CHAPTER 5:
RESEARCH DESIGN AND METHODOLOGY OF THE STUDY

5.1 INTRODUCTION

The main components of market driving have been related to market sensing, influencing of customer preferences and alliance formation activities. Firm-internal activities that influence a market-driving ability are entrepreneurial behaviour, strategic orientation, entrepreneurial capital and corporate entrepreneurial management. The outcomes of a market-driving ability have been described as increasing firm performance and relative competitive advantage. The building of a theoretical model of all these components has been described in chapter four.

The management question that needs to be addressed is: Can market driving and market-driving ability and its influencing factors be assessed in the South African healthcare industry?

In order to address the management question from an empirical perspective, the following chapter outlines the research problem and objectives of this study as well as the research methodology. Aspects that are included in the discussion of the research methodology are the research design, sampling procedures, data collection and data analysis approaches.

5.2 RESEARCH PROBLEM

In chapter two it was pointed out that entrepreneurship and marketing research share a substantial amount of commonality. Various concepts relating to innovation, flexibility, change and opportunities, as well as managerial and organisational principles, are commonly used in both disciplines. One of the goals of both disciplines is to understand and describe firm performance and relative competitive strength. Research at the interface is especially concerned with the explanation of exceptional performance, which cannot be explained with the current understanding of a market-driven organisation. Exceptional performance has been associated with a firm's ability to achieve market driving (Kumar *et al*., 2000; Schindehutte *et al*., 2008).

It has been argued that market driving is a specific organisational ability that requires several activities to be able to shape, change and create the market structure and/or the behaviour of market players. It has also been stated that in order to pursue market driving, certain firm-internal capabilities need to be demonstrated and the outcomes of a market-driving approach result in firm performance and relative competitive strength.

The purpose of this study is to measure market driving and determine firm-internal factors that influence an organisation's market-driving ability in the South African healthcare industry.

The management question that is derived from this is: Can market driving and market-driving ability and its influencing factors be assessed in the South African healthcare industry?

From the management question the following more specific research questions can be formulated (Cooper & Schindler, 2008:118):

- Can market driving be measured by assessing a firm's activities in market sensing, influencing customer preferences and alliance formation?
- Can internal factors such as a firm's orientation towards corporate entrepreneurial management; entrepreneurial capital; strategic orientation and entrepreneurial behaviour predict market-driving ability?
- Can firm performance and relative competitive strength be related to the market-driving ability of a firm?
- Do moderating factors such as management level and industry focus influence the strength of the relationship between the internal factors and market-driving ability?

The construct of market driving, its influencing factors and the outcomes are currently not well understood. So far no formal study has been conducted in South Africa that addresses the measurement of market driving and determines influencing factors on market-driving ability and its consequences.

5.3 RESEARCH OBJECTIVES

The primary research objective is to measure market driving and determine firm-internal factors that influence an organisation's market-driving ability in the South African healthcare industry.

The primary research objective is supported by secondary objectives which are classified into objectives that can be achieved by means of literature study and by means of an empirical case study.

The literature study determined:

- The link between entrepreneurship and marketing research at the interface;
- The constructs and concepts that are common to the disciplines of marketing and entrepreneurship;
- Various research studies that investigate market-driving activities in firms;
- Constructs and concepts that have been taken from the marketing and entrepreneurship field to explain market driving; and
- Constructs and concepts from both disciplines that are considered to impact on market-driving ability.

On the basis of the literature study a conceptual model of market-driving ability in corporate entrepreneurship was developed. Statistical modelling by means of a case study was used to determine the predictive quality of the model.

The empirical study was to determine:

- Whether market driving can be measured by market sensing, influencing of customer preferences and alliance formation;
- Which firm-internal factors influence market-driving ability;
- Whether market-driving ability influences different outcome parameters; and
- Whether moderating variables influence the relationship between firm-internal factors and market-driving ability.

The scope of the research is the South African healthcare industry, which comprises four different segments: the pharmaceutical industry, medical device manufacturers, wholesalers and distributors of pharmaceuticals and open medical schemes. The research did not consider environmental factors that might influence a firm's decision making, such as the current development of a national health insurance system in South Africa.

5.4 HYPOTHESES

In chapter four, propositions for this study were outlined. Cooper and Schindler (2008:64) state that propositions are statements about concepts that may be true or false. Once the propositions are formulated for empirical testing, they are formulated as hypothesis. Hypotheses are more tentative in nature.

The hypotheses for this study were derived from the main purpose of this study: to build a model to measure market driving and determine firm-internal factors that influence an organisation's market-driving ability. Jaccard and Jacoby (2010:170) emphasise that the path diagram is the essence of multiple hypotheses.

The null hypothesis reflects the concept that there is no difference between two groups, whereas the alternative hypothesis states that there is some difference. If the null hypothesis can be rejected, it signifies support for the alternative hypothesis. The alternative hypotheses can be formulated as exploratory or directional. Exploratory hypotheses do not postulate any direction of the difference between two groups, whereas directional hypotheses do (Diamantopoulos & Schlegelmilch, 2000:132-133).

For the purpose of this study, both exploratory and directional hypotheses were formulated. Exploratory hypotheses are used for the measurement models (H1 to H15) and the moderating effects models considering management level (model 2) (H22 to H25) and industry focus (model 3) (H26 to H29). Directional hypotheses (H16 to H21) are used for the structural direct effects model (model 1).

The hypotheses were tested with SmartPLS (Ringle, Wende & Will, 2005). The procedures are outlined in section 5.5.5.2.

The hypotheses for this study were outlined in chapter one.

5.5 RESEARCH METHODOLOGY

The following paragraphs outline the research methodology, which comprises the research design, sampling, data collection and data analysis.

5.5.1 Research design

The study was designed as a formal study in the South African healthcare industry. The two parts of the study were the literature review and the empirical study. The literature study provided insights into the field of research, helped to clarify the boundaries of the research, and identified the relevant constructs and concepts that were used to formulate the conceptual framework of market-driving ability in corporate entrepreneurship.

The literature study determined:

- The link between entrepreneurship and marketing and research at the interface;
- The constructs and concepts that are common to the disciplines of marketing and entrepreneurship;
- Various research studies that have investigated market-driving activities in firms;
- Constructs and concepts that have been taken from the marketing and entrepreneurship field to explain market driving; and
- Constructs and concepts from both disciplines that are considered to impact on market-driving ability.

The empirical study covered the conceptual framework, which consisted of measures of market driving and firm-internal influencing factors, moderators and outcomes of market-driving ability. The conceptual framework was transformed into a statistical model. The generated data gave information about the measure of market driving. Furthermore, firm-internal factors that influenced market-driving ability were determined. Moderating effects on the relationship between firm-internal factors and market-driving ability could be identified. Finally, the influence of market-driving ability on outcomes parameters could be established.

5.5.1.2 Purpose of the study

The purpose of the study is fourfold. First, the study aims to give an understanding of the measurement of market driving in corporate entrepreneurship. Second, firm-internal influencing factors on market-driving ability are determined. Third, moderating effects, such as the management level and the industry focus, on the relationship between firm-internal factors and market-driving ability can be identified. Finally, the outcomes of a market-driving ability are assessed, considering firm performance and relative competitive strength.

The study could provide findings to organisations that wish to assess and increase their level of market driving in their business and hence provide a starting point for their internal analysis.

5.5.1.3 Time dimension

According to Bryman and Bell (2007:55), a cross-sectional study requires more than one case, takes place at a certain time, includes quantitative data and examines patterns of association.
The empirical, cross-sectional study was conducted in South Africa between August and December 2010.

5.5.1.4 Topical scope

The topical scope of the study refers to its breadth and depth (Cooper & Schindler, 2008:144). Statistical studies try to cover population characteristics and hence the breadth, whereas case studies are more concerned with an in-depth understanding of the context and the relationships (Cooper & Schindler, 2008:144). This study used a case-study approach. The construct of market driving is so far not well understood and hence insights into the measurement of the construct and its relationships with other constructs are important.

