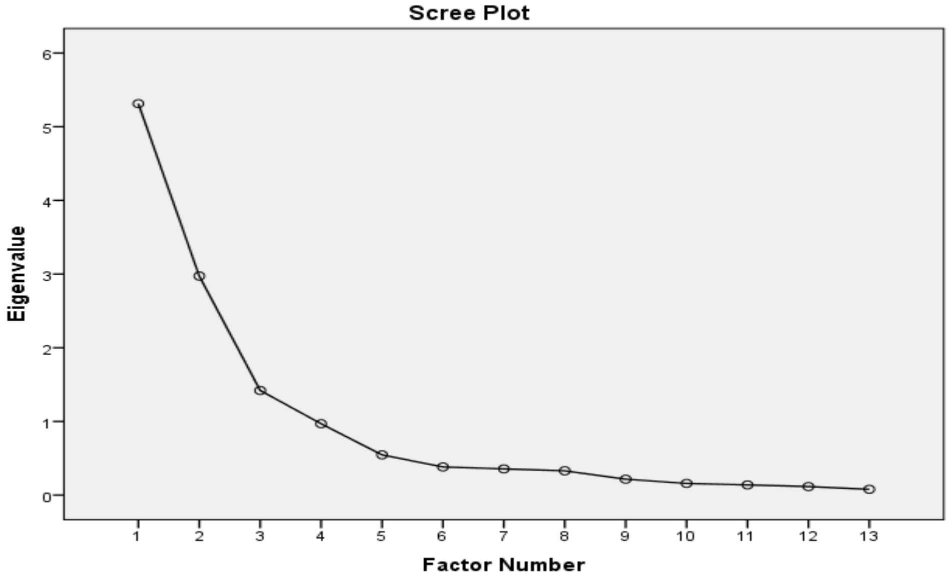
Figure 7.6: Scree plot to determine the number of factors to retain for switching behaviour (N_2)



7.4.3 Scree plot for second round of PAF factor identification for switching behaviour (switching behaviour sample, N_2)

Figure 7.67 shows Catell's (1966) scree test after two items (B7_2 and B8_3) were deleted. The scree test was used to visually confirm the results after the second PAF for the switching behaviour sample.

Figure 7.7: Scree plot to determine the number of factors to retain for switching behaviour during the second PAF (switching behaviour sample, N_2)



7.4.4 <u>Inter-item correlations for switching behaviour (after deleting items</u> B7._2 and B8_3) <u>(switching behaviour sample, N_2)</u>

Table 7.5 represents the correlation matrix for switching behaviour and the three predictor variables, namely: relational switching costs, perceived value and alternative attractiveness after deleting one question from both the relational switching costs and the perceived value scales.

Table 7.5: Correlation matrix for switching behaviour and the three predictor variables after deleting B7_2 and B8_3 (switching behaviour sample, N_2)

Correlation Matrix													
	B7_1	B7_3	B7_4	B7_5	B7_6	B7_7	B8_1	B8_2	B9_1	B9_2	B9_3	B9_4	B9_5
B7_1	1.000												
B7_3	.644	1.000											
B7_4	.702	.853	1.000										
B7_5	.449	.560	.549	1.000									
B7_6	.373	.506	.494	.690	1.000								
B7_7	.373	.551	.509	.629	.772	1.000							
B8_1	.227	.238	.226	.270	.252	.330	1.000						
B8_2	.272	.312	.289	.329	.344	.424	.627	1.000					
B9_1	-.186	-.079	-.071	-.125	-.225	-.272	-.189	-.412	1.000				
B9_2	-.144	-.103	-.070	-.143	-.165	-.234	-.111	-.250	.771	1.000			
B9_3	-.238	-.156	-.117	-.147	-.196	-.170	-.062	-.160	.617	.749	1.000		
B9_4	-.295	-.231	-.187	-.210	-.200	-.155	-.024	-.192	.573	.698	.897	1.000	
B9_5	-.373	-.274	-.260	-.272	-.244	-.206	-.070	-.202	.582	.709	.860	.898	1.000

7.5 VALIDATION OF THE RELATIONSHIP CHARACTERISTICS MEASUREMENT SCALES

7.5.1 Assessment of multicollinearity (switching intention sample, N_1)

Table 7.6 represents the assessment multicollinearity by indicating the variance inflation factor (VIF) and tolerance values for the switching intention sample.

