The Impact of Ambidextrous Market Learning and Product Innovativeness on Product Advantage and New Product Performance

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Abstract

New Product Development is vital to the performance of high-tech firms given the rapid change in technology and markets that they face. Drawing on the ambidexterity literature this study focuses on how firms can employ Ambidextrous Market Learning (AML), that is, the use of exploratory and exploitative market learning strategies simultaneously, to develop successful innovative products. Despite the exponential growth of studies focusing on ambidexterity, the literature portrays the ambidexterity concept as a present or absent – like phenomena. However, in the current study, AML is conceptualised as a continuum of market knowledge that acts as a key source essential in creating customer value in the form of new products. Whilst research into ambidexterity contains abundant evidence of the positive effects of ambidexterity on firm performance, yet there is little discussion in the literature on the effects of AML on product advantage and the role of product innovativeness. A conceptual model comprising the relationship between AML, product advantage and product innovativeness is developed and empirically tested using 178 UK-based high-tech firms.

The findings indicate that AML firms tend to develop products that have high product advantage. The study further focuses on how product innovativeness and product advantage constructs interact to create new product financial performance. Findings also suggest that marketing and technological discontinuity (product innovativeness from the firm's perspective) respectively has a negative and a positive moderating impact on product advantage. In addition, modelling product innovativeness from the customers' perspective (customer discontinuity) in the same model sheds new light on the relationship between product advantage, product innovativeness and product performance. By further examining the moderating effects of marketing and technological discontinuity on the link between AML and product advantage, the analyses reveals the different scenarios in which the benefits of AML firms may outweigh its implementation cost.

Keywords: Ambidextrous Market Learning, Product Advantage, Marketing Discontinuity, Technological Discontinuity, Customer Discontinuity, New Product Performance, Organisational Learning

Definition of key constructs

New Product Financial Performance (NPFP)

NPFP is defined as the extent to which firms are satisfied with the revenue and profit performance of the new products introduced by the company/business unit in the last three years.

Ambidextrous Market Learning (AML)

Drawing on the ambidexterity literature, AML is defined as simultaneous integration of exploratory and exploitative market learning activities within a business unit.

Exploratory Market Learning

Exploratory Market Learning is defined as the pursuit of radical and new market information by going beyond the current product-market knowledge domain.

Exploitative Market Learning

Exploitative Market Learning is defined as the thorough and detailed processing of the market information within the firm/business unit's current domain of market and product experience.

Product Advantage (PA)

Marketing Discontinuity (MD)

MD is one of the two dimensions of product innovativeness from the firm/business unit's perspective. MD arises when firms operate in new marketing domains and result when, for example, the product category, competitors, distribution channels, or new customers are unfamiliar to the firm.

Technological Discontinuity (TD)

TD is the other dimension of product innovativeness from the firm/business unit's perspective. TD arises when firms operate in new technological domains to develop new products or services, for example, new processes associated with the product development, the engineering and design work, or the production technology and process are unfamiliar to the firm.

Customer Discontinuity (CD)

CD is product innovativeness from the customers' perspective. CD is defined as the extent to which the managers believe that their customers are required to change or adapt behaviour patterns when adopting new products in the last three years.

Product Advantage (PA)

PA is defined as the extent to which a new product offers unique benefits that are meaningful to the customers and to the extent to which it is superior to competing products.

Product Meaningfulness (PM)

PM is defined as new products that provide new (unique) attributes and functionalities that customers perceive as appropriate and relevant.

Product Superiority (PS)

PS is defined as the extent to which a new product outperforms competing offerings along existing attributes and functionalities.

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Chapter One: Introduction

1.1 Introduction to research background

In today's markets, the competition is intense, the pace of change is accelerating, and the needs and wants of the customers are constantly altering, and one of the primary means by which firms achieve competitive advantage is by developing successful products and/or services. This is especially true in the case of firms operating in high-tech industries, where developing new products depends greatly upon technological advancements and simultaneously understanding the needs and wants of the customer. Since the competition is high, creating and sustaining *'competitive advantage'* is challenging for firms in high-tech industries. Porter (1985) defines *'competitive advantage'* as *"a firm that is able to create value for its buyers that exceeds the firm's cost of creating it"* (Pg. 3). In addition, in high-tech industries, new technology can replace older technology in a short period (that is, rapidly changing product and market life cycles) (McGrath, 1996). This presents unique challenges and tends be more difficult to create competitive advantage for firms operating in high-tech industries.

High-tech industries have a substantial economic impact, fuelled both by large Research and Development (R&D) spending, and a higher than industry average sales growth. In addition, firms operating in high-tech industries are often with few products and services in the market, as substantial investments are often required to develop the services and products, and therefore it is not just important to have a high market success rate but it is even more important to have higher financial performance. Developing innovative new products is the fundamental means by which a firm can achieve competitive advantage (Porter, 1985). Yet in a recent Nielsen company report (2015), Johan Sjöstrand, the senior Vice President and Managing Director of Nielsen Innovation in Europe said *"New Product* *failure rates are extremely high, but success is no fluke"* (p. 4). This high failure rate of products and services has a high negative impact on the society, the economic growth, and the growth of firms.

In the last two decades, the term *'ambidexterity'* is viewed as an emerging research paradigm in the organisational theory (Raisch and Birkinshaw, 2008), that is considered as a valuable and costly to imitate resource, and therefore a potential source of competitive advantage (Colbert, 2004). Ambidexterity is defined as the coordination and integration of exploratory and exploitative activities in a business unit (Tushman and O'Reilly, 1996). This definition has been broadly applied in different literatures and implies the ability to pursue diverse goals concurrently, such as exploration and exploitation (March, 1991), efficiency and flexibility (Adler, Goldoftas, Levine, 1999), alignment and adaptability (Gibson and Birkinshaw, 2004), or incremental and radical product innovation (Atuahene-Gima, 2005). These various labels, previously used in the literature, essentially underline the same phenomena (Raisch and Birkinshaw, 2008).

The ambidexterity construct initially received critical criticisms from scholars (for example, Ebben and Johnson, 2005; Kyriakopoulos and Moorman, 2004; Miller and Friesen, 1986; Yannopoulos, Auh, and Menguc, 2012). In the existing literature, traditionally exploration and exploitation are viewed as competing activities (Duncan, 1976). Learning theorists demonstrate that exploitation learning tends to limit the amount of exploratory learning and vice versa (for example, March, 1991). Miller and Friesen (1986) argue that researchers and scholars who argue in favour of ambidexterity, practice under the false notion that firms have unlimited resources and implementing different organisational structures that enhances ambidexterity is not straightforward. Firms implementing an ambidextrous culture tend to lose focus in both and the overall results are detrimental (Galbraith, 1973). And, recent studies indicate that ambidexterity has a negative impact on innovative products and hence the firm performance is deteriorated (for example, Atuahene-Gima, 2005).

Despite these early criticisms, the concept of ambidexterity is more prominently used in research that focuses on high-tech industries to explain how these firms can create competitive advantage. Yalacinkaya, Calantone, and Griffith (2007) state *"exploration and exploitation are closely linked, exploitation activities provide financial assets that underpin exploration activities, whereas, exploration activities provide the technological assets and capabilities"* (p. 67). Researchers and scholars argue that exploration and exploitation activities are closely linked and excessive focus on exploration eventually leads to short-term financial failure and excessive focus on exploitation leads to technological exhaustion (for example, Hughes, Martin, Morgan, and Robson, 2010; Jansen, Tempelaar, van den Bosch, and Volberda, 2009; Wang and Rafiq, 2014; Cao, Gedajlovic and Zhang, 2009; Gupta, Smith, and Shalley, 2006; Lee and Ryu, 2002). Therefore, it is possible that primarily focusing on either exploration or exploitation could lead to a biased picture.

In addition, Lewin and Volberda (1999, p. 523) argue, *"These forms need not be contradictory processes. They can be complementary, and organisations must learn how to carry out both forms"*. This indicates that ambidexterity is not necessarily the pursuit of diverse or competing goals concurrently. Day (1994) argues that achieving a competitive advantage is not looking at whether firms emphasize their internal capabilities and performance or look outside to assess their position. He argues that in order to achieve sustainable competitive advantage, knowledge on improving current learning process comes from practices outside the industry. In addition, Kogut and Zander (1992) argue that firms with a broad range of knowledge have a greater possibility of recombining different aspects of knowledge to recognise new opportunities and potentially be more creative. Levinthal and

March (1993) argue that for firms operating in highly volatile markets to achieve survival need to balance and precisely mix exploration and exploitation learning.

Despite the exponential growth of studies focusing on ambidexterity, the literature portrays the ambidexterity phenomenon as 1 and 0s. In the current study, based on the results from recent studies (for example, Cao, Gedajlovic, Zhang, 2009; Lewin and Volberda, 1999; Yalancinkaya et al., 2007), it is argued that ambidexterity can be viewed as a degree of the simultaneous integration of exploration and exploitation activities.

The ambidexterity concept has been hugely applied in studies focusing on New Product Development (NPD) activities in high-tech and manufacturing firms. This is because by simultaneously exploring and exploiting, firms may tend to be more successful in markets where the technological uncertainty is high and where the needs and wants of the customers are constantly altering. Despite the importance of ambidexterity construct in high-tech industries, the results of the meta-analysis conducted by Junni et al., (2013) on the ambidexterity literature found that the ambidexterity - performance hypothesis is non-significant in the context of high-tech industries. In addition, a thorough review of the NPD and ambidexterity literature indicates that no study yet focuses on understanding how ambidextrous firms tend to develop products that have competitive advantage.

In order to answer the above questions, a review of recent NPD literature was undertaken and the results suggest that firms operating in high-tech industries requires greater integration between R&D and marketing capabilities (for example, Adu and Ranchhod, 1998; Bogner and Barr, 2000; Cooper, 1994; Davidow and Chakrabarti, 1988; Gupta, Raj, and Wilemon, 1985; Traynor and Traynor, 1989; 1997; 2004; Van Riel, Lemmink, and Ouwersloot, 2004). For example, Gupta, Raj, and Wilemon (1985) state *"Because the state of the technology and market conditions are continuously changing and competitive pressure to* *keep abreast is high, R&D not only needs to shine in its technical expertise, it also needs to excel in translating market needs into viable products and gearing for anticipated needs"* (p. 289).

Furthermore, Traynor and Traynor (2004) argue *"While high-tech companies have historically relied on their unique technological advantage to remain competitive, firms have found that it is becoming more and more difficult to maintain a competitive edge through technological advantage alone. Be that as it may, high-tech firms have been experimenting with alternative marketing approaches and enlisting marketing talent to aid in their competitive effort on the buying and selling battlefield"* (p. 457). Over the last three decades, scholarly work has witnessed a marked growth in the use of marketing techniques in high-tech industries, and in recent years a relatively new topic in marketing literature has emerged, that links different types of market learning and NPD (for example, Kim and Atuahene-Gima, 2010; Kyriakopoulos and Moorman, 1998; Morgan, 2004; Yannopoulos, Auh, and Menguc, 2012).

Over the years scholars have argued that there are two types of organisational learning, for example, March (1991) in his unprecedented work differentiates between exploration learning and exploitation learning. March (1991, p. 85) defines exploration learning as *"experimentation with new alternatives, having returns that are uncertain, distant and often negative"* and exploitation learning as *"the refinement and extension of existing competencies, technologies, and paradigm exhibiting returns that are positive, proximate, and predictable"*.

The emerging importance of the organizational learning literature in marketing is well accepted and defined as *"the development of new knowledge or the modification of existing knowledge about customers, competitors, suppliers and other constituents through the* *capabilities of exploration and exploitation"* (Ozsomer and Gencturk, 2003, p. 4). Based on March's (1991) definition, findings from a theoretical paper by Levinthal and March (1993) state that there are two types of market learning, that is, exploratory market learning and exploitative market learning. Exploratory market learning is defined as *"the pursuit of radical and new market information by going beyond the current product-market knowledge domain",* and exploitative market learning is defined as *"the thorough and detailed processing of the market information within the firm's current domain of market and product experience"* (Levinthal and March, 1993, p. 97). Kyriakopoulos and Moorman (1998) argue that exploratory market learning may influence product creativity and long-term financial performance, and on the other hand, exploitative market learning may influence product speed and short-term financial performance.

In addition, Yannopoulos, Auh, and Menguc (2012) argue, *"although achieving a proper balance between exploratory and exploitative market learning is not an easy task, but a failure to do so will likely to lead to a decline in organisational performance"* (p. 531). Recent studies (e.g., Kim and Atuahene-Gima, 2010; Yannopoulos, Auh, and Menguc, 2012) have applied this distinction between the types of market learning, and empirically measured how these types of market learning impact product and firm performance. To date, however, the literature is almost silent on how ambidextrous market learning (that is, simultaneous exploratory market learning and exploitative market learning) may affect NPD activities and product attributes.

Henard and Szymanski (2001) in their meta-analysis on the NPD literature identify five key product characteristics (these are: Product advantage, product innovativeness, product price, product technological sophistication, and product meets customer needs) that discriminate between successful and unsuccessful new products. In the existing NPD literature, empirical results provides evidence that the product advantage construct was found to be the most dominant product attribute to define new product financial performance (for example, Calantone, Chan, and Cui, 2006; Henard and Szymanski, 2001; Langerak, Hultink, and Robben, 2004; Li and Calantone, 1998; Montoya-Weiss and Calantone, 1994). Product advantage is defined as the superiority and/or differentiation over competitive offering which is meaningful to its customers (for example, Calantone, Chan, and Cui, 2006; McNally, Cavusgil, and Calantone, 2010). In the existing literature, product advantage is a multidimensional construct consisting of product meaningfulness and product superiority dimensions. Product meaningfulness is defined as, *"new products that provide new (unique) attributes and functionalities that customers perceive as appropriate and relevant"* (Calantone and di Benedetto, 1988, p. 35). And product superiority refers to *"the extent to which a new product outperforms competing offerings along existing attributes and functionalities"* (Calantone and di Benedetto, 1988, p. 36).

The second most important product attribute from the existing literature (Henard and Szymanski, 2001) is product innovativeness. In high-tech industries; product (service) innovation is increasingly valued as a key component of the sustainable success of business operations (Ayers, Dahlstrom, and Skinner, 1997; Cooper, 2000; Kleinschmidt and Cooper, 1991; Danneels and Kleinschmidt, 2001; Page and Schirr, 2008; Song and Parry, 1997). Product innovation is considered as a firm's core value creation capacity and one of its most important competitive advantages (McGrath, 1995). Yet the relationship between product innovativeness and product advantage has resulted in inconsistent and unclear findings (Freel, 2000b; Freel and Robson, 2004). The confounding results are partly attributed to two key reasons, first, the plethora of measures used to assess product innovativeness (Calantone, Chan and Cui, 2006; Danneels and Kleinschmidt, 2001) with conceptualizations either not adequately distinguishing between firm (Danneels and Kleinschmidt, 2001; Garcia and Calantone, 2002) and customer perspective of innovativeness (Atuahene-Gima, 1995; Souder and Song, 1997), or being too broad (Danneels and Kleinschmidt, 2001). Second, scholars have addressed the concept of product advantage construct as product innovativeness (e.g., Atuahene-Gima, 1995; Li and Calantone, 1998).

In addition, Danneels and Kleinschmidt (2001) argue that a failure to distinguish between firm and customer's perspective of product innovativeness leads to unrefined and uni-dimensional conceptualisation of product innovativeness. They argue that by classifying product innovativeness as simply radical and incremental products may be oversimplifying of the construct and this leads to conceptual weakness. Green, Gavin, and Aiman-Smith (1995) argue that product innovativeness should not be seen as types of innovations, rather it should be viewed as a continuum with multiple dimensions.

Despite these scholarly efforts aimed at enhancing our understanding of ambidexterity in NPD process, the existing literature is nonetheless limited in several respects. First, the marketing literature is silent on how ambidextrous market learning affects product advantage. Second, research into the concept of ambidexterity is narrow and to date, a very limited number of studies have examined how firms can simultaneously explore and exploit to achieve superior product innovation, which is an imperative for continuous growth (Brion, Mothe, and Sabatier, 2010). Third, Junni et al., (2013) conducted a meta-analysis of the ambidexterity literature, and argue that implementing an ambidextrous behaviour or culture is not an easy thing to do for firms. They argue that future research should focus on answering the question, "*when do the benefits of the ambidextrous behaviour outweigh its implementation cost*" (p. 310).

Fourth, in the existing literature, the ambidexterity hypothesis is most tested in the high-tech industries, despite the importance of the ambidexterity construct, Junni et al., (2013) in their meta-analysis found this relationship to be a non-significant one. Fifth, despite the importance of developing innovative new products in firm success, empirical evidence exists for positive, negative, and non-significant relationship between product innovativeness and product performance. Thus, further research is required to shed new light on the relationship between product innovativeness, product advantage, and new product financial performance. Finally, despite the importance of product advantage and product innovativeness in the NPD, the relationship between product innovativeness and product advantage is still unclear. In the following sections, the study provides a detailed discussion on the gaps in the two literatures (that is, ambidexterity and NPD).

1.2 Research Questions

1.2.1 The relationship between ambidextrous market learning and Product Advantage

Several NPD studies have associated ambidexterity as an antecedent for product performance (for example, Li and Huang, 2012; Wang and Rafiq, 2014). A few others have also empirically tested how the different types of market learning directly impact product performance (for example, Kim and Atuahene-Gima, 2010; Yannopoulos, Auh, and Menguc, 2012). In addition, an abundance of empirical studies illustrate the importance of ambidexterity on firm performance in the high-tech and manufacturing industries. To date, however, the ambidexterity literature is silent on how ambidextrous market learning may affect product advantage.

There are some advantages in investigating the combined and individual effects of different types of market learning. Scholars examining the individual effects of exploratory and exploitative market learning argue that both types of market learning strategy is quintessential as the other but do not discuss the advantages of implementing a culture that encourages simultaneous integration of exploratory and exploitative market learning. In addition, exploration and exploitation activities are considered as competing organisational activities (Kim and Atuahene-Gima, 2010). However, Yalcinkaya, Calantone, and Griffith (2007) argue that exploration and exploitation activities are closely linked and by focusing too much on exploitation activities, this may lead to technological exhaustion and by focusing too much on exploration activities, firms may fail in short-term financial performance. Moreover, for a firm to successfully explore, first the firm needs to exploit its resources and capabilities to achieve superior performance.

In this study, the key question is to measure the relationship between AML and product advantage.

1.2.2 Operationalization of Product advantage

Calantone and di Benedetto (1988) state that the definition of product advantage combines two distinct components: product meaningfulness and product superiority. This means that for a product to have high product advantage, it should be superior relative to the other products available in the market, that is, the product has to be unique on various dimensions such as quality, benefit, and function (Im, Hussain, and Sengupta, 2008), and also the customers must perceive it as appropriate, relevant and useful (Li and Calantone, 1998).

This illustrates that product is advantageous to the customers if the customers perceive the product to be simultaneously superior and meaningful. Based on the definition of product advantage as unique benefits that the product offers and the extent to which it is superior to competing products (Atuahene-Gima, 1995; Calantone and Di Benedetto, 1988; Li and Calantone, 1998), the existing literature has frequently operationalized product advantage as an aggregate construct consisting of product meaningfulness and product superiority (Rijsdijk et al., 2011). Rijsdijk, et al. (2011), however, argue that these are two distinct components of product advantage. Product meaningfulness is defined as the new offerings or new (unique) attributes and functionalities whereas product superiority refers to the degree to which a product outperforms competing products along existing attributes and functionalities.

The aggregate conceptualization assumes that meaningfulness and superiority contribute equally to product advantage. However, a new product can be meaningful to its customers without being superior to competing products (Szymanski et al., 2007). Hence, the need to disaggregate the product advantage into its components. The above also suggests that products have high advantage only when they are superior to competing products and at the same time offer meaningful advantages to the customers. Therefore, in this study, the product advantage construct is measured as a second-order construct consisting of product meaningfulness and product superiority as its elements. Henard and Szymanski (2001) state *"although product advantage is arguably, a second-order factor composed of product characteristics predictors, in the existing literature it is frequently captured and reported as a single order construct"* (p. 365).