5.5.1.5 Research environment

The research environment refers to studies that are conducted in the actual environment under so-called field conditions and studies that are conducted under laboratory conditions (Cooper & Schindler, 2008:145).

The study took place under field conditions in the South African healthcare industry.

5.5.1.6 Participants' perception

Participants' perceptual awareness influences the response behaviour. Participants might change their response behaviour when they notice that they are being observed or questioned (Cooper & Schindler, 2008:145). Sometimes respondents might answer questions according to what is considered socially acceptable.

Although respondents were asked to answer every question according to their personal perception, it needs be considered that respondents in this study might have adapted their response behaviour. Further, respondents were assured that there were no correct or incorrect answers and that confidentiality of all their responses was guaranteed. However, it cannot be established whether participants changed their response behaviour in the interviews.

5.5.2 Sampling

A sample is considered as a subset of a given population of interest. Reasons for using a sample instead of a census of the whole population of interest are mainly attributed to cost and time issues (Cooper & Schindler, 2008:375; Diamantopoulos & Schlegelmilch, 2000:10-11).

The sample for this study consisted of employees in different management levels in the South African healthcare industry.

When a sample is drawn from the population, a sampling error occurs which describes the difference between the results based on the sample versus the results that would have been obtained if the population was investigated. The sampling error can be statistically evaluated if the sample was obtained by means of probability sampling. The basic sampling techniques are described as probability and non-probability sampling. Probability sampling follows a procedure whereby every respondent in the defined population has a non-zero chance of getting selected. Non-probability sampling leaves the sample selection to the discretion of the researcher (Cooper & Schindler, 2008:379-380; Diamantopoulos & Schlegelmilch, 2000:12-13).

Non-probability sampling is frequently used (Levy & Lemeshow, 2008:19). Reasons for choosing non-probability sampling can be attributed to cost and time issues. Whereas probability sampling requires more planning to ensure that the correct respondents are identified, non-probability sampling does not require these procedures. However, from non-probability sampling no generalisations about population parameters can be made (Cooper & Schindler, 2008:396-397).

The methods of non-probability sampling are convenience sampling, purposive sampling and snowball sampling. In convenience sampling, the researcher is free to choose whom to interview. Purposive sampling can be judgement sampling or quota sampling. Judgement sampling requires the respondent to fulfil some criteria. In quota sampling, several criteria that are found in the population are applied to the sample, for example the distribution between male and female employees. Snowball sampling can be applied in research situations where respondents are difficult to identify and contact. Respondents that have been identified based on previous probability or non-probability methods refer the research to persons with similar characteristics (Babbie, 2010:193; Cooper & Schindler, 2008:397-399).

The study used a non-probability sample using purposive sampling and snowball sampling. From an initial list with contact details of persons, the relevant industries and the relevant management level were identified. Additionally, screening criteria of minimum turnover and minimum number of employees were introduced to ensure that the firms included represented medium to large sized enterprises in South Africa. In a second step, a snowball sampling technique was applied. Persons from the original list were asked to refer other colleagues from their organisation. The reason for choosing a non-probability sampling technique was that respondents in management positions are difficult to identify and to contact.

In order to determine the response rate for this study the following formula was applied (Bryman & Bell, 2007:196).

$$\frac{\text{Number of usable questionnaires}}{\text{Total sample – unsuitable or uncontactable members of the sample}} \quad \text{x } 100$$

In total, 6015 contacts were made, of which 602 contacts did not meet the screening criteria, either regarding the management level or the organisational characteristics relating to minimum turnover or number of employees. Out of the remaining 5413 contacts, 962 interview appointments could be made, which resulted in 328 conducted interviews. The reason for the low number of realised interviews was related to busy work schedules which prevented respondents from participating. Hence the response rate for this study was:

$$\frac{328}{6015 - 5053} \text{ x } 100 = 34.1\ \%$$

5.5.3 Data collection

Data collection involves the gathering of secondary and primary data. Secondary data can be gathered by means of a literature research in books, journals, and reports. Electronic databases available over the internet provide access to full text articles in electronic format (Bryman & Bell, 2007:107-108). This study made much use of electronic databases to identify relevant articles.

The primary data can be collected by using a communication approach or observation (Cooper & Schindler, 2008:214). This study used a communication approach in the form of a fully structured survey. The survey was conducted using telephone interviews.

The advantages of telephonic surveys have been described as follows (Cooper & Schindler, 2008:223).

- They are more cost efficient than personal interviews.
- They make it possible to cover a wide geographical area.
- They offer better access to hard-to-reach participants through repeated contacts.

The major disadvantages are described as (Cooper & Schindler, 2008:223):

- Lower response rate than personal interviews.
- Limitations to the interview length.
- The fact that illustrations cannot be used.

In communication research, various sources of error can occur, such as interviewer error and participant error (Cooper & Schindler, 2008:215).

Interviewer error occurs when the interviewer cannot achieve full participant cooperation, which then results in a sampling error, since the sample tends to be biased. If the interviewer fails to record answers accurately or completely, a data entry error occurs. Other interviewer errors include cheating, influencing respondents' behaviour or the failure to establish an appropriate environment (Cooper & Schindler, 2008:218). Although interviewer error cannot be ruled out for this study, precautions were taken to avoid interviewer error. Answers were thoroughly recorded, quality checks were conducted and respondents were ensured anonymity and confidentiality.

Participant errors occur if the respondent does not have the required information, does not understand his or her role in the interview or lacks motivation to cooperate (Cooper & Schindler, 2008:219-221). A non-response error occurs when the person does not provide usable responses and differs from those respondents who do respond on the characteristics of interest. In order to generalise findings it is necessary to report non-response error (Dooley & Lindner, 2003:101).

To determine non-response error, three different methods are described, of which at least one should be applied to research (Armstrong & Overton, 1977:396-397). First, results from the survey can be compared with known values from the population. Second, subjective estimates considering, for example, socioeconomic differences between respondents and non-respondents, can be conducted. Third, extrapolation methods can be used. Extrapolation assumes that late respondents behave in a similar way to non-respondents. A comparison can be conducted between answers of respondents that answer in the early stages of the data collection with those of respondents that participate in later stages (Armstrong & Overton, 1977:397; Dooley & Lindner, 2003:102-103).

In order to test for non-response error in this study, the following H_0 hypothesis was tested using SPSS V.9.0 (2004): There is no difference between the answers of early versus late respondents with regard to the individual questions. The hypothesis was tested using Wilks' lambda (Guthrie, Spell & Ochoki Nyamori, 2002:190). The analysis showed no difference between early versus late respondents (Wilks' lambda = 0.646, $p > 0.10$). Although non-response error cannot completely be ruled out, this result gives more confidence in external validity.

5.5.3.1 Instrument used to collect empirical data

A structured questionnaire was used to collect the empirical data.

The questionnaire started with questions referring to informed consent and assuring confidentiality of all responses. Screening questions referring to the level of management, the industry focus of the organisation, and turnover and number of employees were included to ensure that the sample consisted of relevant subjects and included firms representing medium to large enterprises. Biographical information was also collected. These six questions related to gender, age, industry focus of the organisation, the department the respondent currently worked in, the number of years of experience in the healthcare industry and the number of years the respondent had worked in the current position.

The constructs and concepts of the market-driving model have been outlined in chapter four.

Concepts refer to characteristics associated with certain objects, situations or behaviour. Constructs refer to abstract concepts which are invented for research or theory-building purposes. Constructs are built of more concrete concepts, especially when the object of the study cannot directly be observed (Cooper & Schindler, 2008:57-58). Diamantopoulos and Schlegelmilch (2000:21) note, however, that in research constructs and concepts are often used interchangeably.