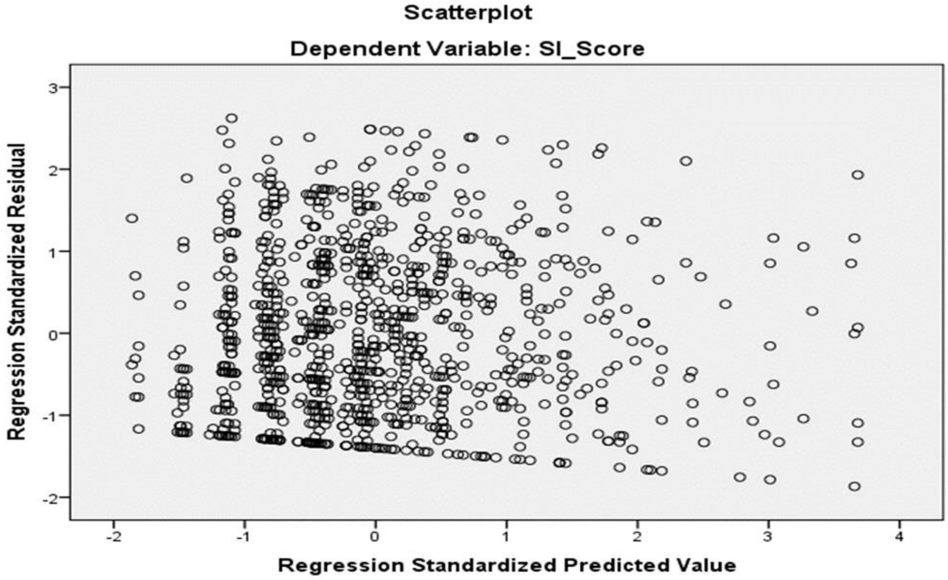
Table 7.6: Assessment of multicollinearity (switching intention sample, N_1)

Switching intention (N_1 = 985)		Unstandardised coefficients	Standardised coefficients	t-value	p-value	Collinearity statistics	
		B	Beta-value			Tolerance	VIF
Model 1	(Constant)	17.714		17.540	0.000		
	Relationship length	-0.124	-0.050	-1.574	0.116	0.946	1.057
	Relationship depth	0.002	0.106	3.266	0.001	0.925	1.081
	Relationship breadth	0.153	0.012	0.369	0.712	0.950	1.053

7.5.2 Linear regression assumptions for relationship characteristics (switching intention sample, N_1)

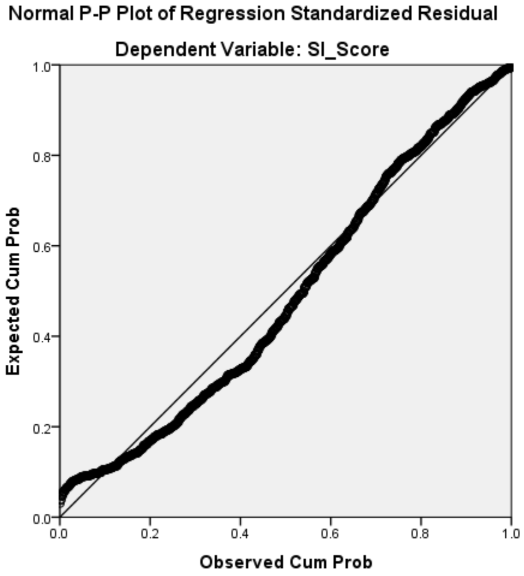
Figure 7.8 presents the scatterplot used to determine whether the assumption of homoscedasticity and linearity were met.

Figure 7.8: Scatterplot for the linear regression assumptions for relationship characteristics (switching intention sample, N_1)



P-P Plots used to determine whether the assumption of normality was met are presented in Figure 7.9.

Figure 7.9: Normality P-P Plot for the linear regression assumptions for the relationship characteristics (switching intention sample, N_1)



7.5.3 Assessment of multicollinearity (switching behaviour sample, N_2)

Table 7.7 represents the assessment multicollinearity by indicating the variance inflation factor (VIF) and tolerance values for the switching behaviour sample.