In line with Rijsdijk et al., (2011), in this study, the second key question that needs answering is whether product advantage is a higher-order construct and is product meaningfulness and product superiority its first-order constructs. In terms of theoretical implications and management practice, there seems to be an ambiguity in the way product advantage is operationalized and this has significant connotations. Despite the importance of product advantage in the NPD literature, no study to date illustrates how product advantage is not an aggregate score of product meaningfulness and product superiority.

1.2.3 The relationship between product innovativeness, product advantage, and new product financial performance

In the NPD literature, scholars frequently state that product advantage and product innovativeness are the two fundamental product attributes that determine the success of new products (for example, Calantone, Chan, and Cui, 2006; McNally, Cavusgil, and Calantone, 2010). To date, however, the relationship between product innovativeness, product advantage and product performance is far from transparent. Evaluating new product financial performance is an important issue in the NPD literature (Biemans and Harmsen, 1995), and in the existing literature, product advantage is found to be the most dominant product characteristics to define new product financial performance. However, how product innovativeness may impact product advantage and new product financial performance is ambiguous. Nonetheless, empirical evidence exists for both arguments (Henard and Szymanski, 2001) as well as for non-significant relationship (Calantone, Chan, and Cui, 2006; Calantone, di Benedetto, and Bhoovaraghavan, 1994).

In addition, in the existing literature on NPD, product innovativeness is used as a reflection of product advantage (for example, Cooper and Kleinschmidt, 1987; Langerak, Hultink, and Robben, 2004; Ali, Krapfel, and LaBahn, 1995; Li and Calantone, 1998). The primary argument has been that products that have unique features or characteristics and that are different from the existing products can be defined as innovative products. This has resulted in problematic situations and as argued by Kleinschmidt and Cooper (1991) that product innovativeness does not necessarily result in enhanced product advantage. They argue that product innovativeness accounts for the technical and marketing discontinuity from the firm's perspective, and a product that brings a behavioural change from the customer's perspective.

Taking insights from Danneels and Kleinschmidt (2001) paper on product innovativeness from firm perspective and customer perspective are different and lack of this differentiation may lead to unrefined and uni-dimensional conceptualisation of product innovativeness, McNally et al., (2010) define marketing and technological discontinuity as *"marketing discontinuity is the firm's ability to serve new customers or face new competitors by developing new product line and technological discontinuity is the firm's ability to use* *new technology to make the product"* (Pg. 361). Marketing and technological discontinuity is product innovativeness from the firm's perspective, which in a nutshell can be defined as the firm's ability to develop innovative products.

On the other hand, product innovativeness from the customer's perspective is the extent to which the product is compatible with the experience and consumption patterns of potential customers. According to Lawton and Parasuraman (1980) product innovativeness from the customer's perspective is *"the degree of behavioural change or learning effort required by potential customers to adopt the new product*" (p. 20). Scholars and researchers have labelled product innovativeness from the customer's perspective differently; for example, 'degree of product newness to customers' by Atuahene-Gima (1995a), 'customer discontinuity' by McNally et al., (2010), 'customer familiarity' by Calantone, Chan, and Cui (2006) and for this study it is labelled as 'customer discontinuity, but essentially they all measure product newness/innovativeness from the customer's perspective.

Whereas, product advantage refers to the superiority that the product offers in comparison to other products available on the market (based on dimensions such as quality, benefit, and functions), in addition to the meaningfulness of the product that is, whether the customers can easily interpret the superiority of the product as relevant and appropriate. In the existing literature, to date, there have been very limited studies that argue that product advantage and product innovativeness are two different attributes (for example, Calantone, Chan, and Cui, 2006; McNally, Cavusgil, and Calantone, 2010). Due to this misalignment between the definitions of product advantage and product innovativeness, the relationship between product advantage and product innovativeness is not easily comprehensible. Therefore, the third key question that needs answering is what is the relationship between product innovativeness, product advantage and new product financial performance.

In addition, despite the limited research on the relationship, the general consensus is that there is a positive direct relationship between product innovativeness and product advantage. However, the NPD literature is silent on how product innovativeness from the firm's and customers' perspective can have an impact on product advantage and new product financial performance. Thus, in line with McNally et al., (2010) and Calantone, Chan and Cui (2006), in this study the next key research question is to measure the relationship between product innovativeness, product advantage and new product financial performance.

1.2.4 "When" does the benefit of implementing an AML culture outweigh its implementation cost?

In the existing literature, Junni et al., (2013) conducted a meta-analysis of the ambidexterity literature, and argue that implementing an ambidextrous behaviour or culture is not an easy thing to do for firms. They argue that future research should focus on answering the question, "*when do the benefits of the ambidextrous behaviour outweigh its implementation cost*" (p. 310).

In addition, in the market learning literature, Kyriakopoulos and Moorman (2004) argue that in the ambidexterity literature the research has shifted its focus from *"whether to how firms can achieve a complementarity of these strategies [i.e. exploratory and exploitative]"*. In this study, taking the two key learning outcomes from both ambidexterity and market learning literature, the key research question is to test *"when"* it is most beneficial for the firm to implement an ambidextrous market learning strategy?

In a nutshell, there are four key research questions raised in the current study and these are as follows:

1. What is the relationship between ambidextrous market learning (AML) and product advantage?

2. Whether product advantage construct a higher-order construct consisting of product meaningfulness and product superiority?
3. By including product innovativeness from the firm's and customers' perspective in one model, this study focuses on the new relationship between product innovativeness, product advantage and new product financial performance.
4. When it is most beneficial for a firm to implement an AML strategy that outweighs its implementation cost.

1.3 Research Objectives

In the previous section(s) of this chapter, the major research gaps in the ambidexterity and NPD literature have been identified. It is important to formally articulate the research objectives of this study. The objectives of this study are three-fold. The foremost objective of this study is to determine the degree to which firms that employ ambidextrous market learning strategy to develop products that have high product advantage. Additionally, the moderating effects of product innovativeness on product advantage and new product financial performance are identified and studied. Therefore, the three objectives of this study are as follows:

1. Examine the relationship between ambidextrous market learning and product advantage, in high-tech firms.
2. Examine the moderating effects of product innovativeness from firm and customer's perspective in one model, shed new light on the relationship between product advantage, product innovativeness and new product financial performance.
3. Examine when the benefits of having ambidextrous market learning strategy outweighs the implementation cost, in high-tech firms.

To accomplish the aims of this study, insights from organisational learning theory were taken. In addition, the Day and Wensley's (1988) source-position-performance (S-P-P) framework was used as a guideline to develop the conceptual model. This study aims to assess whether ambidextrous market learning firms tend to develop innovative products with higher product advantage in comparison to competing products and shed new light on the relationship between product innovativeness – product advantage – new product financial performance. This research covers new ground by combining the key concepts from the existing literature and by operationalizing the key concepts differently and by hypothesising the relationships between the key concepts in a new outlook. Thus, by accomplishing these objectives this study makes key contributions and these are addressed in the next section.

1.4 Contributions from the study

In addressing the major gaps in the ambidexterity and NPD literature this study has key contributions and these are as follows:

1. The most valuable contribution of this study is to examine the relationship between ambidextrous market learning and product advantage. To date to the best of the knowledge of the researcher, in the ambidexterity literature, there are two studies that have empirically tested how the different types of market learning respectively impact product performance (Kim and Atuahene-Gima, 2010; Yannopoulos, Auh, and Menguc, 2012). And while, an abundance of empirical studies illustrate the importance of ambidexterity on firm performance. To date, however, the ambidexterity literature is silent on how ambidextrous market learning may affect product advantage in high-tech industries. This study helps to understand how ambidextrous market learning firms can develop products with superior product advantage which are more meaningful to the customers in comparison to the

competing products. This is a key contribution not just from the literature perspective but also from the managerial perspective, as this study focuses on how ambidextrous market learning firms develop sustainable competitive advantage.

2. The second contribution of this research is the operationalization of product advantage. In the existing literature, based on the definition, product advantage is defined as the shared product elements that encompass product meaningfulness and product superiority. Therefore, the product advantage construct in this study is measured as a higher-order construct which may have significant implications not just in the existing literature but also practical implications to managers
3. The next contribution of this research is to emphasize the relationship between product innovativeness and product advantage. By exploring the moderating effect of product innovativeness on product advantage, this study sheds new light on the relationship between product innovativeness (from the firm's perspective) and product advantage. This is a key contribution not just from the literature point of view but also from the managers' perspective, as this study focuses on the benefits of developing innovative products. In recent years managers and researchers find that developing innovative products seem to have non-significant relationship with product performance.
4. From a managerial point of view, there are number of benefits to be derived from this study. The results indicate when the benefits of focusing on an ambidextrous strategy lead to enhanced product advantage and when there are no benefits of implementing an ambidextrous market learning strategy. The results also shed new light on how firms operating in high-tech industries develop sustainable competitive advantage by focusing on technological development and advancements.

1.4 Thesis Outline

To accomplish the above-mentioned research objectives, this study follows the research plan provided in Table 1.1. First, a review of the ever-growing literature is provided with the view of aiding our understanding of the effect of ambidextrous market learning on new product financial performance. Pertinent literatures that have linked market learning and its components to product performance are therefore assessed. The aim of the literature review is to determine how much research has focused on market learning in an NPD context. Accordingly, distinct areas focused in this study include the use of organisational learning and marketing literature in defining the different types of market learning, how the different types of market learning are used to conceptualise ambidextrous market learning, and how the ambidextrous market learning is operationalized, the unit of analysis used, types of independent and dependent variables studied in this context. Overall, the second chapter provides a clear justification for studying ambidextrous market learning in NPD activities.

Table 1.1 Thesis Outline

Chapters	Research agenda
Chapter One	Introduction
Chapter Two	An in-depth literature review of ambidexterity, organisational learning and marketing in relationship with New Product Development literature
Chapter Three	Research Model and Hypotheses
Chapter Four	Research Methodology
Chapter Five	Main study, Descriptive Analysis and Exploratory Factor Analysis
Chapter Six	Measurement model assessment
Chapter Seven	Hypothesis testing and study results
Chapter Eight	Discussion and Conclusion

Drawing on the conclusions of the literature review, and in line with the research objectives, in chapter three the conceptual model for the study is developed and the hypotheses are discussed in detail. Regarding the hypotheses, the primary focus is on the effect of ambidextrous market learning on product performance mediated by product advantage and product innovativeness.

Chapter four explains the study's research methodology employed to test the conceptual model and the hypotheses. This chapter provides information on the choice of cross-sectional research design; the sampling procedures, data collection techniques, questionnaire design and administration procedures are presented.

In addition, information regarding the implementation of the fieldwork to obtain the data to test the model is presented. In the next chapter (i.e., Chapter five), issues relating to questionnaire modification; characteristics of the respondents contacted; steps taken to ensure high response rate, survey bias assessment are discussed in detail, also Chapter five focuses on providing descriptive statistics of the firms that are studied and the general characteristics of the respondents are provided. In addition, the results of the Exploratory Factor Analysis are presented. This provides evidence of the validity and reliability of the information gathered.

In chapter six, the results of the item assessment and the development of the key constructs used in this study are outlined. Therefore, the psychometric proprieties of the scales are assessed. The primary focus in this chapter is to provide results of the scale reliability, uni dimensionality and validity measures. Chapter six also outlines the results of the various tests to justify the use of higher-order multidimensional constructs used in this study.

The procedure applied and the strategy deployed to test the hypotheses is described in chapter seven. The evaluation of the measurement model and the hypotheses in this study are tested using the aid of Structural Equation Modelling (SEM). The structural equation model was tested in AMOS 22 using a Maximum Likelihood (ML) estimation technique.

Finally, chapter eight presents the conclusion drawn from the results of this study. The primary focus of this chapter is to summarise the key findings related to the study's research goals. In addition, in this chapter, discussion of the theoretical and practical implications of the study is presented. Finally, the chapter concludes with an examination of the limitations of the study is highlighted while providing useful suggestions for future research.

Chapter Two: Literature Review

2.1 Introduction

New product development (NPD) is of paramount importance for firm's competitive advantage as it helps firms to safeguard their market position and improve their likelihood of growth (Griffin and Page, 1996; Kotler, 2003). This is especially true in high-tech industries; where firms have become increasingly reliant on NPD to compete in the ever changing and evolving global marketplace (Fernhaber and Patel, 2012). Consequently, new product and service development researchers have focused on understanding the antecedents of product performance (for example, Atuahene-Gima, 1995; Biemans and Harmsen, 1995; Danneels, 2002; Danneels and Kleinschmidt, 2001; Griffin and Page, 1996; Kleinschmidt and Cooper, 1991; Langerak and Hultink, 2006; Ottum and Moore, 1997; Veryzer and de Mozota, 2005). Despite the fact that product performance construct per se has remained one of the most researched area, yet after five decades of research, *"there are no prescriptive models that can explain how successful products are brought about"* (Poolton and Barclay, 1998, p. 198). In line with this, several research studies have focused on the importance of organisational ambidexterity in NPD activities (for example, Clercq, Thongpapanl, and Dimov, 2013; Gibson and Birkinshaw, 2004; Jansen, Bosch, and Volberda, 2005; Tiwana, 2008).

Ambidexterity is defined as the ability of the firm to explore and exploit simultaneously. This distinction between exploitation activities and exploration activities has been emphasised in the management literature since the seminal work by Burn and Stalker's in 1961. They argue that two different firm structures need to be placed for enhancing firm innovation and efficiency. Initial consensus of the ambidexterity literature suggests that a firm that tends to explore and exploit simultaneously fail to achieve any growth and success, primarily due to the lack of resources and losing sight of the firm's objective(s). But in the recent years, ambidexterity is viewed as a key resource for firm's competitive advantage. In the current competitive markets a firm has to refine, make its current resources effective and focus on implementation and to adapt to the changing needs and wants of the customer the firm has to simultaneously look to experimentation, being innovative and focus on discovery to achieve sustainable growth. In the current study, ambidexterity is viewed as a key resource for firms operating in high-tech industries and the ambidexterity hypothesis is tested in the context of firm's approach to developing innovative products and products with advantages.

Developing innovative products is the cornerstone to success in many industries (Rhee, Park, Lee, 2010) and although conceptual contributions to the product innovativeness literature over the past four decades have been extensive (McNally, Cavusgil, and Calantone, 2010), the relationship between product innovativeness and product performance is presently not fully understood. For example, there is empirical evidence providing a positive, negative, and a non-significant relation between product innovativeness and product performance (Calantone, Chan, and Cui, 2006; Calantone, Di Benedetto, and Bhoovaraghavan, 1994; McNally, Cavusgil, and Calantone, 2010).

These gaps in both ambidexterity and new product development (NPD) research literatures offer excellent opportunities for future research. As such, this study focuses on the aim to deepen our understanding of ambidextrous market learning and its impact on product performance, and the moderating effects of product innovativeness on product advantages and performance in high-tech industries.

2.2 Chapter Organisation

The previous section outlined the research objectives and described the context of this study. This chapter investigates the existing literature, focusing on New Product Development (NPD) in high-tech industry, ambidextrous market learning, product innovativeness, and product performance. To identify the existing theoretical gaps in the research, this chapter is divided into four sections. First, the importance of ambidexterity literature in the NPD literature is discussed, especially in high-tech industry; second, this chapter focuses on why NPD is important for maintaining a competitive advantage;; third, the key factors that discriminate between successful and unsuccessful new products; and finally, the impact of product innovativeness on product performance. In the end a summary is provided to end this chapter.

2.3 Ambidexterity

The concept of ambidexterity is well explained by correlating it to an individual's ability to use both hands with equal ease. In management and business research, a firm that co-ordinates and integrates exploratory and exploitative efforts across firm's business unit is defined as an ambidextrous firm (Gilbert, 2006; Tushman and O'Reilly, 1996; Smith and Tushman, 2005). The concept of ambidexterity has developed significantly since the pioneering work by Burn and Stalker (1961). The results of Burn and Stalker (1961) study emphasises that firms that implement dual structures to manage trade-offs emerging from a simultaneous focus on adaptation and alignment tend to be more successful. In addition, Duncan in 1976 argues that firms need to align their objectives and goals to meet the current customer's demands and while being aligned the firm should adapt to the changing environmental conditions to achieve long-term goals. Therefore, firms need to explore and exploit simultaneously. In its most basic sense, exploration is defined as the ability of a firm to discover, by being able to experiment, be risk taking and being able to innovative (He and Wong, 2004; March, 1991). On the other hand, exploitation is defined as the ability of a firm to refine its current process (es) to make it efficient, being able to implement and able to make production efficient and effective (He and Wong, 2004; March, 1991).

In the last two decades, the results of the two mentioned studies in the previous paragraph have been applied extensively in various organisational contexts, such as, strategic management (for example, Menguc and Auh, 2008; O'Reilly and Tushman, 2008). The primary focus in this literature is focusing on the key drivers of how firms can develop capabilities to explore and exploit simultaneously. Another research area in which ambidexterity is well covered is organisational design (for example, Gibson and Birkinshaw, 2004; Wang and Rafiq, 2014). The organisational design or structure that enables the appropriate integration of exploration and exploitation activities, such as, adaptability and alignment, is the dominant topic for debate in this literature.

The other theoretical area within which the concept of ambidexterity is prevalent is organisational learning (for example, Gupta, Smith, and Shalley, 2006; Katila and Ahuja, 2002). The central theme in these studies is the various antecedents that enhance the augmented effect of the two different forms of organisational learning on firm and product performance. The concept of ambidexterity has been comprehensively applied in the organisational innovation theory as well (for example, Benner and Tushman, 2003; He and Wong, 2004; Jansen, Bosch, and Volberda, 2005). The common theme surrounding ambidexterity and innovation is that exploration activities leads to developing radical products and developing new technologies and on the other hand, exploitation activities leads to developing incremental products, and improving the current product lines.

Ambidexterity is observed as an evolving research paradigm in organisational theory. Scholars have predominantly emphasised that firms that pursue exploration and exploitation simultaneously obtain superior performance (for example, Gibson and Birkinshaw, 2004; He and Wong, 2004; March, 1991). For example, Colbert (2004) argues that exploitation and exploration can simultaneously flourish and this might be considered as a valuable, rare, and costly to imitate resource, and therefore a potential source of competitive advantage. In the existing literature, studies find that firms that can integrate exploration and exploitation capabilities simultaneously tend to develop successful products (Sheremata, 2000) and have superior long-term performance (Tushman and O'Rielly, 1996). However, the simultaneous focus on exploration and exploitation activities still receives critical criticisms from scholars (for example, Kyriakopoulos and Moorman, 2004; Miller and Friesen, 1986; Yannopoulos, Auh, and Menguc, 2012). In the existing literature, traditionally exploration and exploitation are viewed as competing activities (Duncan, 1976).

There are four central controversial key points based on which researchers argue that firms must not engage in both strategies/activities simultaneously. First, learning theorists demonstrate that exploitation learning tends to limit the amount of exploratory learning and vice versa (for example, March, 1991). In addition, engaging in both types of learning is difficult for managers and by focusing on two different types of learning, firms tends to not learn anything useful and may lead to unsuccessful decisions. Second, general management theorists argue that exploration and exploitation strategies compete for limited resources (for example, Miller and Friesen, 1986). They argue that researchers and scholars who argue in favour of ambidexterity, practice under the false notion that firms have unlimited resources and implementing different organisational structures that enhances ambidexterity is not straightforward.

Third, contingency theorists argue that by focusing on exploration and exploitation simultaneously firms tend to lose focus in both and the overall results are detrimental (for example, Galbraith, 1973). And finally, a small group of researchers empirically illustrate that ambidexterity has a negative impact on innovative products and hence the firm performance is deteriorated. For example, Atuahene-Gima (2005) depict that the interaction of exploration and exploitation activities negatively impacts on radical product innovation. Ebben and Johnson (2005), state that by pursuing exploitation and exploration innovation simultaneously, firm's performance deteriorates, as they tend to lose focus on different innovation strategies. Bierly and Daly (2001) tested the impact of ambidexterity on firm performance with a sample of 98 manufacturing firms and found that the relationship was non-significant.