For the purpose of this study, constructs refer to the following independent latent variables: corporate entrepreneurial management, entrepreneurial capital, strategic orientation, entrepreneurial behaviour. Each of these constructs consists of several concepts that are measured by observed variables (indicators). Corporate entrepreneurial management is measured as a formative construct which is formed by the three concepts of risk-taking, management support and the organisational structure of the firm. Entrepreneurial capital is measured as a reflective construct consisting of human, social and financial capital. Strategic orientation is measured as a formative construct. It consists of information generation, information dissemination, interfunctional coordination and innovation intensity. Entrepreneurial behaviour is measured as a formative construct comprising proactiveness and responsiveness to information.

The dependent construct in the model is market-driving ability. Market-driving ability represents the structural part of the model which is influenced by the independent constructs. Market driving represents the measurement part and consists of activities relating to market-sensing, influencing of customer preferences and alliance formation. The impact of market-driving ability on two reflective outcome parameters, firm performance and relative competitive strength was determined.

5.5.3.2 Measurement of the research instrument

The process of measurement involves assigning symbols to characteristics of persons, objects or events. The symbols are most often numbers to allow for statistical manipulation of the data (Diamantopoulos & Schlegelmilch, 2000:22-23).

Carifio and Perla (2007:107-109) emphasise that a clear distinction needs to be made between a scale and response formats. Individual items are judged on a response format which may be a nominal, ordinal, interval or ratio data type. A measurement scale consists of a group of items; however, it has a more complex meaning than the items that form the scale.

The following paragraphs outline the Likert response format and the optimal number of scale points. The type of empirical data that Likert scales produce is discussed.

One of the response formats and scales most often used in various research disciplines is the Likert response format and the Likert scale. Likert (1932:14) suggested a summed scale for the assessment of attitudes in surveys, where items are judged on a response format with five alternatives, ranging from “strongly approve” to “strongly disapprove” (Clason & Dormody, 1994:31).

Various research studies have tried to identify the optimal number of scale points that achieves maximum reliability and validity in the Likert response format (Chang, 1994; Lissitz & Green, 1975; Matell & Jacoby, 1972; Preston & Colman, 2000; Weng, 2004). The studies showed controversial results. Preston and Colman (2000:2), Lissitz and Green (1975:10), Chang (1994:205) and Weng (2004:956) report that some studies show that reliability is independent of the number of response categories; others show that there is an impact. Different studies find support for any number of response categories between two and 11 and even 100. Whereas reliability is an important issue addressed in various studies, validity is examined to a lesser extent, and the aspect of respondent preferences or respondent ability is discussed even less often (Preston & Colman, 2000:3).

Lissitz and Green (1975:12) and Chang (1994:212) find that it is possible to increase internal consistency artificially by increasing the number of scale points. However, this effect levels off after five to six scale points. Maximising reliability possesses the risk of jeopardising construct validity. Churchill and Peter (1984:370) observe that if items are too similar, the risk of construct under-identification is high, since not all aspects of the construct might be captured.

Another important aspect to consider in the design of response format is respondents' preferences and their capabilities. Preston and Colman (2000:9-10) find that response categories of five, seven and 10 are most preferred by respondents. Weng (2004:959) notes that a response format needs to consider the respondents' capability to discriminate. Increasing the number of scale points does not necessarily lead to better discrimination. Weng (2004:969) found that respondents at the level of college students should provide consistent results with seven and six-point response formats. Preston and Colman (2000:13) argue that five-point scales are quick and easy to use.

Although a unanimous answer from previous studies on the optimum number of scale points in the response format could not be obtained, the main aspects considered in the design of the response format for this study were reliability and validity of scale items, as well as respondents' preferences.

The study mainly used items that had been used in previous studies that showed acceptable reliability and validity results. Items taken from previous studies used a seven-point response format (Barringer & Bluedorn, 1999:428; Khandwalla, 1977:639; Lumpkin & Dess, 2001:439; Miller & Friesen, 1982:8; Narver & Slater, 1990:23) a six-point response format (Narver *et al.,* 2004:340) or a five-point response format (Hornsby *et al*., 2002:263; Jaworski & Kohli, 1993:59).

For the purpose of this study four pre-tests were conducted with persons in the South African healthcare industry. The purpose of the pre-tests was threefold. First, respondents were asked to complete the full questionnaire and were timed while doing so. Respondents needed approximately 15 minutes to complete the questionnaire. Second, an item purification process took place. Respondents were asked to check each item for understanding and appropriate wording. Suggestions that resulted were incorporated into the final questionnaire. Third, respondents were asked with which response format they would feel most comfortable. All four persons preferred a five-point response format, which was consequently applied.

The construct of corporate entrepreneurial management was measured by a total of 10 questions measuring the concepts of risk-taking, management support and organisational structure. The five-point response format used anchor labels where 1=strongly disagree, 2=disagree, 3=neither agree nor disagree, 4=agree and 5=strongly agree.

Entrepreneurial capital consisted of the concepts of human, social and financial capital and used a total of 9 questions. The five-point response format used anchor labels where 1=strongly disagree, 2=disagree, 3=neither agree nor disagree, 4=agree and 5=strongly agree.

Strategic orientation was measured by a total of 15 questions covering the concepts of information generation, dissemination, interdepartmental coordination and innovation intensity. The five-point response format used anchor labels where 1=strongly disagree, 2=disagree, 3=neither agree nor disagree, 4=agree and 5=strongly agree.

Entrepreneurial behaviour was measured by six questions relating to proactiveness and responsiveness to information. The five-point response format used anchor labels where 1=strongly disagree, 2=disagree, 3=neither agree nor disagree, 4=agree and 5=strongly agree.

Market driving was measured by partly self-constructed questions. A total of 14 questions were used to assess market sensing, influencing of customer preferences and alliance formation.

For market-sensing activities a five-point response format with anchor labels was used ranging from 1=never used, 2=seldom used, 3=neither never used nor very frequently used, 4=frequently used, 5=very frequently used.

Customer preferences and alliance formation used a five-point response format with anchor labels where 1=strongly disagree, 2=disagree, 3=neither agree nor disagree, 4=agree and 5=strongly agree.

Relative competitive strength was measured by five questions using the five-point response format with anchor labels ranging from 1=very similar, 2=similar, 3=neither similar nor different, 4=different, 5=very different.

Firm performance was measured by three questions using the five-point response format with anchor labels ranging from 1=decreased significantly, 2=decreased, 3=remained the same, 4=increased, 5=increased significantly.

In today's research Likert scales are considered to produce ordinal data. However, when it comes to data analysis, instead of conducting non-parametric tests, means are calculated and parametric tests are performed (Jamieson, 2004:1212). The following paragraphs demonstrate the essential differences between Likert response formats and Likert scales.

The Likert response format is considered to be ordinal. The Likert scale, however, produces, empirically, interval-level scales, which allow for the use of parametric tests (Carifio & Perla, 2007:110,115; Parker, McDaniel & Crumpton-Young, 2002:4). In order to understand this at first sight contradictory claim it is necessary to draw a clear distinction between the response format and the measurement scale. These are considered to be two very different things, based on the properties and the levels they measure. The response format delivers a judgement of a single item (micro level), whereas the measurement scale (macro level) considers a minimum group of items which are analysed (Carifio & Perla, 2007:108,110). The derived indices from a measurement scale are conceptually and empirically different from the item-responding format (Carifio & Perla, 2007:108; Norman, 2010:629). If the derived data are reasonably distributed inferences about means and differences can be drawn. Even in situations of non-normal distributions or skewness various tests such as analysis of variance or the Pearson Correlation Coefficient are very robust (Carifio & Perla, 2007:110-111; Carifio & Perla, 2008:1150; Norman, 2010:629).

Carifio (1978 in Carifio & Perla, 2007:109) showed in a study that data produced from a response format of a 100 millilitre line with two to seven anchor points was empirically linear and interval in character. The same study was applied using a response format of five to seven scale points. The produced data were compared with the first study and shown to be highly correlated. This lends support to the conclusion that Likert scales produce empirically interval data.

For the purpose of this study a Likert response format and Likert-type scales were used, which were considered to produce empirical interval data.