Table 7.7: Assessment of multicollinearity (switching behaviour sample, N_2)

Switching behaviour (N_2 = 128)		Unstandardised coefficients	Standardised coefficients	t-value	p-value	Collinearity statistics	
		B	Beta-value			Tolerance	VIF
Model 1	(Constant)	23.041		12.987	0.000		
	Relationship length	-0.164	-0.084	-0.951	0.343	0.956	1.046
	Relationship depth	0.001	0.120	1.318	0.190	0.899	1.112
	Relationship breadth	-0.953	-0.087	-0.951	0.343	0.895	1.118

7.5.4 Linear regression assumptions for relationship characteristics (switching behaviour sample, N_2)

The scatterplot used to determine whether the assumption of homoscedasticity and linearity were met is presented in Figure 7.10.

Figure 7.10: Scatterplot for the linear regression assumptions for relationship characteristics (switching behaviour sample, N_2)

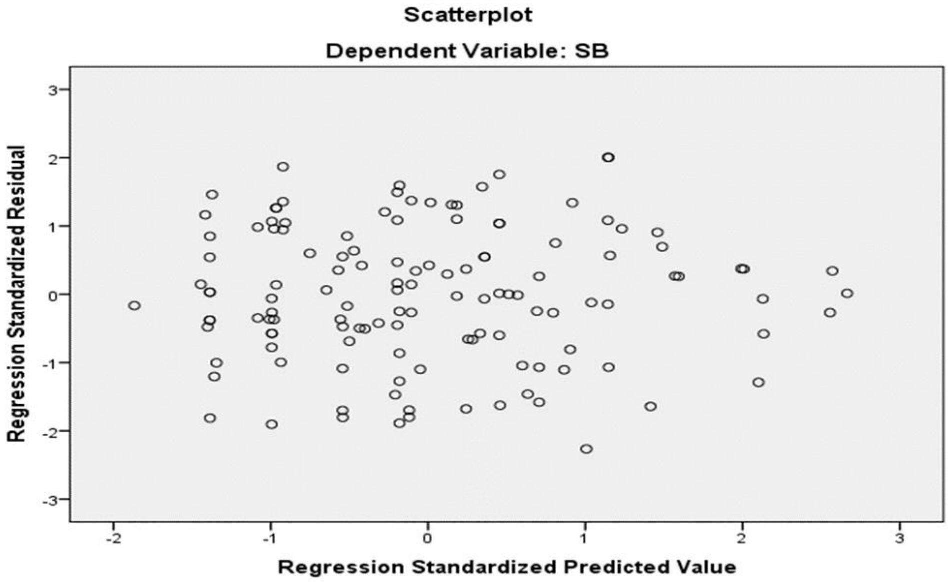
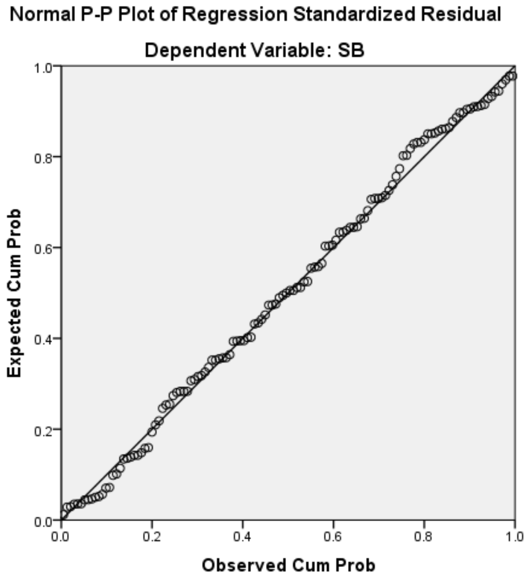


Figure 7.11 presents the P-P Plots used to determine whether the assumption of normality was met.

Figure 7.11: Normality P-P Plot for the linear regression assumptions for relationship characteristics (switching behaviour sample, N_2)



CONSULTA
DISCOVER SCIENTIFIC RESEARCH

6 September 2013

To whom it may concern

USE OF CONSULTA RESEARCH (PTY) LTD ONLINE COMMUNITY

Consulta hereby gives Ms MC van der Merwe permission to use our full online panel as part of the data collection for her Doctoral thesis.

The online panel consists of a database of panel members that regularly complete a variety of surveys for Consulta. Panel members are not offered an incentive to complete surveys and their participation is strictly voluntary.

Upon registration, panel members give consent to participate in the surveys. The potential panel member goes through a double opt-in process, which means that the respondent agrees twice that they are prepared to answer surveys and have the option to withdraw from the panel before being added to the database.