Despite these early criticisms, extensive research suggests that ambidexterity is a necessity for business success, superior product performance, and is crucial for long-term survival and growth of the firm, especially in high-tech firms (for example, Hughes, Martin, Morgan, and Robson, 2010; Jansen, Tempelaar, van den Bosch, and Volberda, 2009; Wang and Rafiq, 2014). Levinthal and March (1993) argue that firms exclusively exploring will suffer from the fact that it never gains the returns of its knowledge, and firms exclusively exploiting will suffer from obsolescence. Likewise, Yalcinkaya, Calantone, and Griffith (2007) argue that by excessively focusing on exploitation strategy firms may reach a technological exhaustion point and by excessively focusing on exploration strategy firms may fail in their short-term financial performance.

Furthermore, Lewin and Volberda (1999, p. 523) argue, *"These forms (exploration and exploitation activities) need not be contradictory processes. They can be complementary, and organisations must learn how to carry out both forms"*. In addition, ambidexterity is viewed as a key source for competitive advantage by developing new products and entering new markets (for example, Hughes, Martin, Morgan, and Robson, 2010). For example, Garcia, Calantone, and Levine (2003) argue that without exploitation, exploration is not possible because without the financial growth achieved via exploitation activities it is difficult to indulge in exploration activities. In addition, organisational learning theorists argue that without having a clear understanding of the current system in place it is hard for someone to go out and explore and search for something new. Hence, from the existing literature it is quite evident that exploration and exploitation activities share some common core or root(s) that is considered as a key source of competitive advantage.

Table 2.1: Key search word(s) used

Key Search Word(s)	**Number of Papers**
Ambidexterity	268
Ambidexterity + Products (New)	71 (32)
Ambidexterity + Product Development Process	22
Ambidexterity + NPD Process	1
Ambidexterity + Product Innovation	29
Ambidexterity + Product Innovativeness	-
Ambidexterity + High-tech (High Technology Industries)	22
Ambidexterity + High-tech industries + Product	10
Ambidexterity + Marketing	60
Ambidexterity + Marketing + Product + High-tech industries	3

To conduct an in-depth analysis on the ambidexterity literature, keywords such as ambidexterity and/or ambidextrous were inserted in EBSCO and Science Direct. This yielded in a total of 268 papers in the summer of 2015. Doing an in-depth analysis of the 268 papers in the literature generated few key results and descriptive analysis revealed that out of these 268 papers, 44 papers are conceptual, around 66 papers are qualitative papers, and 56 papers focus on exploration and exploitation activities but do not measure ambidexterity.

Approximately 98 papers are quantitative papers and measure ambidexterity based on the existing literature. Table 2.1 sheds light on the results when additional key search word(s) were put in with 'ambidexterity/ambidextrous' into EBSCO and Science Direct.

Conceptual studies explaining how ambidextrous firms tend to create successful businesses can be dated back to the early 1960s. A central theme in the early conceptual papers was the integration of exploration of new possibilities and the exploitation of old certainties (for example, Duncan, 1976). But in 1991, one of the key papers in the literature by March steered the discussion on how can firms develop capabilities to simultaneously focus on exploration learning of new possibilities and exploitation of old certainties rather than focusing on whether firms can implement these competing activities. This paper by March in 1991 set a new trend in the organisational learning literature, and that was to find the key drivers of organisational ambidexterity.

In 2004, He and Wong were the first to develop a scale to measure explorative innovation strategy and exploitative innovation strategy and empirically measure its impact on firm's sales growth rate. This started a new trend in the literature, since the pivotal paper by He and Wong in 2004; there have been more than 200 papers, testing the ambidexterity hypothesis. These descriptive statistics provide evidence that though the ambidexterity literature can be dated back to the early 1960s, there has been an exponential growth in the number of researchers focusing on ambidexterity in the last decade. In the next section, five key themes that emerge from the existing literature are discussed in detail and also the key research gaps that need addressing are discussed. In the later sections, a detailed discussion is presented on the key themes emerging from the New Product Development (NPD) literature.

2.3.1 Ambidexterity Literature

There are five key themes emerging from the ambidexterity literature. First, there is a growing interest on the ambidexterity hypothesis and these studies have been conducted in a variety of methodological settings. The primary reason for this could be that as mentioned earlier, the ambidexterity term broadly implies a firm's ability to pursue diverse goals concurrently, such as, exploration and exploitation (March, 1991), efficiency and flexibility (Adler, Goldoftas, Levine, 1999), alignment and adaptability (Gibson and Birkinshaw, 2004), or incremental and radical product innovation (Atuahene-Gima, 2005). This has led to a mix of empirical results. Though the definition of ambidexterity is well defined, their implications/outcomes in different settings have had different meanings. For example, exploring as defined is the ability of a firm to search, experiment, and develop innovative ideas/products; hence the different elements/dimensions of exploration are applied in different methodological settings.

The second key theme emerging from the literature is that, there is a lack of conceptual clarity regarding the way ambidexterity is operationalised (Cao, Gedajlovic, and Zhang, 2009). The crucial argument here is what levels of exploration and exploitation activities are required in a firm to define a firm as ambidextrous? Cao, Gedajlovic and Zhang (2009) illustrate that, although there is a broad agreement on the definition of ambidexterity, nonetheless there are two dimensions of ambidexterity. These two dimensions of ambidexterity are significantly different and overall this ambiguity regarding the ambidexterity construct has had an impact on the way ambidexterity construct is conceptualised and operationalized.

The two dimensions of ambidexterity are: combined and balanced. The central idea behind the conceptualisation of combined dimension of ambidexterity is that a firm can explore and exploit, and learn from both these complementary activities over time, which has an overall positive impact on firm and product performance. On the other hand, the second dimension of ambidexterity is termed as *'balance (between) dimension of ambidexterity'*. The concept of balance dimension of ambidexterity is built on a central idea that an ambidextrous firm explores new competencies and exploit existing competencies in a balanced fashion. In sense, a firm balances the amount of resources spent on exploration and exploitation activities. The different dimensions of ambidexterity are better understood from the table below. The below table provides an example of two firms (that is, Firm A and Firm B) that can be defined as ambidextrous. Both firms are capable of exploiting and exploring (in this example, on a scale of 1 to 10). Yet, these two firms illustrate the different dimensions of ambidexterity. On the one hand, Firm A; tends to explore new competencies more than exploiting existing competencies.

Table 2.2 Difference between the two dimensions of 'Ambidexterity'

Illustration of different conceptualisations of ambidexterity				
	Exploration Score	**Exploitation Score**	**Balance (Between) Dimension of Ambidexterity**	**Combined Dimension of Ambidexterity**
Firm A	10	5	Low	High
Firm B	5	5	High	Low

(Source: Cao, Gedajlovic, and Zhang, 2009)

If ambidexterity is defined as a combination of both exploration and exploitation activities then Firm A (multiplication of exploration and exploitation score is 10X5 = 50) is seen to be more ambidextrous than Firm B (multiplication (or addition) of exploration and exploitation score is 5X5 = 25). On the other hand, if ambidexterity is defined as a balance between exploration and exploitation activities then Firm B (the absolute difference of exploration and exploitation activities is 0) is seen to be more ambidextrous than Firm A (the absolute difference of exploration and exploitation activities is 5).

This division of two dimensions of the ambidexterity construct led to further questions regarding how ambidexterity is perceived. This division between *'balanced'* and *'combined'* dimensions has two major implications. First, researchers and scholars in the organisational studies argue that the organisational structure has an impact on how firms tend to gain the most from being ambidextrous (for example, de Visser et al., 2010). That is, a balance (between) exploration and exploitation activities would require a different structure and hence would also mean the decision making process will be different. This argument led to differentiating between *'structural ambidexterity'* and *'contextual* ambidexterity'.

The concept of structural ambidexterity is best achieved through the creation of dual structures and how the resources are divided between conflicting demands for alignment and adaptability. In sense, structural ambidexterity is perceived as not just a set of processes or strategic decision making ability, it is the way firms implement different structures and whether this can lead to creating successful businesses. Scholars who argue that exploration and exploitation activities are competing and not complementary activities tend to view ambidexterity as *'structural'*.

On the other hand, *'contextual ambidexterity'* is perceived as a set of processes or systems that enables firms to divide the resources between exploratory and exploitative activities. Researchers and scholars who measure contextual ambidexterity in their studies argue that firms focusing on high levels of both exploratory and exploitative activities can be defined as ambidextrous. Contextual ambidexterity is considered as the integration of exploration and exploitation activities in one single business unit, and this can be achieved by implementing a set of systems or carefully building an organisational ambidextrous culture (for example, He and Wong, 2004; Smith and Tushman, 2005; Tushman and O'Reilly, 1996; Wang and Rafiq, 2014).

The division between the different types of ambidexterity (that is, structural versus contextual) and the different dimensions of ambidexterity (that is, combined versus balanced) has huge implications on how the studies are conducted and how ambidexterity is operationalised. There are four different ways in which the ambidexterity construct has been measured in the existing literature, and the table below differentiates between the four different ways of operationalising ambidexterity.

Table 2.3 Different ways of operationalising the 'Ambidexterity' construct

Operationalization	Key Paper(s)	Comment(s)
Addition of the two scales (for example, exploration and exploitation activities)	Jansen et al., (2009)	They argue that by adding the two scales, a formative single item construct explains the essence of ambidexterity and this provides an alternate technique to measuring ambidexterity as a multiplicative term, since there is loss of information.
Subtraction of the two scales (for example,	He and Wong (2004)	They compare the results of the ambidexterity hypothesis by measuring ambidexterity as an interaction term with measuring ambidexterity as an absolute difference term. The second measure resulted in a negative relationship between ambidexterity and firm sales growth rate in comparison to a positive relationship between both the constructs by measuring ambidexterity as an interaction term.
Multiplication of the two activities (that is, exploration and exploitation).	Brion, Mothe, and Sabatier (2010); Morgan and Berthon (2008); Hughes at al., (2010); Gibson and Birkinshaw (2004)	In the existing literature, multiplicative (Interaction) term is the mostly commonly used technique to operationalise ambidexterity. Ambidexterity is measured as a combined dimension and scholars argue that by simultaneously maintaining high levels of both exploration and exploitation tends to create and sustain competitive advantage in the long run and in achieving short term objectives.
Higher Order construct comprising of exploration and exploitation activities as the component factors	Wang and Rafiq (2014); Lubatkin, Simsek, and Ling (2006); Kortmann (2014)	They argue that using interaction term leads to loss of information and in addition, there is a misalignment between the conceptualisation and operationalization of the ambidexterity construct.

Overall, the operationalization of the ambidexterity construct has had huge impact on the ambidexterity and performance hypothesis. Primarily because, studies focusing on the balance dimension of ambidexterity argue that there has to be an optimal mix of exploration and exploitation activities to ensure success and on the other hand, studies focusing on the combined dimension of ambidexterity argue that by simultaneously maintaining high levels of focus on exploiting the current capabilities and exploring new opportunities, firms tend to create and sustain competitive advantage. In the existing literature, some scholars operationalising ambidexterity as balance between exploration and exploitation activities have found negative impact on performance (for example, He and Wong, 2004). In 2013, Junni, Sarala, Taras and Tarba conducted a meta-analysis on the ambidexterity literature and voice their concerns regarding more clarity on the way ambidexterity is conceptualised and operationalised. In fact they argue that the future studies on ambidexterity could conduct additional analysis on the results obtained from operationalising ambidexterity in different ways (see Table 2.3).

The third theme emerging from the ambidexterity literature is that, ambidexterity is important in manufacturing and high-tech industries. For example, Raisch and Birkinshaw (2008); Simsek (2009) argue that ambidextrous firms tend be more successful in industries where the competitive intensity is high and in industries in which knowledge capabilities are a source of competitive advantage. In general, firms operating in high-tech industries have no choice but to explore and exploit simultaneously due to the dynamic market conditions (Wang and Rafiq, 2014; Li et al., 2008; Fernhaber and Patel, 2012). The vast application of the ambidexterity construct in studies focusing on high-tech industries is primarily due to the following reasons:

1. **Due to technological changes –** It is difficult to adapt to a dramatic change in technology and yet at times some firms successfully make this transition across the waves of this technological change primarily due to firms exploring and exploiting simultaneously (Tushman and Anderson, 1986; Fernhaber and Patel, 2012).
2. **Due to globalisation-** It is becoming difficult for firms (not just high-tech firms) to enter a new market, but firms operating in high-tech industries need to enter new

markets to achieve superior firm performance. This is because of the shortening of new product life cycles due to frequent dramatic technological changes. Therefore, firms operating in high-tech industries enter new markets by developing similar products (not radical improvements) for global customers, which in turn can increase the product life cycle (Taylor and Helfat, 2009). Therefore, firms operating in high-tech industries need to explore new markets and exploit the existing markets.

3. **Due to long-term and short-term objectives –** It is evident from the existing literature that to create a sustainable firm, a firm needs to not just focus on the current needs and wants of the customer but also focus on the future needs and wants (market trends) of the customer. And therefore, a firm has to focus both on exploration and exploitation simultaneously.

It is clearly evident from the existing literature that ambidexterity plays a key role in developing a sustaining successful firm performance for firms operating in the high-tech industries. Yet, in the meta-analysis conducted by Junni et al., (2013) they find that the ambidexterity literature has been extensively applied in the manufacturing and high-tech industries. But they have found that the ambidexterity - performance hypothesis is non-significant in the context of high-tech industries (by applying the Hunter and Schmidt, 2004 meta-analytic approach. The Hunter and Schmidt (2004) meta-analysis technique/tool is a REM (Random Effect Model) which provides the significance of the relationship tested and also provides the ρ value (that is, the strength of the relationship)). In addition, in comparison to other industry analysis in their meta-analysis they found that ambidexterity had the lowest effect on performance in manufacturing industries.

The fourth theme emerging from the literature is that there is no clarity regarding the level of analysis and whether ambidexterity outweighs its implementation cost (Junni et al., 2013; O'Reilly and Tushman, 2013). In the existing literature, the earlier consensus was whether it is possible to implement a structure that can implement two competing activities. In addition, an initial argument against ambidexterity was that it was too expensive to develop an ambidextrous culture and this will not lead to improving performance. Then later, the argument shifted from competing activities to complementary activities. Now, the primary question asked in the literature is whether there are any advantages of developing an ambidextrous culture or developing such a contextual framework that enhances ambidexterity.

The final theme emerging from the literature is that, the ambidexterity construct is widely used in the NPD literature. As it can be seen from Table 2.1, 71 papers out of 268 papers link the two literatures. In the existing literature on ambidexterity and NPD, the most commonly used scale for exploration and exploitation are; Exploration and exploitation innovation strategy (developed by He and Wong, 2004); exploration and exploitation innovation learning (adapted from He and Wong, 2004); alignment and adaptability (developed by Gibson and Birkinshaw, 2004); exploration and exploitation product innovation competence (Atuahene-Gima, 2005); and number of radical and incremental innovation developed by the firms as a reflective measure of exploration and exploitation innovation (for example, Ebben and Johnson, 2005). Exploration and exploitation innovation strategy (developed by He and Wong, 2004) is the most widely used scale to measure ambidexterity. Exploration innovation strategy measures whether firms have developed new line of products (that is, facing new competition) in the last five years, and exploitation innovation strategy measures the improvements made in the quality, cost, flexibility, and reduction in the material consumption in the last five years.

In addition, measuring *"innovation ambidexterity"* that is, the ability of the firm to have explorative innovation behaviours (that is, developing new markets and new technologies) and exploitation innovation behaviours (that is, improving the existing market needs and current technologies) have been mostly used to measure exploration and exploitation activities that measure ambidexterity in directly. Studies linking ambidexterity and NPD literature have used a variety of scales ranging from single item scales (Ebben and Johnson, 2005) to using multi-item scales measuring the new technology used in developing new products (a reflective scale to measure exploration innovation competence) and upgrading/enhancing the existing knowledge for developing products (a reflective scale to measure exploitative innovation competence).

Due to the use of variety of definitions and measures of ambidexterity in the context of NPD, this has led to mixed empirical results. For example, negative relationship between ambidexterity and product performance (for example, Atuahene-Gima, 2005); non-significant relationship (for example, Venkataram, Lee and Iyer, 2007); positive relationship (for example, Gibson and Birkinshaw, 2004). Therefore, Lavie and Rosenkopf (2006), state that *"In the future, scholars who employ the exploration and exploitation framework should conceptually relate their constructs back to March's (1991) original definition"* (p. 202).

In addition to inconsistent results due to the variety of scales used to measure ambidexterity, measuring exploration innovation activities as a reflective measure of developing new product line or radical products and measuring exploitation innovation activities as a reflective measure of improving the current product line or incremental products limits our understanding on the following questions; whether ambidextrous firms tend to develop innovative products, what is the relationship between ambidexterity and product innovativeness, and whether these innovative products tend to be successful.

Ambidexterity provides basis for New Product Development (NPD) activities that leads to developing successful products (for example, Hughes, Martin, Morgan, and Robson, 2010; Jansen, Tempelaar, van den Bosch, and Volberda, 2009). Despite the importance of ambidexterity literature in NPD, the literature has been silent on how ambidextrous firms develop innovative and successful products. For example, (Brion, Mothe, and Sabatier, 2010) state, *"no studies have examined how firms can simultaneously explore and exploit to achieve superior innovation, which is a prerequisite for sustained performance"* (p. 151).

To summarise, though the concept of ambidexterity is not new and it is well defined there are key gaps in fully understanding its overall effect on product and/or firm performance. There are still key questions that need answering, for example, do ambidextrous firms develop innovative and successful products, does ambidexterity outweighs its implementation cost, at what level (that is, firm level, business unit level or project level) should contextual factors that enhance ambidexterity be implemented. In addition, is ambidexterity a source of competitive advantage, especially in firms operating in high-tech firms? How should the ambidexterity construct be conceptualised and operationalised? Finally, how ambidextrous firms (taken from the marketing perspective) can develop innovative products and whether these innovative products tend to be successful? Hence, in the next section, the above mentioned research gap will be addressed.

2.3.2 Role of Market Learning in NPD

Griffin and Hauser (1996), report that high-tech firms require greater integration between R&D and marketing. This is essentially because the market conditions and the state of the technology are continuously evolving and competitive pressure to keep abreast is high. In such circumstances, R&D not only needs to shine in its technical expertise, it also needs to surpass in translating market needs into viable products and services. Diverse studies focusing in the NPD literature since the 1930s have consistently found that thorough understanding of customer needs and wants, the competitive situation and the market & environment evaluation enhances product differentiation and is the most critical information for successful product development (for example, Cooper and Kleinschmidt, 1993; Maidique and Zirger, 1984; Rothwell, 1972; Veryzer and Mozota, 2005).

In recent years, there has been an exponential growth in studies linking marketing and NPD activities. This has reinvigorated interest in closely related subjects such as the use of market information in NPD (Deshpande and Zaltman, 1982; Menon and Varadarjan, 1992), link between marketing capabilities and NPD (O'Connor and Veryzer, 2001; Weerawardena, 2003), impact of market knowledge on new products (Li and Calantone, 1998; Ottum and Moore, 1997), link between customer inputs and various NPD activities (Perks, 2000; Salavou and Lioukas, 2003), and market orientation (Atuahene-Gima, 1995; Baker and Sinkula, 1999a). While a relatively new topic in marketing that has emerged, which is linking market learning and NPD (Kim and Atuahene-Gima, 2010; Morgan, 2004). In recent years, researchers have taken insights from organisational learning and marketing and argued that market learning plays a crucial role in developing successful products and services.

It was well established more than two decades ago by Handy (1990) that organisational learning capabilities and knowledge assets is more valuable to the firm than its material assets. The organisational learning literature has significantly evolved since the pioneering work by Simon (1953). Srivastava, Fahey, and Christensen (2001) illustrate that organisational learning is a type of capability that can leverage market-based knowledge to achieve competitive advantage. Slater and Narver (1995) argue that organisational learning and market orientation go hand in hand, and this helps firms reduce the market and technological uncertainty and therefore, provide managers with a competitive edge.

Existing literature suggests that continuous commitment to learning is central to product development in high-tech firms (Rhee, Park, and Lee, 2010). Some researchers have stated that practices facilitating learning and effective knowledge transfer are particularly important for product development (for example, Kogut and Zander, 1992; Lin, McDonough, Lin, and Lin, 2013; Teece and Pisano, 1994). The emerging importance of the organisational learning literature in marketing is well accepted and defined as *"the development of new knowledge or the modification of existing knowledge about customers, competitors, suppliers and other constituents through the capabilities of exploration and exploitation"* (Ozsomer and Gencturk, 2003, p. 4).