Some of the questions were negatively worded, which required reverse coding before analysis could be conducted (Spector, 1992:22). The scaling for the following questions was reversed: questions 2, 9, 10, 12, 13, 18, 23, 31, 36, 54, 57.

5.5.3.3 Reliability and validity of the measuring instrument

The extent to which measures are free of systematic and random error indicates the validity of the measure. Reliability is indicated by an absence of random measurement error (Cooper & Schindler, 2008:293; Diamantopoulos & Schlegelmilch, 2000:33).

Reliability is concerned with the reproduction of consistent measures. Reliability considers stability, internal reliability and inter-rater consistency (Bryman & Bell, 2007:162-164). Stability is assessed with the test-retest method, which requires the administration of the same test to the same sample at a different time (Bryman & Bell, 2007:162; Cooper & Schindler, 2008:293). Due to the cross-sectional characteristic of this study, test-retest reliability could not be determined.

Internal reliability or internal consistency refers to the assessment of homogeneity among items. Various tests can be performed to determine reliability (Bryman & Bell, 2007:164; Cooper & Schindler, 2008:294).

Reliability is a prerequisite for validity, but it is not a sufficient condition (Diamantopoulos & Schlegelmilch, 2000:33; Nunnally & Bernstein, 1994:90). Validity describes the extent to which the measures of a concept actually measure that concept. Various types of validity can be distinguished. Internal validity includes construct validity, content validity and criterion related validity (Babbie, 2010:150; Bryman & Bell, 2007:164; Cooper & Schindler, 2008:290).

In order to determine the appropriate reliability and validity measures for this study, it is important to recall the different measurement types for constructs and concepts. The parts of the construct needed to be assessed differently, because some of the constructs, such as corporate entrepreneurial management, strategic orientation, entrepreneurial behaviour and market driving were constructed as first-order reflective, second-order formative constructs (Burke Jarvis *et al*., 2003:205). Further, it needs to be considered that reliability and validity were assessed as part of the overall statistical model which used partial least squares path modelling. The properties of partial least squares path modelling (PLS-PM) are outlined in section 5.5.5.2.

The reliability of reflective concepts can be assessed by composite reliability and outer standardised loadings. Compared with Cronbach's alpha, composite reliability considers that indicators have different loadings which measure their contribution to the explanation of the latent variable. However, the interpretation of composite reliability is the same as for Cronbach's alpha. The outer standardised loadings determine the correlation between the indicator and the latent variable that it is supposed to measure, which should be higher than 0.7 (Henseler *et al*., 2009:299). However, Chin (1998:325) notes that outer loadings with 0.5 and 0.6 can also be considered if research development is in early stages. Henseler *et al.* (2009:299) also note that eliminating of indicators should only be conducted if composite reliability increases. This study considered a cut-off criterion of 0.5.

The loadings of the reflective first-order constructs showed that 10 items out of a total of 62 measurement items had to be removed, as they did not meet the cut-off criterion of 0.5. Although proactiveness showed low loadings for two out of three indicators, one indicator with low loadings was retained, since latent variables with only one indicator cannot determine measurement error (Fornell, 1983:445). Baumgartner and Homburg (1996:144) note that even latent variables with two indicators might be problematic. Annexure B shows the table with original indicator loadings.

Validity of reflective concepts and constructs was determined by convergent and discriminant validity. Convergent validity is determined with the average variance extracted (AVE). This describes the amount of variance that is captured by the latent variable relative to the amount due to measurement error. An AVE value of at least 0.5 indicates that 50% of the variance of the indicators is accounted for by the latent variable (Chin, 1998:321; Fornell & Larcker, 1981:46; Henseler *et al*., 2009:299).

AVE was calculated for each measurement model after items with low loadings had been removed. Considering all first-order reflective concepts that were used for this study, human capital showed a low AVE value (0.4781). Further, the second-order reflective construct entrepreneurial capital also demonstrated a low AVE value (0.2666). The following table summarises the AVE values for all reflective concepts.

TABLE 5.1: AVE values for reflective concepts

Reflective concept/construct	AVE
Proactiveness (PRO)	0.5826
Responsiveness (RESP)	0.6100
Information generation (GEN)	0.5878
Information dissemination (DIS)	0.7087
Interdepartmental coordination (COO)	0.6569
Innovation intensity (INN)	0.7922
Financial capital (FIN)	0.7144
Human capital (HUM)	*0.4781*
Social capital (SOC)	0.5334
Entrepreneurial capital (CA)	*0.2666*
Risk-taking (RISK)	0.7301
Management support (MGT)	0.7488
Organisational structure (STRU)	0.8309
Alliance formation (ALL)	0.6284
Market sensing (SENS)	0.5540
Customer preferences (CUST)	0.5587
Relative competitive strength (COMP)	0.6349
Firm performance (PERF)	0.7687

Discriminant validity can be assessed by the Fornell-Larcker criterion on a construct level (Fornell & Larcker, 1981:41) and cross-loadings on an indicator level (Henseler *et al.,* 2009:299-300). The Fornell-Larcker criterion determines how much more variance a latent variable shares with its indicators than with other latent variables representing a different block of indicators (Chin, 1998:321; Henseler *et al.,* 2009:299; Ringle, 2004:21). As the only reflective construct on the second-order level is entrepreneurial capital (CA), a meaningful comparison with the other constructs, which are formative, cannot be made. Hence, the Fornell-Larcker criterion is not established for this study.

On the indicator level, cross-loadings were examined. For that purpose correlations between the indicators and their respective latent variable were conducted. An indicator should load higher on the respective latent variable than on other latent variables (Chin, 1998:321; Henseler *et al*., 2009:300; Ringle, 2004:21).
Cross-loadings were examined for the first-order reflective concepts, excluding items that were removed due to low outer loadings. No cross-loadings could be found, which indicates discriminant validity of the reflective concepts. The table is presented in Annexure 3.

Table 5.2 summarises the discussed reliability and validity measures for reflective concepts.

TABLE 5.2: Reliability and validity for reflective concepts

Reflective concepts	**Description**
Reliability measures	• Composite reliability > 0.70 satisfactory • Outer standardised loadings > 0.707; however in early stages of scale development 0.50 and 0.60 acceptable
Validity measures	• Convergent validity: AVE > 0.5 • Discriminant validity: Fornell-Larcker criterion, cross-loadings

Sources: Chin (1998:325); Henseler *et al*. (2009:299)

In formative constructs reliability cannot be assessed in the same way as with reflective constructs, as indicators can have a positive, negative or zero correlation between each other and the latent variable (Diamantopoulos & Winkelhofer, 2001:271; Diamantopoulos *et al*., 2008:1215). However, validity is an important aspect of formative measurement models and can be assessed on both a theoretical and a statistical level (Henseler *et al*., 2009:301).

The theoretical aspects of validity concern content specification and indicator specification (Diamantopoulos & Winkelhofer, 2001:271-272).

Content validity is considered to be satisfactory if it covers a range of meanings that the concept covers (Babbie, 2010:155; Cooper & Schindler, 2008:290). In formative constructs this aspect is very important, since the exclusion of relevant facets of the construct could lead to an incomplete specification of the latent variable (Diamantopoulos & Winkelhofer, 2001:217). Nunnally and Bernstein (1994:102) note that content validity requires a plan and procedure to test the material before it is administered.

For this study content validity can be considered good. The questionnaire was tested and discussed with four industry experts, who made sure that the questionnaire captured the necessary constructs and was sound in terms of instructions, content, wording and timing.

Indicator specification addresses the issue of capturing a wide variety of meanings of the construct (Diamantopoulos & Winkelhofer, 2001:271). Indicator specification was also discussed with the industry experts and was considered to be adequate.