The opt-in procedure clearly explains that participation in the surveys is voluntary and that panel members have the option to withdraw from the panel at any time. Details of the terms and conditions can be found by clicking on the following link:
http://www.consultapanel.co.za/TermsAndConditions.aspx

Thus, panel members give "overall" consent to participate in all surveys, which implies that consent has already been given by all panel members to participate in Ms van der Merwe's study. In addition, respondents will be given the option to unsubscribe from the particular study, should they wish to do so.

Yours faithfully,

Ingrid Olivier
COMMUNITY MANAGER

Olivier
....
Signature

12/09/2013
....
Date

Consulta Research (PTY) LTD. Reg No. 1998/011948/07 VAT Reg No. 4920165448

Central Park | Building 1
Corner Witch hazel and Esdoring Street
Highveld Techno Park | Centurion | 0046
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www.consultapanel.co.za | www.clientx.co.za

Questionnaire A

SECTION 1: Screening questions	
A1 Are you able to independently choose which mobile network you use?	
Yes	
No	
A2 Which mobile network service do you currently use? If you currently make use of both contract and pre-paid, kindly select the one you consider to be your primary service.	
Contract	
Prepaid	
SECTION 2: Categorisation question	
A3 Which one of the following mobile networks do you consider to be your main provider?	
Cell C	
MTN	
Telkom Mobile (8ta)	
Virgin Mobile	
Vodacom	
SECTION 3: Branching question	
A4 Have you switched from another mobile network within the past 6 months?	
Yes	
No	

SECTION 4: Construct questions												
A5	**Please indicate the extent to which you agree or disagree that the statements below describe how you feel about switching from your current mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
A5.1	I expect to stay with my current mobile network for the foreseeable future	0	1	2	3	4	5	6	7	8	9	10
A5.2	When my contract with my current mobile network expires, I am likely to switch to another mobile network	0	1	2	3	4	5	6	7	8	9	10
A5.3	I have often considered changing from my current mobile network to another mobile network	0	1	2	3	4	5	6	7	8	9	10
A5.4	I am likely to switch to a mobile network that offers better services	0	1	2	3	4	5	6	7	8	9	10
A5.5	I am likely to switch to another mobile network because I have experienced problems with my current mobile network	0	1	2	3	4	5	6	7	8	9	10

A6	**Please indicate the extent to which you agree or disagree that the statements describe how you feel about the relationship that you have with your current mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
A6.1	I would miss dealing with the staff at my current mobile network if I switched to another mobile network	0	1	2	3	4	5	6	7	8	9	10
A6.2	I am more comfortable interacting with the staff working for my current mobile network than I would be if I switched to another mobile network	0	1	2	3	4	5	6	7	8	9	10
A6.3	The staff at my current mobile network matter to me	0	1	2	3	4	5	6	7	8	9	10
A6.4	I like talking to the staff at my current mobile network	0	1	2	3	4	5	6	7	8	9	10
A6.5	I like the public image that my current mobile network has	0	1	2	3	4	5	6	7	8	9	10
A6.6	I support my current mobile network as a firm	0	1	2	3	4	5	6	7	8	9	10
A6.7	I care about my current mobile network's brand / company name	0	1	2	3	4	5	6	7	8	9	10
A7	**Please indicate the extent to which you agree or disagree that the statements describe how you feel about the value that you receive from the services that you purchase from your mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
A7.1	My total monthly bill from my current mobile network is acceptable	0	1	2	3	4	5	6	7	8	9	10
A7.2	My current mobile network offers good value for money	0	1	2	3	4	5	6	7	8	9	10
A7.3	My current mobile network offers better value for money than what I would pay for the same service at another mobile network	0	1	2	3	4	5	6	7	8	9	10
A8	**Please indicate the extent to which you agree or disagree with the following statements about the difference between your current mobile network and other mobile networks.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
A8.1	All in all, other mobile networks would be more fair than my current mobile network	0	1	2	3	4	5	6	7	8	9	10
A8.2	Overall, other mobile networks' policies would benefit me much more than my current mobile network's policies	0	1	2	3	4	5	6	7	8	9	10
A8.3	I would be much more satisfied with the service available from other mobile networks than the service provided by my current mobile network	0	1	2	3	4	5	6	7	8	9	10
A8.4	In general, I would be much more satisfied with other mobile networks than I am with my current mobile network	0	1	2	3	4	5	6	7	8	9	10