Based on this definition, scholars suggest that exploratory and exploitative marketing activities should be conceptualised and measured by evaluating the similarity or uniqueness of the target segment, positioning, product, or distribution channel, under the assumption that new segments, etc., are innately more exploratory than current segments (for example, Levinthal and March, 1993; Kim and Atuahene-Gima, 2010; Ali, Peters, He, and Lettice, 2010). On the other hand, organisational learning scholars (for example, Huber, 1991; March, 1991; Slater and Narver, 1995) suggests that the type of learning should be deduced from whether or not the firm does or does not rely on its current knowledge and skills or whether it must acquire new knowledge and skills.

In line with the above classification and based on March's (1991) definition, findings from a theoretical paper by Levinthal and March (1993) state that there are two types of market learning, that is, exploratory market learning and exploitative market learning. Exploratory market learning is defined as *"the pursuit of radical and new market information by going beyond the current product-market knowledge domain"*, and exploitative market learning is defined as *"the thorough and detailed processing of the market information within the firm's current domain of market and product experience"* (Levinthal and March, 1993, p. 97). Consequently, exploratory market learning is defined as the usage of market information beyond its current product-market experience, that is, through market experimentation, and by obtaining market information through contacts with non-customers and emerging competitors. On the other hand, exploitation market learning is defined as the usage of market information obtained by analysing the current customers and competitors products.

Kyriakopoulos and Moorman (1998) show that exploratory and exploitative market learning may influence product performance variables like short-term financial performance, product speed and product creativity. They argue that exploitative market learning enhances the firm's knowledge on the current customers, and competitors; and exploratory market learning expand the firm's knowledge on the future customers and help firm predict the future market needs and wants. In addition, Yannopoulos, Auh, and Menguc (2012) inform us that new product performance is significantly enhanced when congruency exists between the types of learning (exploration and exploitation market learning) and market orientation. Ali, Peters, He, and Lettice (2010) state that market based learning has now gained empirical support, with exploration and exploitation market learning having a considerable impact on aspects of performance such as market share, overall performance, and new product success. In addition, Kim and Atuahene-Gima (2010) illustrate that exploratory market learning contributes to the differentiation of the products and exploitation market learning enhances cost efficiency. To date, however, the ambidexterity literature is almost silent on how ambidextrous market learning (that is, simultaneous exploratory market learning and exploitative market learning) may affect product advantage.

To summarise, in the ambidexterity literature there are key gaps in fully understanding its overall effect on product and/or firm performance. There are still key questions that need answering, for example, how simultaneous exploration and exploitation market learning (that is, ambidextrous market learning) may affect product performance? How can ambidextrous market learning (AML) firms develop products that are advantages in comparison to its competitive products but also develop innovative products? Hence, the next section focuses on the NPD literature to understand what are the key product characteristics that define a successful product? In addition, an in-depth analysis of the NPD literature reveals emerging concepts and key gaps that need addressing, will be presented.

2.4 New Product Development (NPD) in High-tech firms

Why is new product development so important to a firm's key strategic goals? Driven partly by rapidly changing markets and technologies and partly by the more recent demands of the financial community for dramatically increased sales and profits, with an estimated one – third of the average organization's sales are derived from new products. Consequently, organizations with great new products are the darlings of the stock market (Brown, Leavitt, Wright; 2005). Progress is measured by the effectiveness of new product produced by the organization. At times the organization can suffer from stagnation, if a good new product strategy is not developed. Product planning is gaining more and more attention due to its impact on the business.

New product development (NPD) is a dominant driver of substantial profitability, maintaining a competitive advantage and ensuring firm's survival (Brown and Eisenhardt, 1995; Ernst, 2002). Product planning is gaining more and more importance due to its impact on firm performance. This is especially true in the case of firms operating in high-tech industries, where developing new products depend greatly on science and technological advancements and simultaneously understanding the needs and wants of the customer. In high-tech industries, the competition is intense, the pace of change is accelerating and the needs and wants of customers are constantly altering and firms are confronted with developing innovative products. Developing new products in high-tech industries depend greatly on science and technological advancements that lead to new or improved products and services. High-tech industries have a substantial economic impact, fuelled both by large Research and Development (R&D) spending, and a higher than industry average sales growth. Therefore product development and planning is quintessential in the constantly evolving marketplace.

The NPD literature is extensive and spans over seven decades of research. In the NPD literature the primary focus is on understanding the key 'product characteristics' that enhances product performance. Scholars in this stream have produced a large amount of empirical evidence concerning the factors that enhances the new product success. In 2001, Henard and Szymanski conduct a meta-analysis on the NPD literature and identified five key product characteristics that discriminate between successful and unsuccessful new products. The five key factors are as follows:

1. Product advantage
2. Product meets customer needs
3. Product price
4. Product technological sophistication
5. Product innovativeness

In a nutshell, an extensive literature review on NPD, discloses five key product characteristics that determine the success of new products and from these five, product advantage and product innovativeness are the two fundamental variables. Hence, in the next two sections, these two key product characteristics will be discussed in detail.

2.4.1 Product advantage

In the existing NPD literature, product advantage is the most commonly used antecedent to new product financial performance. In the existing literature, product advantage is defined as the *"superiority and/or differentiation over competitive offering"* (for example, Calantone, Chan, and Cui, 2006; Evanschitzky, Eisend, Calantone, and Jiang, 2012; Henard and Szymanski, 2001; McNally, Cavusgil, and Calantone, 2010; Rijsdijk, Langerak, and Hultink, 2010). In the existing literature, to this point, there have been three meta-analyses papers on the success factors of product performance (Montoya-Weiss and Calantone, 1994; Henard and Szymanski, 2001; Evanschitzky, Eisend, Calantone, and Jiang, 2012). In all the three meta-analyses papers, product advantage was found to be empirically the most dominant product characteristics to define product performance. Evanschitzky, Eisend, Calantone, and Jiang (2012) conducted a regression analysis and found that 86 studies (articles published from 1999 through 2011) out of 202 articles measuring various product characteristics and product performance hypothesis used the product advantage construct as the key variable. The product advantage construct concerns the extent to which a product offers unique benefits and the superiority over competing products, and it is considered as the most valuable determinant of product performance.

Henard and Szymanski (2001), state that the product advantage construct comprises of several distinct product characteristics, such as product meaningfulness and product superiority. In addition, Calantone and di Benedetto (1988) state that the definition of product advantage combines two distinct components: product meaningfulness and product superiority. They define product meaningfulness as, *"new products that provide new (unique) attributes and functionalities that customers perceive as appropriate and relevant"* (p. 35). And product superiority refers to *"the extent to which a new product outperforms competing offerings along existing attributes and functionalities"* (p. 36). Therefore, for a product to be superior relative to the other products available in the market, the product has to be unique on various dimensions such as quality, benefit, and function (Im, Hussain, and Sengupta, 2008), and also the customers must perceive it as appropriate, relevant and useful (Li and Calantone, 1998). Hence, these are two key inter-dependent product characteristics. Im, Hussain, and Sengupta (2008) illustrate that the superiority of the product exists as long as the product is also meaningful to the customer. Based on this line of reasoning product advantage comprises of two distinct and indispensable components (that is, product meaningfulness and product superiority) and by firms focusing on developing products that are simultaneously superior to the competing products and are meaningful to the customer tend to be superior.

Though there is a broad agreement on the definition of product advantage, there are two key themes emerging in the NPD literature. First, there is a lack of conceptual clarity regarding the way product advantage construct is operationalised in the literature (Rijsdijk, Langerak and Hultink, 2010). They argue that the product advantage construct consists of two components, i.e., product meaningfulness and product superiority. But in the existing literature, there is no distinctions made between the two components. In addition, Henard and Szymanski (2001) state *"although product advantage is arguably, a second-order factor composed of product characteristics predictors, in the existing literature it is frequently captured and reported as a single order construct"* (p. 365).

The second theme emerging from the literature is that, a number of scholars have addressed the nature of product advantage construct as product innovativeness (for example, Atuahene-Gima, 1995; Cooper and Kleinschmidt, 1987; Langerak, Hultink, and Robben, 2004; Li and Calantone, 1998). For example, Li and Calantone (1998) use product advantage to define the extent to which software's have unique features and argue that for a product to be unique it needs to be innovative. In addition, Langerak, Hultink, and Robben (2004) measured product innovativeness using the scales for product advantage and measured the relationship between product development speed and product innovativeness. They argue that the new product must be radically different to be superior and unique from the competing products only if it is innovative. It is important to distinguish between the indicators to measure product advantage and product innovativeness.

In the recent years scholars have started to address this problem and advised future researchers to clearly distinguish between the two variables (for example, Calantone, Chan, and Cui, 2006; McNally, Cavusgil, and Calantone, 2010; Rijisdijk, Langerak, and Hultink, 2010). For example, Calantone, Chan, and Cui (2006) state that using the product advantage construct as an indicator of product innovativeness is problematic as innovativeness do not necessarily lead to enhanced product advantage. In addition, Szymanski, Kroff, and Troy (2007) and Rijsdijk, Langerak, and Hultink (2010) noted that in the existing literature researchers have inaccurately conceptualised innovativeness as product superiority construct. Hence, due to these misapplied measures of product innovativeness as product advantage has misled scholars and practitioners. Hence, Calantone, Chan and Cui (2006), advice future researchers to measure product innovativeness and product advantage as two distinct constructs.

Due to this inconsistent clarity regarding the conceptualisation of product advantage and product innovativeness, the relationship between product advantage and product innovativeness is still not well defined. In addition, a very limited number of research studies explore the relationship between product advantage and product innovativeness. For example, McNally, Cavusgil and Calantone (2010) found that product advantage positively impacts customer discontinuity (product innovativeness) and on the other hand, Calantone, Chan and Cui (2006) found that product innovativeness positively impacts product advantage. This gap in the literature needs immediate addressing as this gap has a huge theoretical and practical implication as well. To completely understand the importance of addressing this issue, the next section presents an in-depth analysis on the product innovativeness construct.

2.4.2 Product Innovativeness

The second most dominant product characteristics used in the NPD literature is product innovativeness. Product innovativeness is defined as the perceived newness/originality/uniqueness offered by the product (for example, Cooper and Kleinschmidt, 1991; Danneels, 2002; Danneels and Kleinschmidt, 2001; Garcia and

Calantone, 2002). In the meta-analysis study by Evanschitzky, Eisend, Calantone, and Jiang (2012) results reveal that 83 articles out of 202 articles use the product innovativeness construct to predict product performance. Danneels and Kleinschmidt (2001), states that *"innovative products present great opportunities for firms in terms of growth and expansion into new areas. Significant innovations allow firms to establish a competitively dominant position and also provide newcomer firms an opportunity to gain a foothold in the market."* (p. 357).

As mentioned in the previous section, considerable studies in the existing literature demonstrate that product innovativeness is a crucial driver for product performance especially in high-tech industries; this is fundamentally because innovative products foster great opportunities for firms in terms of growth and expansion, and significantly innovative products establish a competitive advantage and offer firms perfect circumstances to gain a foothold in a market (Akgun, Keskin, and Byrne, 2012; Cooper, 2000; Damanpour, 1991; Danneels and Kleinschmidt, 2001; Kleinschmidt and Cooper, 1991; Lau, Yam, and Tang, 2011; van Riel, Lemmink, and Ouwersloot, 2004). In addition, as mentioned earlier, in high-tech industries the product life cycle tends to be shorter and hence, firms need to develop innovative products regularly.

The management of innovative products is particularly critical in high-tech industries. The significance of product innovativeness in NPD is even more evident in high-tech industries, as firms operating in high-tech industries continue to invest highly in R&D, and new technology. The average length, resources, and complexity involved in these scientific explorations are much higher than in other industries. The employment of product innovativeness has gone through a considerable debate and angst in both the academic as well as the trade press in the recent times. The primary reason for this stress is moderated by the sobering statistics regarding product innovativeness and product failures (Iyer, LaPlaca, and

Sharma, 2006). Despite nearly four decades of research, the nature of product innovation is yet to be fully understood (McNally, Cavusgil, and Calantone, 2010). Henard and Szymanski (2001) illustrate that there is no significant direct main effect of product innovativeness on product financial performance.

The emphases for more research to further understand the relationship between product innovativeness and product performance and also the relationship between product innovativeness and product advantages; stems from the ambiguity surrounding the conceptualisation of product innovativeness construct. An intensive analysis of the literature illustrates that there are various definition used to define the product innovativeness construct. This leads to diversity of approaches to measuring and operationalizing the product innovativeness construct. For example, Garcia and Calantone (2002) define innovativeness as *"the degree of 'newness', highly innovative products are seen as having a high degree of newness and 'low innovative' products sit at the opposite extreme of the continuum"* (p. 112). On the other hand, Syzmanski, Kroff, and Troy (2007) define product innovativeness as, *"the degree of newness or difference from the existing alternatives and the usefulness or meaningfulness of the innovative feature"* (p. 44). Henard and Szymanski (2001) state that *"product innovativeness is the 'perceived newness/originality/uniqueness/radicalness of the product"* (p. 364). Though the common focal dimension(s) used to define product innovativeness is newness (for example, Cooper, 1979; Langerak and Hultink, 2006; Sethi and Sethi, 2009) the conceptualisation of product innovativeness varies drastically.

There has been an array of ways to classify the basis of relative newness/originality/uniqueness. For example, scholars and researchers have used labels such as: *'innovative versus non-innovative'* (for example, Cooper and Kleinschmidt, 1987); *'discontinuous versus continuous'* (for example, Veryzer, 1998; Reid and de Brentani, 2004), *'evolutionary versus revolutionary'* (for example, Kline and Rosenberg, 1986), *'incremental* *versus radical'* (for example, O'Connor, 1998; O'Connor and Veryzer, 2001), *'major versus minor'* (for example, Drummond et al., 1999, Cooper and Kleinschmidt, 1991), *'really new'* (for example, Schmidt and Calantone, 1998; Song and Montoya-Weiss, 1998), *'breakthrough'* (for example, Zhou, Yim, and Tse, 2005; Mascitelli, 2000), and *'Disruptive innovations'* (for example, Danneels, 2004).

These various labels used in the existing literature are used to define product innovativeness has led to a key question, that is *'what is new about the product?'* To answer this question in the existing literature there are two key typologies of product innovativeness used and these are: the Booz, Allen, and Hamilton (1982) typology and the Henderson and Clark (1990) typology (please see detailed explanation of these two typologies in Appendix 2A). These two typologies use different and distinct features of product innovativeness to differentiate between the various categories of innovation. In turn, from these two typologies there are two key questions raised in the literature. First should product innovativeness be measured as types of product innovativeness/newness or as degree of newness? And second, is there a difference between product innovativeness from the firm's perspective and customer's perspective. These two questions will be looked into in-detail in the next two sections.

2.4.2.1 Types and Degree of Product Innovativeness

In the existing literature, following the Henderson and Clark (1990) typology, there have been various labels (see the previous section) used to differentiate between innovative/new/unique products and not so innovative products. In the NPD literature use of types of innovation is considered effective as different types of innovation provides clear understanding of whether innovative products are more successful in comparison to non-innovative products (Song and Montoya-Weiss, 1998; Kline and Rosenberg, 1986). In addition, differentiating products based on the types of innovativeness leads to better understanding of what organisational features (such as, organisational design, structure, marketing, knowledge, organisational learning) are required.

But on the other hand, a small group of scholars and researchers argue that rather than using types of product innovation, we should focus on measuring the degree of product innovativeness (for example, Calantone, Chan, and Cui, 2006; Danneels and Kleinschmidt, 2001; Garcia and Calantone, 2002; McNally, Cavusgil, and Calantone, 2010). In addition, Green, Gavin, and Aimah (1995) argue, *"a classification of projects as simply as radical and incremental may be oversimplifying the product innovativeness construct"* (p. 205). They argue that product innovativeness should be viewed as a continuum with multiple dimensions and not as types of product innovativeness. Danneels and Kleinschmidt (2001) argue that product innovativeness when conceptualised as a degree rather than discriminating based on types of product innovativeness, yields better understanding of the impact of product innovativeness on product performance.

A very small number of researchers and scholars have clearly identified the criteria used for classifying the difference between innovative and non-innovative products (for example, Danneels and Kleinschmidt, 2001; McNally, Cavusgil, and Calantone, 2010). For example, the labels radical innovation versus incremental innovation is most commonly used in the ambidexterity literature and to a great extent in the studies focusing on product innovativeness. Radical and incremental innovation is defined as the *"radical innovation involves fundamental changes in technology for the firm, typically address the needs of emerging customers, are new to the firm and/or industry, and offer substantial new benefits to customers",* and on the other hand incremental innovation is defined as the *"product improvements and line extensions that are usually aimed at satisfying the needs of existing customers"* (Atuahene-Gima, 2005, p. 65).

Though the above definitions clearly indicate how and why certain products can be defined as new/unique or innovative, but it does not measure how innovative or new the product is. For example, Danneels and Kleinschmidt (2001) argue that in the market there are products that fall under the definition of radical innovation but these products require different sets of skills, learning, synergy, resources and organisational design/structure. Hence, labelling as different types of product innovations has no empirical evidence on the findings. Danneels and Kleinschmidt (2001) argue that though there is a tremendous interest on product innovation, there is a lack of clear understanding of what product innovativeness mean. They argue that product innovativeness entails two key facets that are highly relevant to the firm developing innovative products, that is, fit and familiarity. They argue that firms developing new products (radical or incremental) need to first check how familiar are they with the process of developing this new product and how closely does this new product fit their skills and resources.

In addition, Kleinschmidt and Cooper (1991) conducted an analysis of 195 products developed and found that financial success rates of highly innovative products were almost as high for non-innovative products. Therefore, rather than focusing on different types of product innovation which do not explain much about the skills or resources required to develop the new product nor does the different types of innovation provide any clear evidence regarding how these different types of product innovation perform financially and in the market. In addition, McNally, Cavusgil, Calantone (2010) argue that one of primary causes for mixed results between product innovativeness and product performance is due to defining product innovativeness as different types of innovation.

In the existing literature, the conceptualisation of product innovation as a continuum with different dimensions is relatively new (for example, McNally, Cavusgil, Calanton, 2010; Danneels and Kleinschmidt, 2001). This question whether there are types of product innovation or product innovation should be viewed as a continuum with multiple dimensions led to another key question – What are these multiple dimensions of product innovation. That is, what factors contribute to defining product innovativeness? The next section of this chapter focuses on what are the different dimensions of product innovation and is there a difference between product innovation from a firm's perspective and customers' perspective.

2.4.2.2 Different attributes of product innovation

As mentioned, there are two key typologies of product innovation used in the existing literature. Based on the Booz, Allen, and Hamilton (1982) typology, there are two key dimensions (the x- and y- axis) of product innovation, that is, market and technological. When developing a new product a firm may have to shift from or learn new technologies (for example, Green, Gavin and Aiman-Smith, 1995; Song and Parry, 1997; Swink, 2000) to develop new products and on the other hand, some new products may take firms against new competitors or the firms may have to target a new customer group (for example, Souder and Jenssen, 1999; Souder and Song, 1998; Gatignon and Xuereb, 1997).

In addition, Kleinschmidt and Cooper (1991) argue that new product development takes firms into new market and technical situations and when firms develop new products an in-depth understanding of the marketplace, the resources dedicated to marketing, technological synergies, and an in-depth knowledge of the technology (new) applied are the key essential factors/skills required. In the existing literature it is unanimously agreed that there are two key elements of product development, one, the technology required to develop the new product and two, understanding the needs and wants of customer (for example, Danneels, 1998; Dougherty, 1992). In the existing literature, this further led to differentiating between product innovativeness from the firm's and customers' perspective. The next section of this chapter focuses on the difference between product innovation from a firm's perspective and customers' perspective.