On the statistical level, formative constructs need to be assessed regarding multicollinearity. Multicollinearity presents a serious problem to formative measurement, as it makes it difficult to determine each concept's influence on the overall construct (Diamantopoulos & Winkelhofer, 2001:272). Multicollinearity can be determined by the variance inflation factor (VIF). VIF values of higher than 10 indicate collinearity (Henseler *et al.,* 2009:302). In formative measurement more conservative values are applied, which signify multicollinearity even at values of 3.3 (Roberts & Bennett Thatcher, 2009:18). For this study multicollinearity was determined for the formative constructs of the model. Entrepreneurial behaviour (BE), strategic orientation (SO), corporate entrepreneurial management (CE) and market driving (MD) were submitted to test multicollinearity. It was found that multicollinearity was not a problem in this study. Table 5.3 summarises the VIF values.

TABLE 5.3: VIF values for formative constructs

Formative construct	VIF
BE	1.837
SO	2.809
CE	1.766
MD	2.485

Note: Values were generated in SPSS V.9.0 (2004)

External validity can be assessed by correlating the formative construct with other related variables (Diamantopoulos & Siguaw, 2006:270; Foedermayr, Diamantopoulos & Sichtmann, 2009:61; Henseler *et al*., 2009:301). Diamantopoulos and Winkelhofer (2001:272) suggest relating the formative construct to an overall global item that summarises the main aspects that the construct measures. In order to assess external validity for the second-order formative constructs entrepreneurial behaviour (BE), strategic orientation (SO), corporate entrepreneurial management (CE) and market driving (MD), the questionnaire included two items per construct that summarised the essence of each construct. Correlation analysis between the formative constructs and these two indicators showed significant correlations, which allowed the establishment of external validity. The following table summarises the formative constructs, the indicators and the significance level.

TABLE 5.4: External validity of second-order constructs

Indicator	Formative second-order constructs			
	BE	SO	CE	MD
Q46	0.195*			
Q47	0.239*			
Q48		0.146*		
Q49		0.187*		
Q44			0.191*	
Q45			0.198*	
Q59				0.218*
Q60				0.228*

Note: Correlation values are generated in SPSS V.9.0 (2004); * indicates significance at 0.01 level.

Construct validity, including nomological validity, can be established for formative constructs (Diamantopoulos *et al.,* 2008:1216). Nomological validity can be established by examining the construct's relation to other related constructs in the model. The theoretical relationship of the respective constructs should be based on previous research (Diamantopoulos *et al*., 2008:1216; Foedermayr *et al*., 2009:63; Henseler *et al*., 2009:302).

In order to determine nomological validity and at the same time identify the formative construct, each construct was related to the outcomes parameters of the model: firm performance (PERF) and relative competitive strength (COMP). As mentioned in the previous chapters, each of the formative constructs has theoretically and/or empirically been related to one or both of these outcomes parameters. All formative constructs: entrepreneurial behaviour (BE), strategic orientation (SO), corporate entrepreneurial management (CE) and market driving (MD) were shown to be significantly related to the two outcomes parameters, firm performance (PERF) and relative competitive advantage (COMP), which demonstrates nomological validity.

Table 5.5 summarises the path coefficients between the constructs and the outcomes parameters, the t-values and the respective significance levels.

TABLE 5.5: Establishing nomological validity for formative constructs

Constructs	Path coefficient	t-value
BE → PERF	0.2635*	4.1422
BE → COMP	0.2805*	5.4004
SO → PERF	0.2231*	4.0732
SO → COMP	0.3258*	6.3229
CE → PERF	0.2329*	4.3879
CE → COMP	0.2512*	4.7712
MD → PERF	0.2928*	5.3490
MD → COMP	0.3142*	5.9127

Note: t-values are generated via bootstrapping in SmartPLS (Ringle *et al*., 2005); t-values > 2.576 are significant at 0.01 level (*) for a two-tailed test (n=328)

Table 5.6 summarises the discussed validity measures for formative constructs.

TABLE 5.6: Validity of formative constructs

Formative constructs	Description
Validity measures	• Content validity & indicator specification • Multicollinearity: VIF values < 3.3 • External validity • Construct validity: nomological validity

Sources: Diamantopoulos *et al*. (2008); Foedermayr *et al*. (2009); Henseler *et al*. (2009)

5.5.4 Data analysis with structural equation modelling

The purpose of the following paragraphs is threefold. First, the discussion outlines the two approaches to structural equation modelling based on their technical aspects. Second, on the basis of a limited selection of articles in the field, it covers the application of each approach in research. Third, it presents reasons for the use of the partial least squares approach in this study.

The aim of structural equation modelling is to explain the structure among latent variables which are measured with observed variables (Diamantopoulos, 1994:105).

The advantage of structural equation modelling over first-generation techniques such as principal component analysis, discriminant analysis or multiple regressions is the greater flexibility between data and theory. Relationships can be modelled between multiple independent and multiple dependent variables; latent variables can be used; measurement errors can be considered; and theoretical assumptions can be tested against empirical data (Chin, 1998:297; Chin & Newsted, 1999:308). Kaplan (2009:13) notes that the relationships between variables are referred to as path analysis as well as simultaneous equation modelling. Hence, the terms path modelling and equation modelling are used interchangeably.

In general there are two approaches to structural equation modelling (SEM).

First, a covariance-based approach (CBSEM) can be taken, which is analysed with various tools. The most popular tool is Lisrel (Linear Structural Relations) which has been developed by Jöreskog (1973 in Sörbom & Jöreskog, 1982:382). Lisrel has been widely used in previous research studies and hence has become synonymous with SEM (Chin, 1998:295; Dijkstra, 1983:67; Haenlein & Kaplan, 2004:285).

Second, a partial least squares approach (PLS) which was developed by Wold (1978 in Jöreskog & Wold, 1982:265) can be used. The PLS approach is related to principal components and canonical correlations analysis, and allows for estimation of latent variables in two or more dimensions (Jöreskog & Wold, 1982:265).

The distinguishing characteristics of the two approaches from an applied research perspective are related to the purpose of the study and the level of theory development.

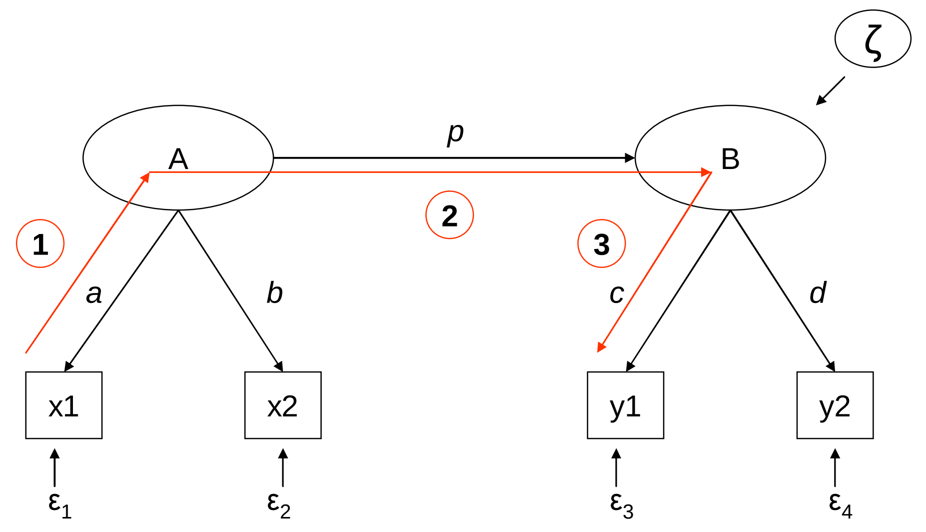
It is held that CBSEM is more theory oriented and emphasises theory confirmation. The focus is on fitting the model to the data. If fit cannot be achieved with the specified model, a modification of the model can easily be achieved (Diamantopoulos, 1994:106; Jöreskog & Wold, 1982:270; Rigdon, 1998:260).

PLS is often used in more complex situations and in situations where theory is not well developed. Hence, the data have a stronger impact than in CBSEM analysis (Chin, 1998:296; Jöreskog & Wold, 1982:270).