A8.5	Overall, other mobile networks would be better to do business with than my current mobile network	0	1	2	3	4	5	6	7	8	9	10

A9 How long have you been with your mobile network?	
Less than 6 months	
6 to 12 months	
12 to 18 months	
18 to 24 months	
2 - 5 years	
5 - 8 years	
8 - 12 years	
12 - 15 years	
Longer than 15 years	
A10 What is your average monthly bill with your mobile network?	
R0 – R200	
R201 – R400	
R401 – R600	
R601 – R800	
R801 – R1000	
R1001 – R1250	
R1251 – R1500	
R1501 – R1750	
R1751 – R2000	
R2001 – R2500	
R2501 – R3000	
R3001 – R3500	
R3501 – R4000	
R4001 – R4500	
R4501 – R5000	
Above R5001	
A11 Which of the following additional services have you purchased from your mobile network? Check ALL that apply.	
Data bundles	
Roaming	
SMS bundles	
Other (Please specify)	
None of the above	
SECTION 5: Demographic questions	
A12 Please specify your year of birth.	

Questionnaire B

SECTION 1: Screening questions	
B1 Are you able to independently choose which mobile network you use?	
Yes	
No	
B2 Which mobile network service do you currently use? If you currently make use of both contract and pre-paid, kindly select the one you consider to be your primary service.	
Contract	
Prepaid	
SECTION 2: Categorisation question	
B3 Which one of the following mobile networks do you consider to be your main provider?	
Cell C	
MTN	
Telkom Mobile (8ta)	
Virgin Mobile	
Vodacom	
SECTION 3: Branching question	
B4 Have you switched from another mobile network within the past 6 months?	
Yes	
No	
B5 From which mobile network did you switch in the last 6 months? In other words, with which mobile network were you previously? Please select the network that you most recently switched from.	
Cell C	
MTN	
Telkom Mobile (8ta)	
Virgin Mobile	
Vodacom	

SECTION 4: Construct questions

B6	**Please indicate the extent to which you agree or disagree that the statements below describe how you feel about switching from your previous mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
B6.1	When I originally joined my previous mobile network, I expected to stay with them for long	0	1	2	3	4	5	6	7	8	9	10
B6.2	I intended to switch to another mobile network as soon as my contract with my previous mobile network expired	0	1	2	3	4	5	6	7	8	9	10
B6.3	I often considered changing networks when I was with my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B6.4	I intended to switch from my previous mobile network to a mobile network that offered better services	0	1	2	3	4	5	6	7	8	9	10
B6.5	I often had problems with my previous mobile network, which made me decide to switch to my current mobile network	0	1	2	3	4	5	6	7	8	9	10

B7	**Please indicate the extent to which you agree or disagree that the statements describe how you feel about the relationship that you had with your previous mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
B7.1	I miss dealing with the staff at my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B7.2	I am more comfortable interacting with the staff working for my current mobile network than I was interacting with the staff at my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B7.3	The staff at my previous mobile network mattered to me	0	1	2	3	4	5	6	7	8	9	10
B7.4	I liked talking to the staff at my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B7.5	I like the public image that my previous mobile network has	0	1	2	3	4	5	6	7	8	9	10
B7.6	I supported my previous mobile network as a firm	0	1	2	3	4	5	6	7	8	9	10
B7.7	I cared about my previous mobile network's brand / company name	0	1	2	3	4	5	6	7	8	9	10
B8	**Please indicate the extent to which you agree or disagree that the statements describe how you feel about the value that you received from the services that you purchased from your previous mobile network.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
B8.1	My total monthly bill from my previous mobile network was acceptable	0	1	2	3	4	5	6	7	8	9	10
B8.2	My previous mobile network offered good value for money	0	1	2	3	4	5	6	7	8	9	10
B8.3	My current mobile network offers better value for money than what I paid for the same service at my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B9	**Please indicate the extent to which you agree or disagree that the statements describe how you feel about the difference between your previous mobile network and other existing mobile networks.**											
	The scale below ranges from 0 to 10, where: 0 = Do not agree at all; 10 = Completely agree.	**Do not agree at all**										**Completely agree**
B9.1	All in all, my current mobile network is more fair than my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B9.2	Overall, my current mobile network's policies benefit me much more than my previous mobile network's policies	0	1	2	3	4	5	6	7	8	9	10
B9.3	I am much more satisfied with the service available from my current mobile network than the service provided by my previous mobile network	0	1	2	3	4	5	6	7	8	9	10
B9.4	In general, I am much more satisfied with my current mobile network than I was with my previous mobile network	0	1	2	3	4	5	6	7	8	9	10