2.4.2.3 Product innovation from firm's and customers' perspective

As mentioned in the previous section, innovativeness is defined as the 'degree of newness'. Following the Booz, Allen, and Hamilton typology of classifying new products, a small group of scholars and researchers have divided product newness based on two perspectives (that is, firm perspective and customer/market perspective) (for example, Calantone, Chan, and Cui, 2006; Danneels and Kleinschmidt, 2001; Garcia and Calantone, 2002; McNally, Cavusgil, and Calantone, 2010). Booz, Allen, and Hamilton state that new products can be classified primarily on the newness to the firm and newness to the customers. Products that are new to the firm may not necessarily be new to the customers (because the firm may be developing new product line); on the other hand, products can be new to the market but not necessarily new to the firm (firms may reposition their products to a new market). Booz, Allen and Hamilton argue that new products can be technically new to firm (for example, new product lines, improvements or incremental changes to the existing products and reducing the cost of developing new products by applying new technologies to the process of developing new products). In addition, they argue that new products may take the firm away from their existing knowledge about the markets, the competitors, the needs and wants of the customer and repositioning these products.

Based on the Booz, Allen and Hamilton typology, Danneels and Kleinschmidt (2001) develop a scale to measure product innovativeness from the firm's perspective that measures how familiar firms are in their marketing and technical synergies to develop new products. They argue that when developing a new product, a firm may require shifting from its existing technological knowledge and adapt a new R&D process or apply a new production processes, and/or require to learn a new state of the science and technology. This technology diversification required by a firm for developing innovative products is defined as 'technological discontinuity'. McNally, Cavusgil and Calantone (2010) define technological discontinuity as *"technological discontinuity arises from operating in new technological domains and involve new processes or technologies associated with innovation (e.g., the technology that is associated with nanotechnology)"* (p. 993). For example, for developing new products, a firm may require to learn new technology or software – that is use of (such as, SQL, Structured Query Language, computer language) and implement these changes to accommodate improvements in developing new innovative products. Or in the case of Internet based firms such as, Amazon or eBay, such firms had to implement new distribution processes to efficiently and effectively deliver their services/products.

On the other hand, some products may require a firm to shift from the existing market knowledge, new competitor knowledge, employing new distribution channels, targeting a new customer group, and/or developing new product categories. This market diversification is required by a firm for developing innovative products is called 'marketing discontinuity'. McNally, Cavusgil and Calantone (2010) define marketing discontinuity as *"marketing discontinuity arises from operating in new marketing domains and result when, for example, the product category, competitors, distribution channels, or customers are unfamiliar to the firm"* (p. 993). For example, the case of iPhones developed by Apple Computers. Apple Computers had limited knowledge regarding the mobile telecommunication industry and had to learn the needs and wants of the new target customer to enter the mobile telecommunication industry. They had to exercise new distributing channels and develop a new product category.

In the existing literature, there is not much empirical research conducted on product innovation by separating innovativeness into marketing and technological attributes (Danneels and Kleinschmidt, 2001; McNally, Cavusgil and Calantone, 2010; Garcia and Calantone, 2002). Though the above definitions are based on the Booz, Allen and Hamilton's typology, they do not provide any additional information concerning what makes a new product new to the customers. Lawton and Parasuraman in 1980 take insights from psychology and human behaviour literature and define product innovativeness from the customers' perspective as *"the degree of behavioural change or learning effort required by potential customers to adopt the new product*" (p. 20). Scholars and researchers have labelled product innovativeness from the customer's perspective differently; for example, 'degree of product newness to customers' by Atuahene-Gima (1996), 'customer discontinuity' by McNally, Cavusgil, and Calantone (2010), 'customer familiarity' by Calantone, Chan, and Cui (2006), 'customer switching cost by Eliashberg and Robertson (1988) and for this study it is labelled as 'customer discontinuity', but essentially they all measure product newness/innovativeness from the customer's perspective by adapting the Lawton and Parasuraman (1980) definition of product innovativeness from the customers' perspective.

There is an abundance of research done on how customers perceive product as innovative. The focus of this literature primarily works on innovation adoption and diffusion. Lawton and Parasuraman (1980), Rogers (1995), and Holak and Lehmann (1990), Danneels and Kleinschmidt (2001) state that the innovation attributes, behavioural changes and adoption risk have been consistently linked to innovation adoption. For example, O'Connor (1998) illustrate that highly innovative products tend to provide better performance because of their ability to offer greater product functionalities or new innovative attributes. They argue that when customers adopt a new technology or highly innovative products there is an element of learning required. Customers have to learn regarding the new features, new attributes of the product and more importantly customers have to learn to use the product. In addition, Kuester, Gatignon and Robertson (1999) in their book show that by adopting a new technology there is a huge change in the established behaviour patterns of the customers. They exhibit that continuous innovative products hardly require any behavioural change compared to discontinuous innovative products.

Despite the interest on product innovativeness from the customer's perspective, the empirical research in the NPD literature focusing on customer response to innovative products offers mixed findings (Henard and Szymanski, 2001; Szymanski, Kroff, and Troy, 2007). For example, Langerak, Hultink, and Robben (2004) found positive effects of product innovativeness from the customer's perspective on product performance outcomes, but others illustrate a negative effect (for example, Atuahene-Gima, 1995a; Montoya-Weiss, 2001; McNally, Cavusgil, and Calantone, 2010). Consequently, there is a clear and important research gap emerging from the literature that needs further investigation.

2.5 Product Performance

The two studies that investigate and identify all currently used measures of product development success and failures are Griffin and Page (1993; 1996). In 1990 they surveyed 189 PDMA members concerning how their firms developed new products, and their results show that 76 per-cent of the respondents' measure development performance using financial measures. On the other hand, 82 per-cent used non-financial measures such as, market share, customer acceptance, sales-volume goal, revenue growth, and market position. They state that measuring success is multifaceted and is very difficult to define success. In the existing literature, based on these two critical articles, researchers and scholars have measured and defined product performance. They argue, *"No single measure suffices for gauging the success of every product development project"* (Griffin and Page, 1996, p. 478). They argue that every firm over time develops new products for different reasons (for example, Kuczmarski, 1992). They focus on the Booz, Allen, and Hamilton typology (see Appendix 2A) and state that every firm develops product to either enter a new market or to gain better market share, or to improve their financial returns or to achieve competitive advantage. Table 2.4 (adopted from Griffin and Page, 1996, p. 489) clearly indicates the use of different product performance measures. From the above figure it is evident that the two most used and dependable product performance measures are financial performance and market performance.

Table 2.4 Most useful success measures by project strategy

	Low	**Newness to the market**	***High***
High	**New to the Company** Market share, revenue satisfaction, met profit goal, and competitive advantage		**New to the world** Customer acceptance, customer satisfaction, met profit goals, Return on Investment (ROI), competitive advantage
Newness to the firm	**Product Improvements** Customer satisfaction, market share, met profit goals, competitive advantage	**Additions to existing lines** Market share, revenue growth, met profit goal, competitive advantage	
Low	**Cost Reduction** Customer satisfaction, customer acceptance, met margin goal, performance or quality	**Product Repositioning** Customer acceptance, market share, met profit goal, competitive advantage	**Project strategy** Financial measures, customer measures

(Adopted from Griffin and Page, 1996, p. 489)

Griffin and Page (1993), state that to measure product success firms generally use financial measures. In addition, they argue that measuring sales-volume goals is also a promising measure, as in any project strategy (above figure) the number of units/products sold is an adequate way to measure market share and customer satisfaction as well. Therefore, in line with the results published by Griffin and Page (1993; 1996), in this study product performance is measured using the financial performance scale. This in addition provides useful insight into whether the benefits of implementing ambidextrous market learning strategy outweigh its implementation cost.

2.6 Research Gaps

To conclude, the review of two literatures has provided useful insights into the gaps in the ambidexterity and NPD literature. Appendix 2B provides a list of empirical studies conducted linking ambidexterity and NPD literature. As it can be seen in Table 2.1, there are about 110 papers linking the two literatures, but out of these 110 papers, there are around 45 are qualitative papers and around 30 conceptual papers. There are around 35 papers linking ambidexterity and NPD literature. As seen from the Appendix 2B, most studies measure ambidexterity as *'innovation ambidexterity´* that is, the firm's resources or learning that is required to develop incremental and radical innovations. Though this sheds new light and expands our knowledge regarding the ambidexterity hypothesis, this is limited and the results in the existing literature are non-significant in the high-technology context. Therefore, linking the two literatures there are key research gaps and these are as follows:

1. Though the ambidexterity construct is extensively covered in the NPD literature, the literature is silent on how *'ambidextrous market learning'* impacts product advantage.
2. Due to the conceptualisation of innovation ambidexterity, the results in the existing literature are limited in expanding our understanding regarding how ambidextrous firms tend to develop innovative products.
3. One of the key research gaps in the ambidexterity literature is whether there is any benefit in implementing an ambidextrous culture. The existing literature is primarily focused on the various antecedents (or cultural factors) of a firm that enhances an ambidextrous culture. But as scholars (Junni et al., 2013) argue that from the ambidexterity literature it is evident that implementing ambidextrous culture is rare, difficult and hard to implement but yet scholars working in the ambidexterity

literature work under the impression that being ambidextrous is a source of competitive advantage. The key question is to find in which scenarios or context is it beneficial to implement such a structure and do ambidextrous market learning firms tend to develop products that are always financially successful?

4. In addition, most studies do not focus on how ambidextrous firms tend to develop new products that are financially successful; hence most studies do not measure how ambidexterity may impact various product characteristics. The exception to this rule are studies by Kortmann (2014), Blome, Schoenherr and Kaesser (2013) who argue that based on the bi-polar view of ambidexterity (that is, due to focusing on exploration and exploitation activities) firms tend to develop innovative and cost-effective products. This provides some useful insights but as seen from the NPD literature, product innovativeness is different for customers and firms, and not differentiating between the two may provide very limited insights. In addition, as seen from the NPD literature, the two key product characteristics that have an impact on product performance are product advantage and product innovativeness. Despite its importance, the primary product characteristics covered in the ambidexterity and NPD literature are cost and innovation. This is even more essential in high-tech industries, where firms face turbulent environment and is difficult for firms to develop products which have high benefits.
5. There are several major gaps in the research on NPD literature, for example, our understanding of the relationship between product innovativeness and product advantage is still very limited. This is primarily due to the early conceptualisation of product advantage as – product superiority, product meaningfulness and product uniqueness (or product innovativeness). The other theoretical research gap in the NPD literature is the operationalisation of product advantage as a higher-order construct.

2.7 Summary

This chapter has provided a comprehensive assessment of the recent works that have advocated and conflicted the superiority of ambidexterity. The assessment shows that different literature streams, including technological innovation, organisational design/structure, strategic management, and organisational learning, have contributed to the research on ambidexterity. A major conclusion from the literature assessment is that the role of exploratory and exploitative market learning has rarely been conceived in the ambidexterity literature. In addition, there is a research gap in the NPD literature with respect to the relationship between product innovativeness, product advantage and product performance.

Drawing from the two literatures, two key points consequently emerged. First, being ambidextrous in terms of marketing is beneficial as it enables firms to exploit the current/existing customer needs, and explore new emerging markets and hence, focusing outside the current market boundaries. The second key fact that emerges is there is a gap in our understanding of how ambidextrous firms tend to develop innovative products and thus, academic research should be focused on examining the consequences of ambidextrous firms in different organisational contexts.

In the next chapter, a conceptual model is presented with the objective of addressing the various research gaps mentioned in the current chapter and in the previous chapter. The next chapter first focuses on the conceptual model proposed and how this model covers the research gaps presented in this chapter. Then, based on the existing literature, the research hypotheses are developed and explored.

Chapter Three: Conceptual Framework, Research Model and Hypotheses

3.1 Introduction

Drawing on the theoretical perspectives from ambidexterity, marketing strategy and new product development (NPD) literature, chapter three proposes a research model to delineate the relationship between factors including: ambidextrous market learning, product innovativeness, product advantage, and new product financial performance. To achieve this objective, this chapter is organised in three sections. The first part introduces the theoretical framework used to develop the conceptual model. In the second part, proposed research model between ambidextrous market learning and product performance is presented. In the third part of this chapter, the hypotheses linking the independent, dependent, mediating and moderating variables are discussed in detail. And finally, a summary of the chapter is presented.

3.2 Theoretical Framework

As mentioned in the previous chapter, in the existing literature, the concept of ambidexterity has been applied extensively in various organisational contexts. Hence, researchers have often adopted insights from various theories to underpin the antecedent(s) and the consequence(s) of ambidexterity. In this section, the primary objective is to focus on the key theories used by researchers to justify the use of various predictors, the methodological settings in which these studies have been conducted and to support their findings. Then the focus shifts on the S-P-P framework and the key theory (that is, Organisational Learning) that underpin the current study.

A review of the ambidexterity literature suggests that most of the studies draw on Day and Wensley's (1988) source-position-performance (S-P-P) framework. The Resource-Based

View (RBV) of the firm (Barney, 1991; Barney and Clark, 2007) is the mostly commonly used theory to underpin the studies in the ambidexterity literature (for example, Hughes et al., 2010; Hoang and Rothaermel, 2010; Jansen, Justin, Simsek and Cao, 2012; Lin et al., 2012). The RBV theory provides a basis for understanding how firms create competitive advantage by using valuable and non-substitutable resources (that is, tangible and intangible) to generate short-term success and also to develop a sustainable competitive advantage. The RBV theory argues that firms create resources (for example, innovation strategy, differentiation strategy, learning orientation, market orientation in the ambidexterity literature) that act as a source in the S-P-P framework. That is, the *"positional advantage"* is gained by the firm being ambidextrous, the *"sources of advantage"* are the antecedents taken from different literatures and *"performance outcomes"* is measured using firm or product performance. These sources act as the basis for creating sustainable competitive advantage, which leads to generate firm or product performance. The RBV theoretical perspective is largely used to explain the product or firm performance and has a huge impact on building frameworks in the ambidexterity literature.

Despite the extensive use of the RBV theory in the literature, there are five other theories that have received substantial importance from the researchers working on the ambidexterity construct. The second is the dynamic capability view (DCV) (for example, O'Reilly and Tushman, 2008) theory proposed by Teece et al., (1997) and is defined as the *"the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments"* (Teece et al., 1997, p. 516). O'Reilly and Tushman (2008) argue that a firm's ability to simultaneously explore new product-market domain and exploit the existing opportunities can be defined as a dynamic capability of the firm, that not all firms have and hence some firms in comparison tend to create sustainable competitive advantage. Though, the RBV and DCV of the firm is primarily built on the idea how various resources are used to create competitive advantage, O'Reilly and Tushman (2008) argue that Teece et al., (1997)'s concept of dynamic capability essentially states that firms need to sense and seize opportunities; and to maintain a competitive advantage the firm may need to enhance, combine and even if necessary need to reconfigure and this as they argue that it is at the heart of the ability of a firm to be ambidextrous.

The third is the contingency theory initially proposed by Woodward (1958) and Burns and Stalker (1961). In the book *"The management of innovation"*, Burns and Stalker introduce the idea that firms need to reorganise their organisation based on the environmental factors. This idea was soon developed into how firms can create/reorganise firm structures to adapt to the changing environments and the idea of ambidexterity was hence grown. Contingency theory primarily focuses on the behaviours of the leaders or the decision makers in the firm that provided the structure based on their (leaders') understanding of the environmental factors. That is, how firm leaders or decision makers perceived the internal factors of the firm would fit the external factors that would lead to significant performance. The contingency theory has a huge impact on other literatures such as, entrepreneurship and organisational design. Clercq, Thongapapanl and Dimov (2014) argue that the contingency theory explains the ambidexterity construct as firms need to understand the external factors in order to explore or exploit or be ambidextrous.

The fourth theory that has been extensively used to underpin the ambidexterity construct is organisational behaviour theory (for example, Gibson and Birkinshaw, 2004; DeVisser et al., 2010; Brion, Mothe and Sabatier, 2010). The underlining principle of the organisational behaviour theory is the study of humans/individuals in an organisational setting (Moorhead and Griffin, 1995). Gibson and Birkinshaw (2004) argue that *"although ambidexterity is a characteristic of a business unit as a whole, it manifest itself in the specific actions of individuals through the organisation"* (p. 211). The fifth theory that has been applied to the ambidexterity construct is network theory (for example, Tiwana, 2012). Wasserman in 1994 argue that the existing literature on management and organisation is one dimensional, as researchers tend to view organisations as single entities; in fact this is far from the reality and argue that there is a structure of relationships between social entities. Tiwana (2012) argue that the knowledge that is created and integrated from different entities (strong and weak ties) is an essential antecedent of being ambidextrous.

Finally, the theory that has been used extensively to underpin the ambidexterity construct is the organisational learning theory (for example, Filippini, Guttel, and Nosella, 2012; Kodama and Shibata, 2014; Yang, Zhou, and Zhang, 2013). In the existing literature, the organisational learning theory is mostly used as an underlining (or implicitly used) theory to explain the ambidexterity concept (for example, March, 1991; Levinthal and March, 1993). In the ambidexterity literature, insights from types of knowledge created (March, 1991) are generally taken to distinguish between the different types of learning or activities that lead to different types of knowledge (that is, exploration and exploitation) has been applied extensively in the ambidexterity literature.

In addition, in recent years scholars and researchers have taken insights from stakeholder management theory (for example, Minoja, 2012) and economic theory (for example, Petkovic and Orelj, 2013) to underpin the antecedent(s) and the consequence(s) of ambidexterity. In the next section, the S-P-P framework used to underpin the conceptual model and the organisational learning theory used to underline the ambidextrous market learning construct in this study are discussed in detail.

3.2.1 Organisational Learning

The organisational learning theory is primarily defined as the way or the process or the mechanism of creating, retaining and transferring knowledge (Simon, 1953). Under the big ‘umbrella’ of organisational learning theory there are many subfields, such as, knowledge management (Nonaka and Takeuchi, 1995), different processes used to create different types of knowledge (organisational design) (Nonaka, 1994), types of knowledge created (Polanyi, 1966; March, 1991), learning organisations (Senge, 1990), types of knowledge transfer processes (Huber, 1991), and organisational behaviour (Cyert and March, 1992). In the ambidexterity literature, insights from types of knowledge created (March, 1991) are generally taken (that is to differentiate between explorative and exploitative learning).

Over the years, many typologies of organisational learning have been developed to classify the nature of knowledge (for example, Spender, 1996; Nonaka and Takeuchi, 1995) but these typologies are based on different forms of tacit and explicit knowledge. Polanyi originally introduced the term tacit knowledge in 1966. Tacit knowledge is defined as "knowledge that cannot be adequately articulated by verbal means". On the other hand, explicit knowledge in comparison to tacit knowledge is defined as "knowledge that can be acquired, coded and transferred". This brings back to the various stages involved in the process of organisational learning, that is, how tacit and explicit knowledge is created and what information leads to generating the two different types of knowledge.

Nonaka (1994) argues that tacit and explicit knowledge requires different types of knowledge creation. This lead to what kind of process is required to develop tacit and explicit knowledge. Tacit knowledge creation required firms/individuals to explore and experiments that would eventually lead to learning of information that cannot be verbally articulated. In comparison, explicit knowledge creation required firms/individuals to focus on the current process and make this process more efficient and hence the steps used to improve the process could be easily acquired, coded or transferred.

Over the years, based on the above definitions, researchers have characterised different types of organisational learning. For example, Argyris (1977) defines organisational learning as the process of "detection and correction of errors" and differentiates between adaptive learning versus generative learning. Adaptive learning also known as single-loop learning is defined as "solving problems in the present without examining the appropriateness of current learning behaviour". The primary focus here is concerning how firms solve problems by adapting to the present situation. On the other hand, generative learning also known as double-loop learning, which is defined as "continuous experimentation and feedback in an on-going investigation of the very way firms go about defining and solving problems". The major difference between adaptive learning and generative learning is the same difference between adaptability and creating.

The difference between explorative learning and exploitative learning is similar to the difference between single-loop learning and double-loop learning (Argyris, 1976), and is similar to the difference between adaptive and generative learning (Argyris and Schon, 1974; 1978) which leads to the difference between tacit and explicit knowledge (Nonaka, 1994). In the context of organisational learning, Argyris and Schon (1978) define single-loop learning as the adaption or adjustments made by the firm to maintain its current policies or achieve its present objectives and goals. On the other hand, double-loop learning is defined as the modification of the firm's norms, policies and objectives in order to remain successful.