The basic principles of Structural Equation Modelling (SEM) have been outlined in chapter four. The basic components in CBSEM and PLS are a measurement model and a structural model. The measurement model (exogenous model in PLS) describes how each latent variable is operationalised via its observed variables and considers measurement error. The structural model (endogenous model in PLS) was presented as a path diagram to demonstrate the relationships between the latent variables and their measurement error or disturbance terms (Diamantopoulos, 1994:106,109; Haenlein & Kaplan, 2004:286-288).

For explanation purposes of both approaches Figure 5.1 will be used, which shows a two-block model. Two latent variables, A and B, are each captured by a block of reflective indicators. The relationships between the latent variables and their respective indicators represent the measurement model. The structural model is represented by the hypothesised relationship, p, between the latent variables A and B (Chin, 1998:298).

FIGURE 5.1: Two block model used for CBSEM explanation



Source: adapted from Chin (1998:298)

5.5.4.1 Covariance-based structural equation modelling (CBSEM)

Model specification and estimation

The latent variable B (Figure 5.1) can also be described as an endogenous variable, as it is influenced by A. Latent variable A is considered to be an exogenous variable, as it is not influenced by any other variable in the model. Since endogenous variables cannot totally be accounted for by their exogenous variables, a disturbance term needs to be considered (MacCallum, 1995:19). Measurement error of the observed variables is measured by eta (ε) and the disturbance term of the dependent variable B is measured by zeta (ζ) (Chin, 1998:298). Error terms of the endogenous latent variable account for the fact that other variables (systematic errors or random errors) influence the latent variable besides the specified variables in the model (MacCallum, 1995:19).

After the model has been conceptually defined and the path diagram has been set up, the model needs to be specified. The relationships in the path diagram are translated into linear equations for the structural and the measurement part as well as for error terms of the model. The equations are then transferred into parameter matrices which imply a certain covariance matrix (Diamantopoulos, 1994:110-112).

In a next step the covariance matrix from the empirical data set is calculated (Chin, 1998:299). Before parameters are estimated, the model needs to be identified. Identification means that a unique set of parameter estimates can be generated. This can be considered to be the case if the number of equations is at least equal to the number of unknowns. If this is the case the model can be considered as just-identified (Diamantopoulos, 1994:114-115; Rigdon, 1995:359; Rigdon, 1998:257).

Parameters are estimated using a fitting function which specifies how closely the hypothesised covariance matrix matches the empirical covariance matrix. The fitting function most often used is the maximum-likelihood function (ML), which provides consistently robust estimates of parameters. In addition, it provides several fit functions to assess how well the theoretical model fits the data (Diamantopoulos, 1994:116). The parameters a, b, c, d are estimated based on a reproduction of the data covariance matrix (indicated by the red lines and numbers in Figure 5.1) onto the hypothesised matrix. In order to solve these equations the variance of A and the loading of c need to be set to 1. In the first block x1 and x2 covary through A, which can be represented by a*b. In a further step the relationships between x1 and y1 can be estimated, which requires the estimation of p. Parameter c is set to one which allows for a*p. The process is continued until all parameters are estimated and best reproduce the sample covariance matrix (Chin, 1998:300).

Evaluating model fit

A final step in CBSEM is to assess model fit. The measurement model is assessed with regard to observed variables and the extent to which they are free from measurement error. Squared multiple correlations are calculated for the observed variables. Coefficients are between zero and one. The closer the coefficient is to one, the better the observed variable captures the latent variable. The coefficient of determination (R^2) indicates how well the group of observed variables capture the respective latent variables. The closer R^2 is to one, the better the latent variable is explained by its indicators (Diamantopoulos, 1994:121).

The structural model considers indices that capture the structural relationships between the latent variables as well as indices to assess the model as a whole. The structural relationships are assessed with the total coefficient of determination, which shows the strength of the relationship for all structural relationships together (Diamantopoulos, 1994:121).

The overall model is evaluated by the chi-square statistic (χ^2), root mean square error of approximation (RMSEA), goodness-of-fit index (GFI), root mean squared residual (RMSR) and the comparative fit index (CFI) (Diamantopoulos, 1994:121; Rigdon, 1998:268; Sörbom & Jöreskog, 1982:386-387).

The chi-square statistic (χ^2) implies whether the hypothesised covariance matrix adequately reproduces the sample covariance matrix. A high value indicates poor reproduction, whereas low values indicate good reproduction. As the chi-square statistic is sensitive to various influences such as non-normality and sample size, it should be interpreted with caution (Diamantopoulos, 1994:121-122; Hu & Bentler, 1995:87; Rigdon, 1998:268; Schumacker & Lomax, 2010:85; Sörbom & Jöreskog, 1982:386).

The root mean square error of approximation (RMSEA) minimises the effects of sample size in chi-square statistics. Values between 0 and 0.05 are considered as good overall fit (Rigdon, 1998:270).

Similar to the chi-square statistic, the goodness-of-fit index (GFI) determines how closely the hypothesised model reproduces the observed covariance matrix. The adjusted goodness-of-fit (AGFI) considers the degrees of freedom in the model (Diamantopoulos, 1994:122; Schumacker & Lomax, 2010:87). As the GFI is independent of sample size it is a relatively robust measure. Values for GFI should be between zero and one (Sörbom & Jöreskog, 1982:387).

The root mean squared residual (RMSR) reflects the amount of variance and covariance not reflected in the model. The closer the value is to zero, the better the fit (Diamantopoulos, 1994:122). The comparative fit index (CFI) describes the overall model fit compared with a worst-case alternative. The CFI ranges between values of zero and one. The closer the CFI is to one, the better the model explains the covariance among the measures (Rigdon, 1998:270).

5.5.4.2 Partial least-squares path modelling (PLS-PM)

Partial least squares (PLS) aims to maximise the variance of the dependent variables explained by the independent variables (Chin & Newsted, 1999:313; Haenlein & Kaplan, 2004:290). In order to obtain parameter estimates, PLS consists of three components. First, the measurement part relates the observed variables to their respective indicators. Second, the structural part represents the relationships between the latent variables. The third part relates to weight relations, which are used to estimate case values for the latent variables (Cassel, Hackl & Westlund, 1999:437; Chin & Newsted, 1999:315; Haenlein & Kaplan, 2004:290).

Model specification and estimation

For a detailed explanation of the PLS procedure, Figure 5.2 is used to describe the steps involved in model estimation. In a first step, the measurement model, which relates the observed variables to their latent variables, is estimated. For this purpose case values for each latent variable, A and B are estimated as a weighted sum of its indicators (x1, x2 and y1, y2). In order to obtain the weights it is necessary to first determine the measurement model of each latent variable (indicated by the red lines and numbers in Figure 5.2). In cases where the measurement model is reflective, simple regression models are calculated, where loadings of the observed variables determine the impact on the latent variable. In formative measurement models, coefficients link the observed variables to the latent variable. The latent variable scores for A and B are then calculated as a weighted average of their observed variables using weight relations as an input (indicated by number 2 in Figure 5.2) (Chin, 1998:301-302; Esposito Vinzi, Trinchera & Amato, 2010:50-52; Haenlein & Kaplan, 2004:291; Wold, 1982:2-3).

To determine the weight relations, an iterative procedure between inside and outside approximation is conducted until convergence of the case values is achieved (Lohmöller, 1989:41). First, an outside approximation determines case values for each latent variable. The latent variables, A and B, are estimated based on a weighted average of their observed variables. The weights are calculated in the form of principal components for reflective measurement models and with regression analysis for formative models (Haenlein & Kaplan, 2004:291). Second, an inside approximation is conducted which calculates case values for the latent variable based on its association with other latent variables. For the inner approximation, weights can be estimated using a path weighting scheme, a centroid weighting scheme or a factor weighting scheme. Most research applies the path weighting scheme, which considers regression coefficients (Esposito Vinzi *et al.,* 2010:53; Haenlein & Kaplan, 2004:291; Lohmöller, 1989:42). However, whatever scheme is chosen, the variation of the final results is considered to be minor (Haenlein & Kaplan, 2004:291). This study applied the path weighting scheme.