B9.5	Overall, my current mobile network is better to do business with than my previous mobile network	0	1	2	3	4	5	6	7	8	9	10

B10 How long were you with your previous mobile network?	
Less than 6 months	
6 to 12 months	
12 to 18 months	
18 to 24 months	
2 - 5 years	
5 - 8 years	
8 - 12 years	
12 - 15 years	
Longer than 15 years	
B11 What was your average monthly bill with your previous mobile network?	
R0 – R200	
R201 – R400	
R401 – R600	
R601 – R800	
R801 – R1000	
R1001 – R1250	
R1251 – R1500	
R1501 – R1750	
R1751 – R2000	
R2001 – R2500	
R2501 – R3000	
R3001 – R3500	
R3501 – R4000	
R4001 – R4500	
R4501 – R5000	
Above R5001	
B12 Did you purchase any of the following additional services from your previous mobile network? Check ALL that apply.	
Data bundles	
Roaming	
SMS bundles	
Other (Please specify)	
None of the above	
SECTION 5: Demographic questions	
B13 Please specify your year of birth.	

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FACULTY OF ECONOMIC AND MANAGEMENT SCIENCES

RESEARCH ETHICS COMMITTEE

Tel: +27 12 420 4102
E-mail: berendien.lubbe@up.ac.za

19 September 2013

Strictly confidential

Prof Y Jordaan
Department of Marketing Management

Dear Professor Jordaan

Project:	A comparison between switching intention and switching behaviour in the South African mobile telecommunication industry
Researcher:	MC van der Merwe
Student No:	04252071
Promoter:	Prof Y Jordaan
Department:	Marketing Management

Thank you for the application you submitted to the Committee for Research Ethics, Faculty of Economic and Management Sciences.

I have pleasure in informing you that the Committee formally approved the above study on 17 September 2013. The approval is subject to the candidate abiding by the principles and parameters set out in the application and research proposal in the actual execution of the research.

The approval does not imply that the researcher, student or lecturer is relieved of any accountability in terms of the Codes of Research Ethics of the University of Pretoria if action is taken beyond the approved proposal.

The Committee requests that you convey this approval to the researcher.

We wish you success with the project.

Sincerely

PROF BA LUBBE
CHAIR: COMMITTEE FOR RESEARCH ETHICS

cc: Student Administration

New Member Registration Form

Page 1

Community Research:

If you enjoyed this survey, you now have the opportunity to become part of a Research Community.

What is a Research Community?: A Research Community has regular discussions on various business and market practices. You can make a difference and improve service levels and product offerings by sharing your views on topics such as financial matters, media use, lifestyle and technology, through surveys and discussions.

By being part of a Research Community you are able to influence thinking and have early access to insights of what's to come, and be eligible for awards based on your participation when applicable.

Would you like to join in and participate in community research surveys?

- ○ Yes
- ○ No

Page 2

CLICK THE APPLICABLE BOXES TO INDICATE YOUR PREFERENCE. YOU MAY SELECT MULTIPLE OPTIONS. YOU MAY ALSO DESELECT OPTIONS YOU ARE NOT INTERESTED IN.

	Online surveys	Telephonic interviews
Research across all industries	☐	☐

Add

From: The ConsultaPanel Team [mailto:frontdesk@consultapanel.co.za]
Sent: 24 October 2013 02:06 PM
To: patterns@mweb.co.za
Subject: Have your say! Tell us why consumers switch network providers.

This email contains images. Please remember to enable images for it to display correctly.

consulta your survey panel

Hi Ethel

New mobile telecommunications questionnaire!

ConsultaPanel – like the inquisitive busybody that we are – has partnered with a Doctoral student from the Department of Marketing Management at the University of Pretoria as part of our recently launched initiative to explore deeper into the mobile telecommunications industry. We present you with the latest questionnaire in our mobile telecommunications campaign.

This questionnaire aims to investigate **what influences consumers to switch mobile network service providers.**

Click here to have your say.

This questionnaire will close as soon as we have enough responses, so get started ASAP!

Remember that you can also complete the questionnaire on your ConsultaPanel Dash smartphone or tablet!

Ciao,

The ConsultaPanel Team