In line with this typology March (1991) in his seminal work differentiates between explorative learning and exploitative learning. March (1991, p. 85) defines explorative as *"experimentation with new alternatives, having returns that are uncertain, distant and often negative"* and exploitative as *"the refinement and extension of existing competencies, technologies, and paradigm exhibiting returns that are positive, proximate, and predictable"*. The difference between exploration and exploitation learning exhibits special features in the social context of the organisation. March's (1991) differentiation between explorative and exploitative learning has key elements derived from tacit versus explicit, single-loop versus double-loop, and adaptive learning versus generative learning.

The above differentiation between the two types of organisational learning was further developed in the context of marketing and in 1995, Slater and Narver define market learning as *"Organisational learning is valuable to a firm's customers in this context because it focuses on understanding and effectively satisfying their expressed and latent needs through new products, services, and ways of doing business"* (p. 66). Further in 1998, Kyriakopoulos and Moorman differentiate between exploratory marketing strategy learning and exploitative marketing strategy learning. This further led to empirically measuring exploratory and exploitative market learning (please see Chapter 2) by Kim and Atuahene-Gima (2010). Therefore, organisational learning theory acts as an underlining theory to define exploratory and exploitative market learning constructs in the conceptual model of this study.

In addition, to taking insights from the organisational learning literature to measure exploratory and exploitative market learning; product innovativeness measured from the firm's perspective and customer's perspective are at the heart of the organisational learning literature. As mentioned, organisational learning theory is primarily defined as the way or the process or the mechanism of creating, retaining and transferring knowledge (Simon, 1953); product innovativeness is the process of creating new knowledge that leads to developing innovative products (Atuahene-Gima, 1995; Danneels and Kleinschmidt, 2001; McNally, Cauvsgil and Calantone, 2010).

Atuahene-Gima (1995) argue that the degree of innovativeness is defined as the degree of learning effort required to develop the new product and from the customer's perspective it is, the degree of learning effort or behavioural change required to adopt the new product. Danneels and Kleinschmidt (2001) argue that the process of developing highly innovative products generally requires the firms to learn new things about the markets and the technology. Therefore, in this study, exploratory and exploitative market learning, marketing discontinuity, technological discontinuity and customer discontinuity are measured by taking insights from the organisational learning theory. The next section focuses on the S-P-P framework that is used to analyse the market learning as an important source of advantage.

3.2.2 S-P-P Framework

In the existing literature, researchers and scholars (for example, Day and Wensley, 1988; Porter, 1985) argue that for a firm to achieve superior performance, it requires to hold an advantage over its competitors. There are two main frameworks used in the existing literature to bridge the gap between strategy and firm performance. The framework by Mason (1939) and Bain (1968) traditional known as the structure – conduct (strategy) - -performance paradigm (S-C-P) of Industrial Organisation (IO) offers a systematic model for evaluating the competition within an industry (Porter, 1981). The second framework which is most commonly used in the strategic management literature is the Day and Wensley's (1988) Source – Position – Performance (S-P-P). A similar framework put forth by Hunt and Morgan's (1995) Resource (comparative advantage) – Competitive advantage – Performance (micro and macro) offers a systematic tool for assessing the firm's strength (resource and capabilities) for achieving success.

The framework put forth by Mason (1939) and Bain (1968) is derived from the industrial organisation economics. Researchers and scholars using the S-C-P framework, focus on the industry structure, particularly the entry and mobility barriers. Bain (1956) argue that economies of scale, product differentiation, and cost advantages have an effect on the potential entrant sellers in well-established industries, i.e. the discipline of economics. The concept of the entry barriers is extended by Caves and Porter (1977) to the existing firms in the industry, and argues that mobility barriers raised by the current competition have a significant impact on the strategy implementation and performance of the firms.

It is evident that the S-C-P strategy formulation primarily focuses on the industry structure and how firms can engage (Conduct/strategy) in activities that lead to increased barriers. The roots of S-C-P framework indicate that as firms heighten the entry barriers, is the extent to which higher profits can be earned (Porter, 1987). This framework has been applied in various branches of strategic management, for example, diversification strategy (Singh and Montgomery, 1987), mergers and acquisition (Hopkins, 1987), strategic planning and management (Grant and King, 1979), and market segmentation (Porter, 1980).

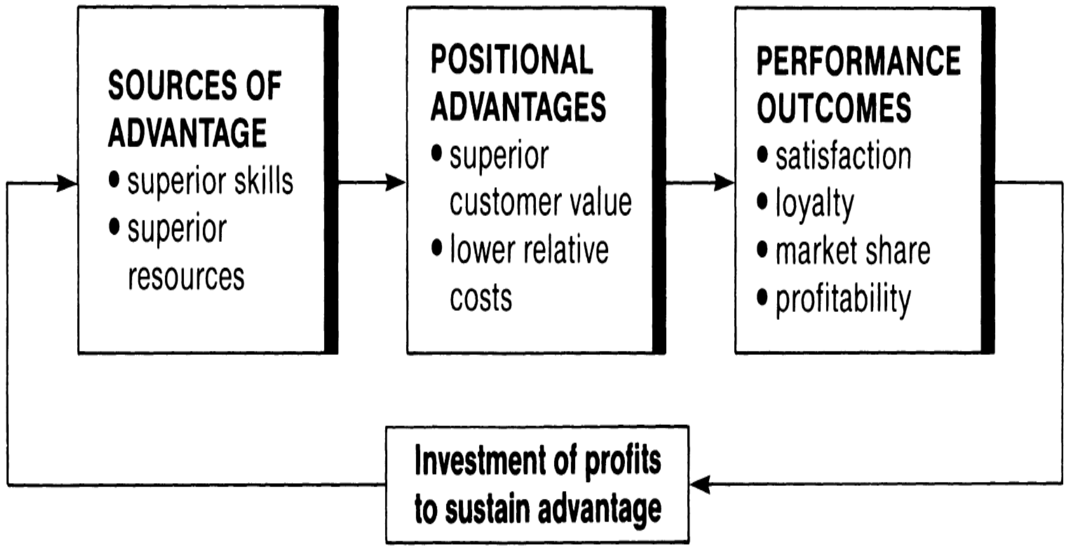
Despite the extensive use of the S-C-P framework in the existing strategic management literature, this framework has limitation. First, McWilliams and Smart (1993) argue that *"the transfer of theory from one discipline to another may lead to inappropriate and costly generalisations and predictions"* (p. 63). This framework integrates the industry-level of analysis and many scholars and researchers predict firm-level performance and phenomenon. Therefore, by not appropriately applying this framework, there are many costly generalisations and predictions both for practical and theoretical purposes.

As mentioned this framework indicates that firms formulate their strategy based on the industry structure, this eliminates more firm orientated issues, such as, core competencies, strategic decision making process, organisational learning, leadership role and resources that create competitive advantage (Prahalad and Hamel, 1990; Hitt, Hoskisson, and Harrison, 1991). And finally, Day and Wensley (1988) argue that the S-C-P framework assumes that the industry structure is static and these conditions are sustained over time. However, Levitt (1960), and McWilliams and Smart (1991) argue that in a changing industry conditions, firms that devote their resources towards creating a competitive advantage by meeting the current and anticipating needs and wants of customers, tend to develop superior performance.

On the other hand, Day and Wensley (1988) argue that *"superior performance requires a business to gain and hold advantage over competitors is central to contemporary strategic thinking"* (p. 1). Researchers and scholars have long argued that firms need to first focus on the reasons for current success or lack of (for example, Barney, 1991; Day, 1984; Day and Wensley, 1988; Hunt and Morgan, 1995; Wernerfelt, 1984). They argue it is challenging for managers to fully understand the ambiguity of the environment they work in. It is not possible for the managers to cope with the industry trends and analyze the emerging patterns of the market. Therefore, they explain that if managers base their strategic decisions on competitor(s) and adopt a customer-oriented perspective, then it is easy to interpret how the firm can have an edge over its competitors.

The elements of competitive advantage of S-P-P framework are as shown in Figure 3.1. Day and Wensley (1988) argue that source of advantage is to do with the ability of the firm to perform various business activities effectively and/or efficiently than its competitors. In order to achieve positional advantage, firms need to create superior skills and/or resources, for example, superior technical skills, marketing skills, networking skills, and learning faster than the competitors. These superior skills are not easy to achieve and as illustrated by Hall (1993) these skills are a function of cultural, functional, positional, or regulatory capabilities.

Figure 3.1 S-P-P Framework



(Adapted from: Day and Wensley, 1988, p. 3)

The positional advantage element of the S-P-P framework is defined as *"analogous to competitive mobility barriers that could deter a firm from shifting its strategic position"* (Day and Wensley, 1988, p.3). In the existing strategic management literature, it is argued that there are two ways to create an advantage, first, customer-focused (for example, Bhide, 1986; Day, 1984; 1994) and the other is by competitor-centred (for example, Porter, 1985). Firms that are competitor-centred tend to develop strategies that create relatively lower cost to develop new products and on the other hand, firms that are customer-focused tend to develop strategies that create superior customer values.

In the existing literature, researchers and scholars argue that, in order for firms to create competitive advantage, firms need to develop strategies that are competitor-centred (for example, Caves, 1984; Day, 1984; Porter, 1985). And, on the other hand, scholars argue that, in order for firms to create competencies that create customer value, firms need to develop strategies that are customer-focused (for example, Churchill and Suprenant, 1982; Day et al., 1979). Day and Wensley (1988) argue that if firms need to create positional advantage, firms need to create a balance between the competitor-centred and customer-focused strategies.

The S-P-P framework indicates when firms evaluate the strengths and weakness of the firm; the firm can then accordingly build a strategy that would create a positional advantage for the firm in the market. In order to create a positional advantage, firms need to not only deploy resources and skills to enhance competitive advantage but also need to focus on creating sustainable advantage by setting barriers that make imitation difficult. In doing so, firms can achieve customer satisfaction and hence create customer loyalty that leads to high market share and more profitability.

The current model is derived on the S-P-P framework, and argues that ambidextrous market learning is a key source of advantage. In the NPD literature, the continuous commitment to learning is considered as one of the key elements to developing successful products in high-tech industries (for example, Rhee, Park, and Lee, 2010). Day (1994a) argues that the superior ability to learn is critically important in the NPD process, essentially due to the following reason: The firm needs to create an atmosphere for learning so it can develop new products that create value for its customers in these constantly changing conditions of the market and technology. Therefore, the ability to learn faster than the competitors is considered as a source of sustainable competitive advantage and a difficult to imitate competency.

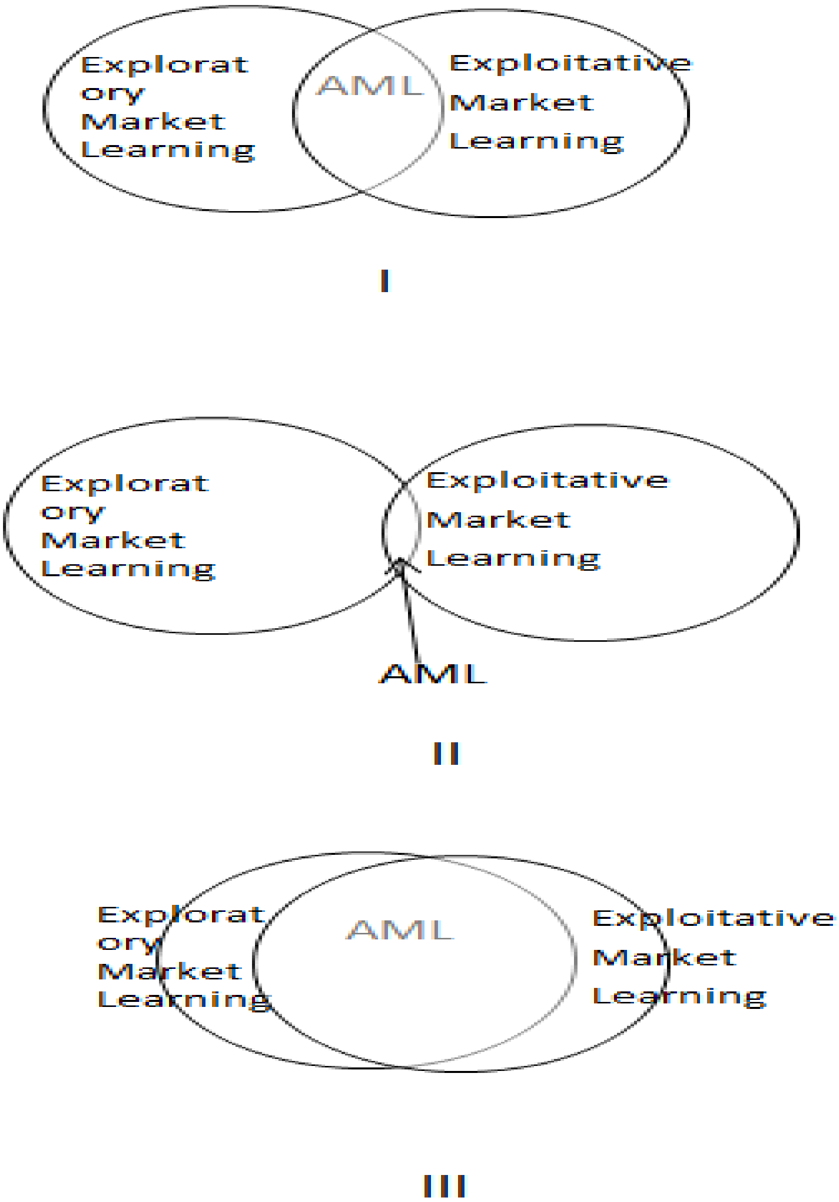
As illustrated in Chapter 2, since the 1930s have consistently found that thorough understanding of customer needs and wants, the competitive situation and the market & environment evaluation enhances product differentiation and is the most critical information for successful product development (for example, Cooper and Kleinschmidt, 1993; Maidique and Zirger, 1984; Rothwell, 1972; Veryzer and Mozota, 2005). Firms that implement an ambidextrous market learning culture tend to develop products that are simultaneously superior to its competitors and are meaningful to the customer (i.e. product advantage). In this study, it is argued that, firms that develop products with higher product advantage tend to enhance competitive advantage and difficult to imitate competency (i.e. positional advantage). In this study, it is argued that AML firms tend to develop positional advantage and hence create superior financial performance.

3.3 Conceptual Model

In this section a detailed discussion of the conceptual model that relates ambidextrous market learning (AML) with product advantage, product innovativeness and product performance is presented. This conceptual framework integrates three key literature streams (see chapter 2), that is, ambidexterity, marketing and New Product Development (NPD). As explained in the previous section, this conceptual model is based on the S-P-P framework and organisational learning theory underpins the AML construct. That is, the information gained from simultaneously learning about the market in an exploration and exploitation manner act as the key source of advantage. As mentioned in the previous chapter that in this study, ambidextrous market learning is not measured as zeros and ones, that is, there are different levels of ambidextrous market learning and this is pictorial depicted in Figure 3.2. In this study, the information gained from ambidextrous market learning is taken as the *"source of advantage"* that acts on product advantage which creates the *"position for advantage"* and that leads to new product financial performance. Hence, this study draws from the Day and Wensley's (1988) S-P-P framework. The conceptual model is presented in Figure 3.3.

The purpose of this study is to test the ambidextrous market-learning hypothesis in the particular context of product advantage. Recent studies in the domain of ambidexterity have shown that exploration and exploitation activities are not just mutually exclusive at the business unit level, but provide the basis for successful product development (for example, Gibson and Birkinshaw, 2004; Hughes, Martin, Morgan, and Robson, 2010; Wang and Rafiq, 2014). Li, Lin, and Chu (2008) argue that, for a firm to achieve success it must understand and respond to the needs of their existing customers and markets, and simultaneously discover and adapt to the emerging markets and their customer's changing needs. In addition, it is important for a firm operating in high-tech industries that it explores new opportunities and at the same time builds upon the existing opportunities. Without understanding the current customers' needs and wants (that is, current opportunities) it is unwise and hard to explore and pursue new market information that takes the firm beyond its current product-market domain. As mentioned in the previous chapter, in the existing ambidexterity literature, the concept of simultaneously pursuing exploratory and exploitative activities has been operationalised in four different ways (that is, addition, subtraction, multiplication of exploration and exploitation activities and measuring ambidexterity as a higher-order construct (HO)).

Figure 3.2 Different levels of Ambidextrous Market Learning



In recent years, the use of Higher-Order (HO) multidimensional constructs (that is, latent constructs comprised of standalone variables) in the organisational and management literature is increasing at an alarming rate (Edwards, 2001; Law, Wong, and Mobley, 1998; Williams and O'Boyle, 2008). There are several reasons for the increased interest in HO multidimensional constructs. The first reason pertains to the idea that the HO multidimensional construct may prove quite valuable and may be better predictors of criteria that span multiple domains (Jenkins and Griffith, 2004). The second reason is if a single phenomenon is examined separately under the condition of two or more variables, then it is more parsimonious to examine the higher-order construct rather than the individual variables (Kelley, 1927). Third, the use of HO multidimensional constructs does not cause such high losses of information in comparison to the other methods (Johnson, Rosen, and Chang, 2011).

Despite the potential advantages, HO multidimensional constructs receive criticisms from scholars. There are three specific controversial points based on which scholars argue against the use of HO multidimensional constructs. The first point is the extent to which the HO multidimensional constructs are derived from the theory, second, are there any other indicators which should be included to model the construct, and finally, their testability (Johnson et al., 2012). They state that, a considerable amount of evidence from the existing literature must be provided to justify the use of HO multidimensional construct, and it is essential to provide guidance for identifying the indicators used to model the HO multidimensional construct and rule out any alternate explanations. In addition, the validity of HO multidimensional constructs is the key controversial point. It is important to not just justify the use of HO multidimensional construct using the existing literature but it is essential to empirically test the use of the standalone component factors of the HO multidimensional construct.

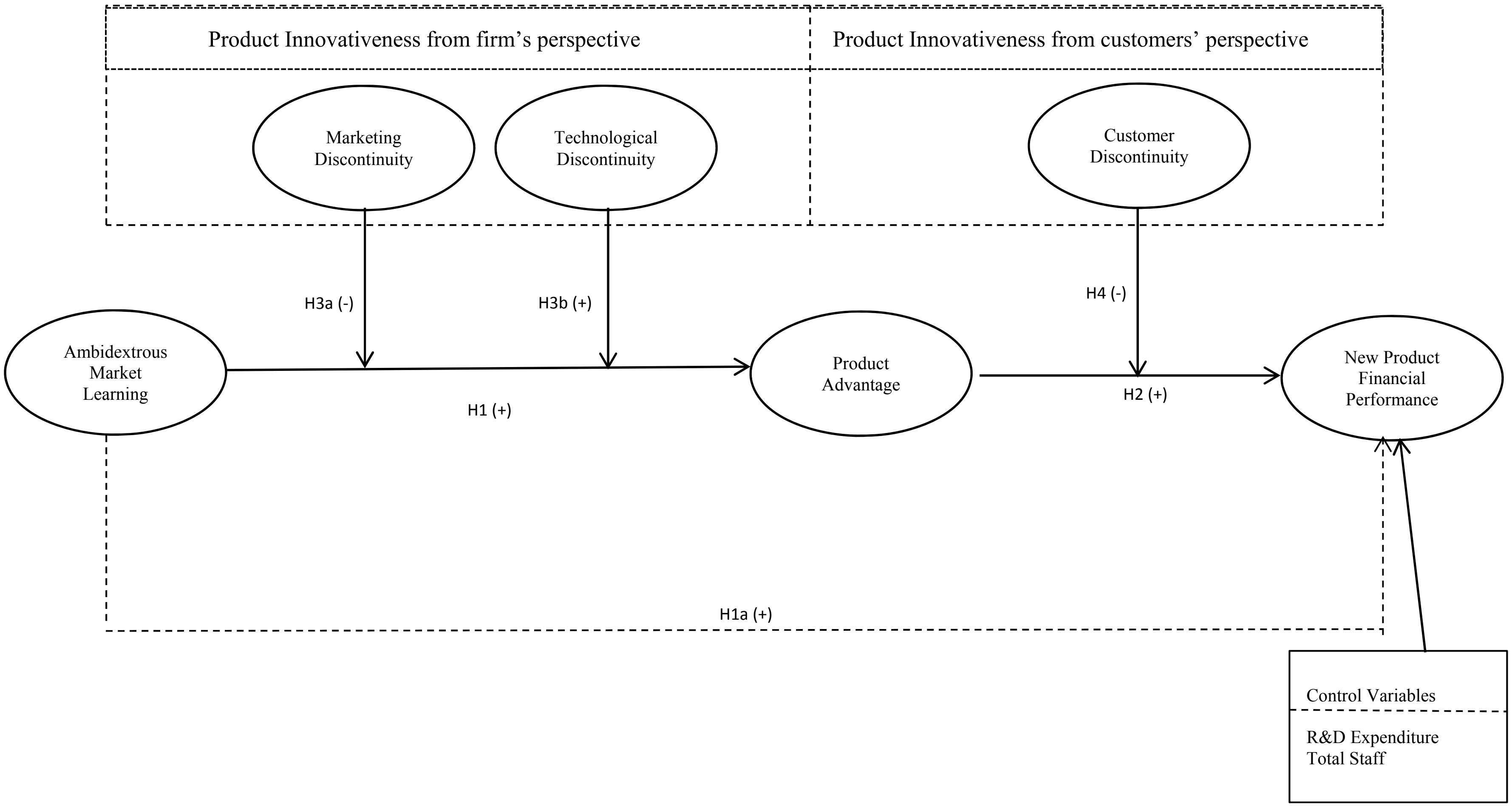
Operationalising AML as a higher-order (HO) construct has certain pros and cons. In addition, Hughes, Martin, Morgan, and Robson (2010), state that any form of calculation (that is, multiplication or absolute difference) results in loss of information and detrimental to interpretability of the data analysis. Lubatkin, Simsek, Ling, and Veiga (2006) illustrate similar disadvantages that are related with operationalizing ambidexterity as a product term score and an absolute difference score. They test three alternative models (ambidexterity as a higher-order construct, ambidexterity as a single index absolute difference term score, and ambidexterity as a single index additive term score) to test the ambidexterity and performance hypothesis, and find that there is considerable loss of information when ambidexterity is operationalized as a product term and an absolute difference term. Considering the benefits, for this study AML is operationalised as a higher-order construct.