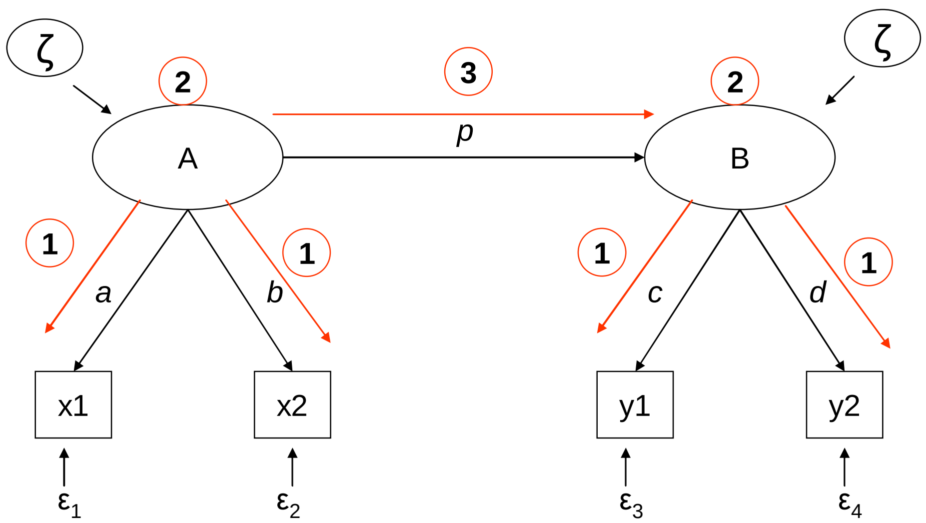
PLS uses information from the inside and outside approach to estimate a score value for each latent variable. Once a first estimate of latent variables has been generated, the outer weights are updated and the algorithm further alternates between inner and outer estimation until convergence (Chin, 1998:303; Esposito Vinzi *et al*., 2010:53,55; Fornell & Cha, 1994:64; Haenlein & Kaplan, 2004:291).

The structural part of the PLS model, which is also referred to as predictor specification, is estimated through ordinary least squares regressions among latent variables (indicated by number 3 in Figure 5.2) (Chin & Newsted, 1999:324; Esposito Vinzi *et al*., 2010:55). Relationships are used for prediction, and not necessarily for structural explanation as in CBSEM (Chin & Newsted, 1999:325-326).

Latent variables have error terms which account for the variance which is not covered by the independent variables. The unit variance of each latent variable equals one. Since exogenous latent variables do not have any predictor variables, their error term equals one (Falk & Miller, 1992:25).

PLS underestimates the paths in the structural model and overestimates the loadings (Chin & Newsted, 1999:329; Djikstra, 1983:81; Haenlein & Kaplan, 2004:292; Tenenhaus, Esposito Vinzi, Chatelin & Lauro, 2005:184). The reason for this can be found in the estimation procedure of the model. In PLS the overall model is divided into parts. One part is estimated while the other part is held constant. However, overall this effect is equalised on the indicator level and estimation becomes more accurate with the number of indicators per construct and sample size (Nitzl, 2010:16).

FIGURE 5.2: Two-block model used for PLS explanation



Source: adapted from Chin (1998:298)

Evaluating model fit

PLS path modelling does not have an overall fitting function to assess goodness of fit of the model. PLS fit is determined in order to assess the predictive power of the model. Therefore each part of the model needs to be assessed: the measurement model, the structural model and the overall model (Esposito Vinzi *et al*., 2010:56; Fornell & Cha, 1994:68).

The assessment of reliability and validity of the measurement model has been outlined in section 5.5.3.3. The main criteria for assessing the measurement model for reflective indicators are AVE, composite reliability and cross-loadings. For formative variables indicators must be specified, and multicollinearity, external validity and nomological validity assessed.

The two primary evaluation criteria for the structural model are the coefficient of determination (R^2) and the level and significance of path coefficients (Hair, Ringle & Sarstedt, 2011:147).

R^2 is estimated for the endogenous constructs and gives the explanatory power of the model (Esposito Vinzi *et al.,* 2010:57; Fornell & Cha, 1994:69; Hair *et al*., 2011:147). In general R^2 values should be high. Chin (1998:323) considers R^2 values of 0.67 as substantial, 0.33 as moderate and 0.19 as weak. Hair *et al.* (2011:147) argue that the level of R^2 must be interpreted within the research discipline. Whereas R^2 values of 0.20 in consumer behaviour are considered to be high, marketing studies consider R^2 values of 0.75 to be high.

The R^2 value for the endogenous construct market-driving ability in the direct effects model was determined at 0.612. According to the values used by Chin (1998:323), this indicates almost substantial explanatory power.

The path coefficients can be interpreted as standardised beta coefficients. Path coefficients can be assessed on their sign and their significance, which leads to an acceptance or rejection of the a priori formulated hypothesis. In PLS the significance levels are estimated via bootstrapping (Hair *et al*., 2011:147; Henseler *et al*., 2009:303).

As PLS does not assume normally distributed data, the bootstrapping procedure is used to determine significance of various parameters. The bootstrapping technique takes the observed sample as if it represented the population and creates a new data set by repeated random sampling with replacement from the original sample. Bootstrapping produces standard errors which can be used for hypothesis testing (Chin, 2010:83; Hair *et al*., 2011:148; Henseler *et al*., 2009:303). For this study bootstrap samples of 500 were used.

Another assessment criterion for the structural model is the effect size (f^2) of the path model. Effect size determines the impact of the exogenous latent variable on the endogenous latent variable. To determine f^2, R^2 value of the overall model considering all exogenous latent variables is taken (R^2 included). Further, R^2 is estimated for a reduced model by excluding the exogenous latent variable whose influence is to be estimated (R^2 excluded). The following formula is applied to calculate f^2 (Henseler *et al.*, 2009:303).

$$f^2 = \frac{R^2_{(included)} - R^2_{(excluded)}}{1 - R^2_{(included)}}$$

In order to show the predictive quality of the overall model, the Stone-Geisser test (Q^2) can be applied using the blindfolding procedure in PLS (Henseler *et al*., 2009:304-305). Q^2 measures how well the observed values are reconstructed by the model and its parameter estimates. Q^2 values higher than zero imply that the model has predictive relevance. Values smaller than zero represent the opposite (Chin, 1998:317-318; Esposito Vinzi *et al*., 2010:60; Fornell & Cha, 1994:72; Tenenhaus *et al*., 2005:174; Wold, 1982:30). Q^2 and the blindfolding procedure can only be applied to endogenous latent variables with a reflective measurement model (Henseler *et al*., 2009:305). The endogenous latent variables in this study are market-driving ability (MD-ability), firm performance (PERF) and relative competitive strength (COMP). Market-driving ability consists of a formative measurement model, hence Q^2 cannot be established. Firm performance and relative competitive strength are represented by a reflective measurement model that allows for the estimation of Q^2.

Table 5.7 summarises the various model evaluation methods.

TABLE 5.7: PLS model evaluation criteria

Model evaluation	**Description**
R^2	Substantial: 0.67; moderate: 0.33; weak: 0.19
Path coefficients	Evaluation in terms of sign, magnitude and significance
Effect size (f^2)	small: 0.02; medium: 0.15; large: 0.35
Q^2	Predictive quality of the model – only for endogenous latent variables with reflective measurement model

Source: Henseler *et al.* (2009:303)

To conclude the overview of the two SEM approaches, the following table provides a summary.

TABLE 5.8: Summary PLS versus CBSEM

	PLS	CBSEM
Approach to theory and data analysis	• Theory development, predictive focus • Limited information approach – limited inference about population	• Theory confirmation, causality focus • Information approach – inference about population
Estimation of measurement / structural model	• Measurement model overestimated • Structural paths underestimated	• Measurement model underestimated • Structural paths overestimated
Estimation of parameters	• Linear multiple regressions	• Replication of covariance matrix
Model evaluation	• Measurement model fit indices: communality index, average variance extracted (AVE) • Structural model: coefficient of determination (R^2), path coefficients, effect size (f^2) • Determining predictive power of the model: blindfolding (Stone-Geisser test Q^2)	• Measurement model fit: Squared multiple correlations of observed variables, coefficient of determination (R^2) • Structural model: total coefficient of determination • Overall model fit: chi-square statistic (χ^2), root mean square error of approximation (RMSEA), goodness-of-fit index (GFI), root mean squared residual (RMSR) and the comparative fit index (CFI)

Sources: Chin (1998); Diamantopoulos (1994); Esposito Vinzi *et al*. (2010); Henseler *et al*. (2009); Rigdon (1998)

5.5.4.3 CBSEM and PLS assumptions and conditions

The following paragraphs outline the controversial research discussion between the two SEM approaches. The specific focus is on the most often discussed issues of sample size and model identification.

Comparisons between PLS and CBSEM are most often based on the maximum-likelihood (ML) estimation procedure of CBSEM. It is noted that several other algorithms, such as generalised least squares (GLS), asymptotically distribution free (ADF), weighted least squares (WLS) or unweighted least squares (ULS) are available. ML and GLS are considered to be rather robust methods when assumptions such as normal distribution of the sample data are not given (Diamantopoulos, 1994:116; Rigdon, 1998:265). Nunnally and Bernstein (1994:480) suggest that for highly non-normal data ULS is more suitable than ML and GLS.

PLS research often claims to be able to accommodate different measurement levels of data as well as formative indicators in measurement (Falk & Miller, 1992:9; Fornell & Bookstein, 1982:440; Haenlein & Kaplan, 2004:291; Schneeweiss, 1991:145). Although these two conditions are easily modelled in PLS, nowadays CBSEM can also handle various data levels as well as formative indicators (Henseler *et al*., 2009:288,290; Jöreskog, 2005:1; Temme & Hildebrandt, 2006:2-3; Thomas, Lu & Cedzynski, 2007:8).

In PLS the appropriate sample size is often estimated by the following rule of thumb. The sample size needs to be equal to or larger than the following:
"1.) Ten times the scale with the largest number of formative indicators … or
2.) Ten times the largest number of structural paths directed at a particular construct in the structural model." (Chin, 1998:311; Chin & Newsted, 1999:327; Chin, Marcolin & Newsted, 1996:39).

Falk and Miller (1992:13-14) suggest an even simpler rule, a case-to-variable ratio limit which requires that there are more cases than variables in a block and that there must be more cases than formative latent variables.

The reasoning behind these rules derives from a data reduction perspective. It is argued that in practical research situations, the researcher is confronted with a limited number of willing participants as well as time and cost constraints (Falk & Miller, 1992:14). Further, as PLS performs a partial estimation procedure which estimates regressions for one block at a time, only the part with the largest multiple regressions needs to be identified (Chin & Newsted, 1999:326; Fornell & Cha, 1994:75).

However, in order to account for the adequate power of the model, it is also necessary to consider various conditions of the respective sample. Low sample sizes (e.g. n = 20) do not allow identification of low-valued structural path coefficients (Marcoulides & Saunders, 2006:iv; Marcoulides, Chin & Saunders, 2009:174). Small sample sizes also mean large parameter standard errors, which negatively influence the accuracy of estimation (Thomas *et al*., 2007:8).

Marcoulides and Saunders (2006:iv) state that the appropriate sample size depends on many factors such as:

- The psychometric properties of the variables
- The strength of the relationship among variables
- The complexity and size of the model
- The amount of missing data
- The distributional characteristics of the variables

The views on sample size in PLS are divergent. In Wold's (1982:4) original work, the issue of 'consistency in the large-sample case' is mentioned. As latent variables are measured as aggregates of their observed variables they include in part measurement error. This results in an overestimation of the measurement model and an underestimation of the structural model in the PLS model. PLS parameters will converge to true population values when the sample size and the number of indicators increase indefinitely. Hence, better estimates can be achieved by increasing sample size and the number of indicators (Chin & Newsted, 1999:329; Djikstra, 1983:81; Haenlein & Kaplan, 2004:292; Tenenhaus *et al*., 2005:184).

Another assumption that needs to be met is the identification of parameters. Identification refers to the necessary condition that unique solutions for parameters can be calculated based on the available empirical data. Identification can be achieved if the number of equations is at least equal to the number of unknowns (Bollen, 1989:88; Diamantopoulos, 1994:114-115; Rigdon, 1998:258). Whereas this condition is not as easily accomplished with CBSEM models, as its main focus is on reproducing the covariance matrix based on a restricted number of parameters, it is considered to be fulfilled in PLS models if they are recursive (Fornell & Cha, 1994:74; Temme & Hildebrandt, 2006:2).

Although researchers often emphasise that PLS and CBSEM are complementary approaches (Jöreskog & Wold, 1982:270), a certain rivalry between the two can be noted. The purpose of the presented analysis was to clearly identify main differences between the two approaches that need to be considered in conjunction with the specific research purpose.

5.5.4.4 Application of PLS for the purpose of this study

As outlined above, both approaches to structural equation modelling have their advantages and disadvantages when it comes to measuring the variables and constructs in the model. In order to identify the approach best suited to fulfilling the purpose of this study the broader research question needs to be considered.

As has been stated in chapter three, the literature on market driving is mainly based on qualitative studies which include constructs and concepts that have primarily been taken from the marketing and entrepreneurship field to explain market-driving. The construct of market driving has not previously been measured. Furthermore, factors influencing market-driving ability are considered to be numerous; but have also not been measured so far. Therefore one of the main research targets of this study is to measure market driving and identify organisational factors that influence market-driving ability in order to assist organisations to become more market driving. This perspective moves the exploratory and predictive aspect to the fore. Moreover, as theory around market driving is not well established, empirical data should receive more weight in the analysis than the theory.

As outlined in the previous discussion, PLS is more data-driven than CBSEM (Chin *et al*., 1996:39; Chin, 1998:295-296,304).

Although both structural equation models can account for formative indicators, the widely held opinion is that PLS is in a better position to account for formative measurement models than CBSEM (Chin, 1998:299; Hair *et al*., 2011:143; Wetzels, Odekerken-Schröder & van Oppen, 2009:180). As outlined in chapter four, the model that is tested in this study consists of mainly formative constructs.

In order to accommodate the primary disadvantage of PLS models which has been described as the 'consistency at large' (Chin, 1998:329; Wold, 1982:4) the sample size for this research was determined at n = 6015. After accounting for unsuitable and unavailable respondents, n = 962 interview appointments could be made. The response rate was 34.1%, resulting in n = 328 usable interviews for data analysis. The ratio of observations to parameters is five. Albers (2010:419) estimated a reliable PLS model with fewer than four observations per parameter. Therefore it is assumed that a reliable model can be estimated with the achieved sample size.

For the purpose of this study SmartPLS (Ringle *et al.,* 2005) and SPSS V 9.0 (SPSS Inc., 2004) were used to conduct the required analysis.

5.6 CONCLUSION

This chapter outlined the research methodology that was used in this study. First, the research problem and objectives were outlined. Then the propositions that were presented in chapter four were formulated as hypotheses, as they were now to be used for empirical testing. A total of 29 hypotheses were formulated, which would be tested using partial least squares path modelling.

A formal study using a non-probability sample from the South African healthcare industry was conducted. The study used a communication approach in the form of a telephonic survey. A total of 328 interviews were realised. The survey used a five-point Likert response format and Likert type scales. Reliability and validity of the measurement instrument were assessed.

Different options of data analysis were discussed and the preferred approach of partial least squares path modelling for the purpose of this study was discussed.

The next chapter presents the most significant results and tests the specified hypotheses.