As mentioned in the previous chapter, the definition of product advantage has evolved in the NPD literature. In the late 1980s products which were superior and more innovative in comparison to the competing products were considered to have product advantage. But in the last decade product advantage is defined as a product that is superior to its competing products and is meaningful to the customer. Product innovativeness is considered as a separate product attribute, primarily because products that are innovative may not necessarily be superior or meet the needs and wants of the customer. In addition, in the existing NPD literature, product advantage is operationalized as a single-order factor (for example, Langerak et al., 2004; Atuahene-Gima, 1995). Henard and Szymanski (2001) state *"although product advantage is arguably, a second-order factor composed of product characteristics predictors, in the existing literature it is frequently captured and reported as a single order construct"* (p. 365).

As mentioned in the previous chapter, the product advantage construct has two key components (that is, product meaningfulness and product superiority). In high-tech industries, products that are not meaningful to customers and do not cater to the needs and wants of the customer tend to not be superior (perceived) even if the product is superior on some dimensions (such as quality, benefits and/or functions). As illustrated by Im, Hussain, and Sengupta (2008) that the superiority of the product exists as long as the product is meaningful to the customer. The aggregate conceptualization assumes that meaningfulness and superiority contribute equally to product advantage. However, a new product can be meaningful to its customers without being superior to competing products (Szymanski et al., 2007). Hence, the need to disaggregate the product advantage into its components.

Though these product attributes are closely tied, measuring product meaningfulness and product superiority as a single construct may be misleading and hence, as argued by Rijsdijk, Langerak and Hultink (2011) that scholars and researchers should make a deliberate distinction between the two components. In this study, it is argued that products that are simultaneously superior in comparison to the competition and meaningful to the customer tend to be financially successful. In line with Cooper (1979) we argue that both dimensions are important characteristics of new products and having both dimensions simultaneously tend to facilitate new product success (p. 98). Therefore, deviating from the existing literature, the product advantage construct in this study is operationalised as a higher-order construct.

Figure 3.3 Conceptual Model



3.4 Hypotheses Development

3.4.1 Ambidextrous market learning – Product advantage

The emerging importance of the organizational learning literature in marketing is well accepted and the process of market learning involves understanding of the customer needs, information about the competitor, suppliers and other constituents. The various stages in this process involve market information generation, dissemination and use (Huber, 1991; Moorman, 1995; Kyriakopoulos and Moorman, 2004). Market information generation stage plays a key role in understanding the trend and changing needs of the market.

Ambidextrous market learning firm is defined as a firm that simultaneously pursues exploratory and exploitative market learning. Exploratory market learning process involves using of market information that enables the firm to learn new things about the market by taking the firm beyond its current product/market experience. In addition, this process also involves the studying of emerging competitors and new technologies. And on the other hand, exploitative market learning process involves using of market information that enables firm to integrate its current market experience through analysis of experience with prior projects, current competitors and technologies. Though, these two market learning processes involve using different market information, the common frame of reference is to focus on customer goals (Kyriakopoulos and Moorman, 2004). Firms that focus on customer goals and implement a marketing strategy around this information are also defined as *"market-driven"* (Day, 1994) or *"outside-in strategic approach"* (March, 1991; Kyriakopoulos and Moorman, 2004).

Day (1994) argues that firms that continuously learn about markets and are market-driven must combine the following five elements in order to keep an open mind to *"new* *information that can help anticipate emerging needs and more accurately forecast market responses to changes in strategy"* (p. 12).

1. Scanning with peripheral vision
2. Buying decision insurance
3. Activating the sensors at the point of customer contact
4. Benchmarking beyond the obvious, and
5. Continuously experimenting

Day (1994) argues that *"scanning with peripheral vision"* is what most managers do. Most managers focus on the readily available data on market trends and tend to suppress curiosity. He argues that for managers to successfully scan the market with peripheral vision they need to go beyond the defined boundaries of the market. In this study, AML is defined as gathering of market information not just from within the boundaries of the firm's product/market domain but also going beyond its boundaries by conducting experiments.

Day (1994) argues that managers should not conduct market research to confirm their decisions or satisfy their curiosity. He argues that market-driven firms view market research as a way to widen and deepen the understanding of the customers, competitors and channel factors. By doing so firms can anticipate changes and ensure poor decision alternatives are discarded. As mentioned in the previous section, this study draws on the S-P-P theoretical framework, and argues that AML acts as a source of advantage and by learning about the current and emerging needs of the markets; firms can cultivate an open minded inquiry and hence can develop products that have high advantage.

The third element put forth by Day (1994) is how firms should focus on the information gathered by the current customers. He argues that the first source of data is a disgruntled customer, as this provides the managers with information on how to create necessary changes to meet the needs and wants of the customer. In this study, AML is measured at a business unit level (can be seen in the next chapter) and by searching for solutions to customer problems by surveying current customers; AML firms can cultivate an open mind to new information.

Day (1994) argues that market-driven firms should focus on analysing the competitors' strategic decision making process. He argues that managers that gather competitor intelligence tend to gather insights into their firm's strength and weakness. This provides the managers a platform to go further and not just study the attitudes, values and management process of the competitors but so that *"they can emulate successful moves before the competition gets too far ahead"* (p. 15). In this study, it is argued that AML firms study emerging competitors and new technologies and by doing so these firms create an atmosphere that recognises potential for improvements.

The last element put forth by Day (1994) is *"continuously experimenting",* he argues that learning firms tend to always focus on experimentation and there is no room for complacency. In this study, AML is defined as gathering of market information not just from within the boundaries of the firm's product/market domain but also going beyond it by conducting experiments.

In this study, firms that implement an ambidextrous market learning culture tend to create a platform that enables open minded data collection which acts as a source of advantage. In addition, AML culture enables firm to shift from a reactive to a sense-and-response approach, which encourages firms to develop products which focuses on customer goals and is superior to the competing products (Day, 2011). As argued by Day (1994) market-driven firms do not lose touch with their markets, are not surprised by shifts in customer requirements, are quicker to respond to market changes than the key competitors, and are prepared to use innovative and new source of gathering market information.

In addition, Day (1994) argues that achieving a competitive advantage is not looking at whether firms emphasize their internal capabilities and performance or look outside to assess their position. He argues that in order to achieve sustainable competitive advantage, knowledge on improving current learning process comes from practices outside the industry. In addition, Kogut and Zander (1992) argue that firms with a broad range of knowledge have a greater possibility of recombining and different aspects of the knowledge to recognise new opportunities and potentially be more creative. Levinthal and March (1993) argue that for firms operating in highly volatile markets to achieve survival need to balance and precisely mix exploration and exploitation learning. Thus, the following hypothesis is suggested:

H1: Ambidextrous market learning is positively related to product advantage.

In this study, AML is hypothesised to have a partial mediation effect on new product financial performance. Slater and Narver (1994a) argue that new product success is *"more likely to result from being market-driven"* (p. 25). In the existing literature, researchers and scholars argue that a widen and deepen understanding of the customers' needs and emerging market trends a key factor to new product success (for example, Henard and Szymanski, 2001; Quinn, 1986). In addition, Kyriakopoulos and Moorman (2004) empirically illustrate that by simultaneously pursuing both exploration and exploitation marketing strategy, increases the new product financial performance. Therefore, the following hypothesis is suggested:

H1a: Ambidextrous market learning is positively related to new product financial performance.

3.4.2 Product advantage – New Product Financial Performance

In the existing NPD literature, considerable number of empirical studies demonstrates that product advantage is commonly used as a predictor of new product financial performance (for example, Calantone, Chan, and Cui, 2006; Henard and Szymanski, 2001; McNally, Cavusgil, and Calantone, 2010; Song and Perry, 1997). As mentioned in the previous chapter, in the existing NPD literature there have been three meta-analysis papers (Montoya-Weiss, 1994; Henard and Szymanski, 2001; Evanschitzky, Calantone, and Jiang, 2012) and in total all the three studies have used more than 300 studies to analyse the literature (from 1990 – 2012). And the most common product characteristic used is product advantage. More than one in three studies (109 studies measure product advantage construct out of 311) have used product advantage as an antecedent to product performance and all the studies find a positive impact on product performance.

In this study product advantage acts as a mediator between ambidextrous market learning and new product financial performance. As mentioned in the previous section, product advantage is hypothesised as a higher-order construct and its components are product superiority and product meaningfulness. As mentioned in the previous chapter, product meaningfulness is defined as, *"new products that provide new (unique) attributes and functionalities that customers perceive as appropriate and relevant"* (Calantone and di Benedetto 1988, p. 34). And product superiority refers to *"the extent to which a new product outperforms competing offerings along existing attributes and functionalities"* (p. 36).

Scholars argue that developing superior products compared to the competing products available in the market can enhance new product financial performance (for example, Henard and Szymanski, Li and Calantone, 1998; McNally, Cavusgil, and Hultink, 2010). In the existing literature (for example, Cooper, 1979; 1992; Calantone and Cooper, 1981) suggests that products attributes such as quality, reliability, and newness tend to have a high impact on product performance. In the latter two meta-analysis (that is, Henard and Szymanski, 2001; Evanschitzky, Calantone, Jiang, 2012) found that the product advantage and product performance hypothesis has standardised path estimates of 0.48 and 0.35. This clearly indicates the product advantage is positively related to product performance. Thus, the following hypothesis is suggested:

H2: Product advantage is positively related to new product financial performance.

3.4.3 Marketing Discontinuity – Product advantage

In the existing literature, product innovativeness is not significantly related with product advantage (for example, Calantone, Cavusgil, Calantone, 2006; Song and Parry, 1999). The primary reason for this may be that, as mentioned in the previous chapter, in the NPD literature some studies measure the product advantage construct as a reflection of superiority, improvements in the quality, dependability and product innovativeness. From the existing literature, how product innovation impacts product advantage is not fully understood. For example, McNally, Cavusgil, and Calantone (2010) show that market and technological discontinuity has an impact on customer discontinuity but show no relationship between product innovativeness from the firm's perspective (that is, market and technological discontinuity) and product advantage. In addition, Calantone, Chan and Cui (2006) illustrate that product innovativeness has a direct positive impact on product advantage. But the product innovativeness construct used in their study is a single item which measures the degree to which the respondents believe their product is innovative in comparison to the competing products. This hypothesis does not provide any in-depth understanding of how product innovativeness has an impact on product advantage. In addition, Song and Parry (1999) illustrate that product innovativeness (a single-order construct measuring both, marketing and technological discontinuity) acts as a moderating variable between marketing and technical proficiency on product advantage. They show that product innovativeness also acts as an antecedent to marketing and technical proficiency. They found that in highly innovative new product development projects, the relationship between marketing proficiency and product competitive advantage and the relationship between technical proficiency and product competitive advantage was weaker in comparison to low innovative new product development projects. In addition, though in the existing literature, the relation between product innovativeness and product performance is studied but yet this relationship is inconsistent (see Chapter 2).

In the current model, product innovativeness from the firm's perspective includes two dimensions, that is, marketing discontinuity and technological discontinuity. Marketing discontinuity is the degree of learning that is needed from firms to operate in new markets, for example, new product category, competing against new competitors, and/or employing new distribution channels. On the other hand, technological discontinuity is the degree to which firms need to learn and implement new technologies to develop new products or new engineering processes to create highly innovative products. Both, marketing and technological discontinuity involves a certain degree of learning to develop products which are superior and meaningful to their customers. Atuahene-Gima (1995) takes insights from the information processing theory and argues that higher degree of product newness (innovativeness) requires more learning as the new technology, market and competition uncertainty is higher in comparison to lower degree of product newness (innovativeness). In line with this reasoning, Song and Parry (1999) suggest that *"the relationship between a firm's skills and resources and new product development proficiencies is moderated by the firm's ability to create information that is transformed into organisational knowledge"* (p. 671). In addition, Tatikonda and Rosenthal (2000) illustrate that the uncertainty involved in developing highly innovative products is much higher and this involves higher levels of market learning to cope with the higher levels of market and technology uncertainties. The information processing theory is a subset of the organisational learning theory (see section 3.2.1) and is defined as information processing social structures (for example, Daft and Weick, 1984; Tushman and Nadler, 1978). They argue that ineffective/non-efficient processing of information relates to failure of products and this is primarily because this ineffective processing of information leads to uncertainty. Moenaert and Souder (1990) define 'innovative uncertainty' as the consequence of consumer uncertainty, technological, competition and resource uncertainty. They argue that the level of uncertainty is higher when firms develop highly innovative products. In the existing NPD literature, there is clear evidence that as the degree of product innovativeness increases the level of uncertainty involved in the processing of information increases as well. In addition, Nonaka (1990) analysed how Canon developed the first mini copier machine that challenged the Fuji-Xerox's market leader position. Nonaka argues that developing innovative products acts as a catalyst for self-renewal firms. A self-renewal firm has to change its approaches that may shift the thinking of the firm and this leads to building a sustainable competitive advantage.

Hence, extending this line of thought, in this study, product innovativeness (from the firm's perspective) is hypothesised to have a moderating relationship with product advantage. The rationale is that developing innovative products reflects the extent of learning and changes in the way the firm thinks (for example, Atuahene-Gima, 1995; Cooper, 1999; Henderson and Clark, 1990; Moenaert and Souder, 1990). Based on this line of thought and information processing theory, in this study, product innovativeness from the firm's perspective is modelled to have a moderating impact on the ambidextrous market learning and product advantage hypothesis.

In the existing literature, knowledge about the market and market synergy has been considered as an important factor to new product success (for example, Kohli and Jaworski, 1990; Song and Parry, 1999). For example, Song and Parry (1999) illustrate that radical products tend to be more successful in familiar markets. This is primarily because, firms are more aware of the needs and wants of the current customers, and develop innovative products to cater to those needs. As the firm tends to go further away from the current market boundaries, it will be more difficult to gauge the superiority of its products. For example, Kanter (1983) argues that developing highly innovative products for new markets require greater new information processes, technical changes, and new organisational design and arrangements. In addition, ambidextrous market learning focus on learning information about new markets and gathering information about the current product-market domain. Therefore, when firms go further away from the current product-market domain (that is, marketing discontinuity), firms should primarily focus on gathering more information about the new markets and strategize to engage more exploratory market learning rather than focusing on being ambidextrous. Therefore, marketing discontinuity negatively moderates the relationship between ambidextrous market learning and product advantage. Thus, the following hypothesis is suggested:

H3a: The positive relationship between ambidextrous market learning and product advantage is lower, the higher the market discontinuity.

3.4.4 Technological Discontinuity – Product advantage

In the existing literature, knowledge about the technology and the importance of the technological development in the process of making new products has been considered as a key factor (for example, Porter, 1985; Bianchi et al., 2014). Technological resources (such as, patents, know-how, technical process, trade secrets, telecommunication, new product development processes) are the key source of competitive advantage (Kline, 2013). As mentioned in the previous section, technological discontinuity is defined as the measure of the degree of technical learning by firms to develop new products. Porter (1985) argues that firms can be unique due to a series of basic drivers and these drivers are the underlying reason for creating/developing a unique activity. He states that firms can implement a differentiation strategy by focusing on technology development. Porter states that *"technology development also takes many forms, from basic research and product design to* *media research, process equipment design and servicing procedures"* (p. 42). This is especially true in high-tech industries; a firm can develop a superior product by knowing what are the limitations and strengths of the current processes and at the same time looking for new technological advancements to improve the current processes. As already, explained in the previous section, product innovativeness from the firm's perspective (that is, marketing and technological discontinuity) act as moderators in the conceptual model. Therefore, when technological discontinuity is coupled with ambidextrous market learning, this will result in a positive impact on product advantage. This is primarily due to how ambidextrous market learning firms gather information about new competitors and how this application(s) of new processes can lead to developing new products with benefits (that is, exploratory market learning). In addition, focusing on the current processes already in place can make the manufacturing of the existing products cost effective and cost effectiveness is considered as a source of competitive advantage (Porter, 1985). Therefore, based on this line of reasoning:

H3b: The positive relationship between ambidextrous market learning and product advantage is higher, the higher the technological discontinuity.

3.4.5 Customer Discontinuity – New product financial performance

Product innovativeness from the customer's perspective (customer discontinuity) is the degree of learning effort required from the customers in order to fully understand its potential advantage and the behavioural change required by the customers when using the innovative product. As customer discontinuity increases, the degree of learning effort required also increase, that is, when product innovativeness increases this increases the behavioural change required by the customers as well. As mentioned in the previous section, taking insights from the information processing theory, customer discontinuity acts as a moderator in the current model. Kleinschmidt and Cooper (1991) find strong evidence that highly innovative and not-at-all innovative products tend to perform equally well. Therefore, they argue that product innovativeness does not have direct impact on product performance; instead it acts as a moderator.

In the NPD literature, the relationship between customer discontinuity and product performance is extensively covered but the relationship between product innovativeness from the customer's perspective and product performance is inconsistent and unclear (for example, McNally, Cavusgil, Calantone, 2010; Atuahene-Gima, 1995). For example, McNally, Cavusgil and Calantone (2010) and Calantone, Chan, and Cui (2006) found a direct negative relationship between customer discontinuity and product performance. Rijsdijk, Langerak and Hultink (2010) used customer discontinuity as a control variable and found a negative impact on product performance. Atuahene-Gima (1995) argues that product innovativeness from the customer's perspective has a moderating relationship between market orientation and product performance but the results were not supported.

The literature suggests that customers unaware of the products due to its radicalness makes it even more difficult for the customers to trust the product and it takes longer to fully understand the potential advantages of the product. This is especially true in the case of firms operating in high-tech industries, primarily due to the reluctance in changing their behaviours to use the new technology. For example, in the case of high-tech Business-to-Business (B2B) firm, if their component manufacturer develops a new product (component) which may require the firm to change all its other components which makes the final product, may be reluctant to use the new product even if the component was superior. Hoeffler (2003) argues that there is a great amount of uncertainty when customers estimate the usefulness of innovative products. In addition, when customers' have to change their behavioural patterns to adopt a new innovative product may not be able to fully understand its benefits (Lawton and Parasuraman, 1980). McNally, Cavusgil and Calantone (2010) argue that developing innovative products tend to fail in the market (in the customer's perspective) primarily because in short-term customers want new products that are easy to understand and is also superior in comparison to the competing products. They argue that highly technologically innovative product is associated with risk and also makes it difficult for customers' to estimate the meaningfulness of the product. On the other hand, it is difficult for the customers' to trust the product by a firm operating in a new product-market domain, even though the product being sold is not highly innovative in comparison to the competitive product.

The above reasoning leads to the next key question and that is, whether customer discontinuity positively moderates the product advantage and new product financial performance hypothesis or does it negatively moderate the ambidextrous market learning and product advantage hypothesis. This is primarily because as mentioned, if the risk involved with adapting new innovative products is high then this will make it difficult for the customers' to fully understand the benefits of the product (that is, product advantage). In the existing NPD literature, scholars (for example, Gatignon and Xuereb, 1997; Veryzer, 1998; McNally, Cavusgil and Calantone, 2010; Calantone, Chan and Cui, 2006) argue that customer discontinuity stems from the compatibility and complexity of the product and hence customer discontinuity is a product attribute that is a feature of product meaningfulness and product superiority. If the product provides unique solutions (that are superior) and provide solutions that no competing product can provide then the customers tend to buy the product even if it entails changing their behaviour and has a high learning cost. Hence, product innovativeness from the customers' perspective in fact acts as a moderator between product advantage and new product financial performance.

Hence, in line with the above-mentioned reasoning, product innovativeness from the customer's perspective (that is, customer discontinuity) will negatively moderate the relationship between product advantage and new product financial performance in the conceptual model.

H4: The positive relationship between product advantage and new product financial performance is lower, the higher the customer discontinuity.

Table 3.1 summarises the proposed hypotheses in this model.

Table 3.1 Summary of the hypotheses

Hypothesis	Relationships	Brief Explanation
H1	Ambidextrous Market Learning ➡ Product Advantage	Ambidextrous market learning is positively related to product advantage.
H1a	Ambidextrous Market Learning ➡ New Product Financial Performance	Ambidextrous market learning is positively related to new product financial performance.
H2	Product Advantage ➡ New Product Financial Performance	Product advantage is positively related to new product financial performance.
H3a	Marketing Discontinuity x Ambidextrous Market Learning ➡ Product Advantage	The positive relationship between ambidextrous market learning and product advantage is lower, the higher the market discontinuity.
H3b	Technological Discontinuity x Ambidextrous Market Learning ➡ Product Advantage	The positive relationship between ambidextrous market learning and product advantage is higher, the higher the technological discontinuity.
H4	Customer Discontinuity x Product Advantage ➡ New Product Financial Performance	The positive relationship between product advantage and new product financial performance is lower, the higher the customer discontinuity.

3.5 Chapter Summary

In this chapter, first a discussion of the key theories used in the literature to underpin the ambidexterity construct and to justify the antecedents and consequences used in the literature was presented. Then the theoretical underpinning used in this study to develop the conceptual model was presented. Accordingly, then the conceptual model used in the current study was presented. Finally, the hypotheses were discussed in-detail which provided an explanation for the conceptual model. Insights were taken from the organisational learning theory to define the key constructs used in the model and insights from the RBV theory just how ambidextrous market learning can be defined as a key source of competitive advantage in high-tech industries. Furthermore, product innovativeness from the firm's and customers' perspective is modelled as a moderator in the conceptual model and their respective relationships are discussed and justified. In addition, the model is controlled using R&D expenditure and firm size, which in the existing NPD literature have been modelled to have a strong impact on the endogenous variable(s) used in the model. In the next chapter, the research methodology used to collect data for testing the above conceptual model is presented.

Chapter Four: Research Methodology

4.1 Introduction

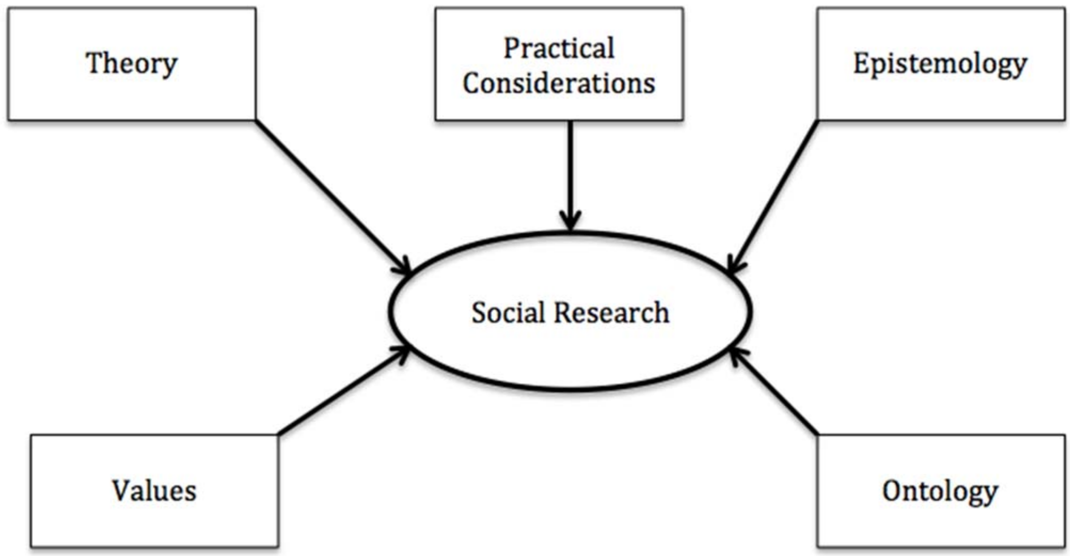
This chapter describes the methodology approach that is employed to collect data for the study. In order to test the model, achieve the research objectives and to verify the hypotheses relating to it as proposed in the previous chapter; it is important that a detailed research plan is outlined. Accordingly, this chapter is organised into five parts meant to address the research design issues. Initially, the most suitable paradigmatic approach within which to conduct this study is considered. The second section describes general data collection matters with a detailed explanation of the choice of research design for this study. The third part of the chapter provides justification for the chosen survey administration methods. Following this in the fourth part, a detailed explanation of pre-test design and process is provided. And in the fifth section reports on issues relating to the main survey study is presented. Finally, a summary is provided to conclude the chapter.

4.2 Influences on social research

In management research, research strategy is profoundly debated, primarily because of the differences on how social reality should be studied. This is mainly because one group of researchers believe that every individual involved in social science research plays a key role and the others believe that there is a single reality and reality follows a given set of laws which can be uniformed and is generalizable. Individual beliefs of the researcher play a key role in defining the research strategy but these beliefs alone do not influence how the research should be designed. Figure 4.1 summarises the various factors that influence research design in management.

Research paradigms that determine the ontology and epistemology of the research are two of the five factors that influence on how to conduct research. The principal orientation to the role of theory in relation to research plays a key role as well. Selecting an appropriate research design is essential as different types of design seek different types of knowledge, and hence different methods of collecting data may better answer the questions posed by the research; hence leading to befitting practical applications.

Figure 4.1 Influences on the conduct of social research



(Source: Bryman, 2004)

In the following sections each factor that influences on the conduct of social research is discussed in detail.

4.2.1 Research paradigms

"At its most abstract level, a research project is usually based on a hypothesis concerning the relationship among chosen concepts." (Losee and Worley, 1993, p. 103). To test these relationships and to achieve the aim of the study, it is essential on the part of the researcher to consider the most appropriate paradigm within which to carry out the research. The definition of the word paradigm is "the generally accepted perspective of a particular discipline at a given time" and a research paradigm is the set of beliefs or principles that

shape and define the way the researcher perceives the world. It "represents a worldview that defines for its holder, the nature of the world, the individual's place in it, and the range of possible relationships to that world and its parts" (Guba and Lincoln, 1994, p. 107). The research paradigm determines the ontology and the epistemology of the research. Selecting the appropriate research paradigm is essential to successfully answering the research questions (Johnson, Buehring, Cassell and Symon, 2006).

The nature of epistemological science ranges along a spectrum from positivism, under which research has historically followed a scientific methods approach, to interpretivism, where reality is interpreted subjectively and assumed to be a social construct. On the other hand ontology science ranges from objectivism that asserts that social phenomena and their meanings have an existence that is independent of social actors, to constructivism which, asserts that social phenomena and their meanings are continually being accomplished by social actors. In the next section, the two core elements of research paradigms will be examined for their suitability for the proposed research, and positivism and objectivism will be proposed as the most appropriate design for this research.

4.2.1.1 Epistemology

The root definition of epistemology is the *"theory of science of the methods or ground of knowledge… it refers to the claims or assumptions made about the ways in which it is possible to gain knowledge of this reality, whatever it is understood to be; claims about what exists may be known"* (Blaikie, 1993, p. 6-7). *"The central issue is the question of whether the social world can and should be studied according to the same principles, procedures, and ethos as the natural sciences."* (Bryman, 2004, p. 11). Based on this central issue there are three epistemological positions that emerge. *Positivism, Realism* and *Interpretivism,* positivism is a scientific approach to research, and affirms the importance of imitating natural sciences. On the other hand, realism shares similar beliefs with positivist with one major difference, that, there is a scientific reality that is separate from our description of it. And interpretivism is gathering the subjective meaning of social action, as social science cannot be imitated as different people view the world differently.

The majority of research in marketing linked with innovation generally adopts a positivist approach. In doing so, most of the studies are quantitative based and use survey methodology. The data collected using surveys are formulated in such a way that suggests that firms are objective social entities, and these entities are organised according to pre-determined stable laws. Positivist researchers approach theory only to generate hypotheses that can be tested, and that the knowledge is gained through gathering facts (Bryman, 2004). A positivist researcher has an existing objective that is based on the literature and it is well structured, and the data is collected in a consistent manner and the researcher aims to avoid bias by remaining neutral and external to the research (Malhotra and Birks, 2000).

The emphasis of this study is on testing the relationship between Ambidextrous Market Learning (AML) and product advantage, and therefore the primary objective of this study is to measure this relation. Hence, the type of knowledge this study investigates is in positivist and deductive sphere.

4.2.1.2 Ontology

All researchers must start from a philosophical position that is either explicit or implicit. The two foundation elements that define the philosophical position in management research are: ontology and epistemology (Blaikie, 1993). Ontology is the *"science or study of being… it refers to the claims or assumptions that a particular approach to social inquiry makes about the nature of social reality"* (Blaikie, 1993, p. 6). The ontological assumptions feed into how the research questions are formulated and how research is carried out. The central point of ontology is the question whether social entities can and should be considered as objective entities or social constructions. These two positions are intermittently referred as *objectivism* and *constructionism.*

Objectivism implies that social phenomena are external facts and that are beyond our reach or influence, and various categories are independent or separate from actors (Bryman, 2004). On the other hand, constructionism implies that individuals/actors are continually accomplishing social phenomena. The underlying difference has a huge impact on the knowledge obtained from the data collected. When social entities are considered as objective entities then the key assumption here is that people learn and apply the rules and regulations, they follow standard procedures. When social entities are considered as social constructs then the key belief is that people are involved and knowledge is viewed as indeterminate. It is believed that rules are far less extensive and less rigorously imposed. The majority of research in marketing linked with innovation generally adopts an objectivism ontological approach. In doing so, most of the studies are quantitative based and use survey methodology. The data collected using surveys are formulated in such a way that suggests that firms are objective social entities, which act on individuals.

4.3 Research Design

Research design is a detailed blueprint that guides a study towards achievement of its goals (Bryman, 2004). The results of the study should resolve the hypotheses that provide evidence of validity and at the same time; the process should be replicable by another independent researcher. Research designs have been classified according to five types: experimental, cross-sectional, longitudinal, case study, and comparative (Bryman, 2004; Kerlinger 1973).

Experimental research design is the least employed in social science research (Bryman, 2004). The key purpose of using an experimental research design is to gain more knowledge on experimental realism (Aronson and Carlsmith, 1968). The internal validity of using this design is very high but there are questions regarding the external validity and reliability of the results obtained. The chief reason for using experimental research design is that the results provide a better understanding of the phenomenon when it is compared (control group) to similar context rather than comparing the phenomenon to something else that is similar to it. In the current study the primary focus is to understand what the relationship between AML and product advantage is and not to test this relationship in comparison to controlled scenario.

As mentioned in the previous section of this chapter, this study is deductive and the aim of this study is to test various relationships between Ambidextrous Market Learning (AML) and product advantage. Hence using a case study or comparative study design would not provide appropriate results. This is primarily because, qualitative research design (that is, case study) is generally used to answer research questions that provide an explanation to as why there is a relationship between the constructs in the study. Quantitative research design (that is, cross-sectional and longitudinal) is generally used to answer research questions that provide an explanation of what is the relationship between the constructs in the study. Hence, qualitative research is mostly used to build theory and on the other hand, quantitative research is used to test the theory (Bryman, 2004). Churchill (2005) notes that longitudinal and cross sectional designs are the dominant forms of research designs used to examine relations between organisational variables in marketing research. Taking into consideration, the extra demand for expenditure in terms of cost and time in longitudinal designs means that it is practically impossible to implement it in academic research. Implementing longitudinal research design in doctoral studies is a less desirable option.

In addition, there are certain limitations in implementing a longitudinal research design. First, the lack of clear guidelines regarding when to conduct further wave(s) of data is one of the major problems. Two, often researchers who employ longitudinal design tend to collect large amounts of data with little apparent planning (Bryman, 2004). Third, the problem of attrition has made longitudinal design less frequently implementable (Bryman, 2004; Rindfleisch, Malter, Ganesan, and Moorman, 2008). In addition, in the current study, the primary focus is to measure how ambidextrous firms tend to develop products and not what is the long-term effect of implementing an ambidextrous culture. Longitudinal studies are primarily used when researchers focus on answering questions such as how in long-term the relationship between the various constructs change. Finally, longitudinal design is more appropriate in comparison to cross-section design, when the sample size is not large and collecting data over a period of time may provide insightful results.

Taking the limitations of longitudinal design in to consideration, a cross-sectional research design was chosen to examine the relationships reported in the previous chapter. Bryman (2004) defines cross-sectional design as "*collecting data at a single point in time from more than one case in order to quantify the data collected with two or more variables, which are then examined to detect patterns of association*" (p. 41). Cross-sectional design is good for examining relationships between variables, but it is not easy to draw casual inferences.

Cross-sectional design makes use of research instruments such as self-completion questionnaires, or structured observation schedules that jeopardise internal validity, but replicability and external validity tend to be strong. But the issues of reliability and measurement validity are primarily matters of the scales used to measure the variables (Bryman 2004). In contrast to longitudinal design, common method variance and casual inferences issues are not well dealt with in cross-sectional research design. Rindfleisch, Malter, Ganesan, and Moorman, 2008 (2008) suggest that data collected using cross-sectional designs can have better common method bias and causal inference through the use of multiple respondents, multiple data sources, or multiple periods.

Consistent with the above recommendations, a retrospective questionnaire was developed for this study, and multiple sources were used to collect data. Though there are a variety of arguments for and against the use of retrospective data. It is argued that it is hard for the respondents to speculate the previous strategies used in the firm because of respondents' faulty memory (Golden, 1992). Golden (1992; 1997) and Glick et al., (1990) argue that there are certain guidelines that researchers should follow to reduce the errors that emerge from using retrospective questionnaires. In line with these recommendations the first step taken was to collect information on behavioural accounts rather than accounts of their beliefs and intentions. Second, the questionnaire had no open-ended questions as respondents may selectively neglect some events.

Third, organisational and industry contexts may influence the quality of the retrospective data collected and to avoid errors emerging from this, the questions asked the respondents to think about the strategies built in the last three years and not longer. This reduces the error occurring from the retrospective data collected. Fourth, Golden (1992) recommend that researchers should try to encourage the respondents to provide accurate information and be adequately motivated. Hence, the respondents were continuously reminded to provide honest answers and reassured that the answers provided by them would be in absolute confidence. This would, it was hoped, give them the confidence to be honest and provide accurate information. In addition, this study conducted rigorous reliability and validity assessments (see chapter six).

To summarise, existing literature on ambidexterity and innovation has largely followed cross-sectional research design for data collection (for e.g., Chang and Hughes, 2012; Li and Huang, 2012; Wang and Rafiq, 2014). The primary reason is because researchers in the existing literature have focused on the short-term effects of ambidextrous culture on performance. In addition, cross-sectional is as powerful tool to collect quantifiable data and evaluate theoretical models as longitudinal studies. And considering the limitations of implementing a longitudinal study (as mentioned in the previous paragraphs) cross-sectional is a more powerful tool to collect quantitative data and provide sufficiently valid and reliable results. As such, examining the consequences of Ambidextrous Market Learning (AML) using cross-sectional data should help to provide invaluable additions to the literature. Thus, cross-sectional research design was adopted to collect data for the current study.

4.3.1 Data Collection Methods

In the previous section as described that cross-sectional research design is the most credible approach to collect data to accomplish the research objectives of this study; now it is imperative to choose a feasible data collection method. Churchill (1995) establishes face-to-face interviews, telephone interviews, online surveys and mail questionnaires as the different types of survey-based data collection techniques. It is important that the researcher decides the most appropriate research instrument to collect data in relation to the current study's research objectives and also to formulate a relevant strategy to administrate it. In the following paragraphs, each survey-based data collection method is evaluated and the most appropriate method is chosen with the considerations of its advantages and disadvantages are noted.

Taking into consideration, the large number of high-technology firms that needed to be contacted and given the number of questions that had to be asked, face-to-face interview method was not apt. After reflecting on the amount of resources (e.g. money and time) required, to travel across UK to collect data from large number of firms this method was discarded. On the other hand, telephone interviews would negate the concerns faced using face-to-face interviews but using telephone interviews to collect data would bring in the issue of building a rapport with the respondent in such short time (Bryman, 2004). It would also be an inconvenient and uncomfortable method given the sensitive nature of the data (for e.g., product performance and market strategies employed); also given the number of questions it would be a source of concern to employ telephonic interviews as a means to collect data. Hence it was decided that using structured interviews for this study would yield inappropriate results and cause major concerns for the researcher and the respondent.

The other mode of collecting data is through self-completed questionnaire. Compared to structured interviews, self-completed questionnaires have many advantages, such as; it is cheaper and quicker to administer the questionnaires. The effects of the interviewer are absent and it is convenient for the respondents as well. There are many disadvantages of using self-completed questionnaires, as there is a greater risk of missing data. In addition the response rate tends to be lower plus it is hard to collect any additional data. Weighing the pros and cons of using self-completed questionnaire to structured interviews, in addition, in the existing literature, there are statistical techniques and tools that can be used to reduce the problems that arise from any of the disadvantages of the self-completed questionnaire was taken into account and it was decided that it would be ideal to use self-completed questionnaire technique for collecting the data.

There are two main modes of administrating self-completed questionnaires. This form of collecting data can be administered using online surveys or postal questionnaires. The most prominent form of administrating data collection in organisation literature is postal questionnaires (Bryman, 2004). The other way of administrating self-completed questionnaires is using online surveys. This method usually involves either mailing the questionnaire or sending a web link containing the questionnaire to the respondents (Dillman, 2000). Compared to postal questionnaire, online questionnaires have many advantages, first, relative to postal surveys; the online questionnaire method is relatively cheap (Bryman, 2004; Dillman, 2000). Second, with online questionnaires, one can be sure of whether the right person has answered the questionnaire. Third, using an online questionnaire, the respondent cannot read the whole questionnaire before answering the first question. Fourth, by using online questionnaire, one can be sure that questions have been answered in the correct order. Overall, given the problems associated with postal questionnaire methods, the online questionnaire method was chosen for the current study with the consideration of its disadvantages.

However, there are few drawbacks of using online survey method. First, a major drawback is lower response rate compared to the response rate using a mail survey method. Puleston (2011) state that response rate from online surveys has fallen by more than 50% in the last five years. Second, there are many firms with strict policies against accepting online surveys. Third, the question concerning the gathering of data in absolute confidence, as Puleston (2011) argue that some respondents may be concerned with the mishandling of data collected by the online survey software company. Puleston (2011) states that some of the respondents are concerned regarding the access of their contact details shared with the online survey companies. And finally, there are a high percentage of undelivered surveys. A study conducted by Roy and Berger (2005) on testing the response rate of online surveys, they found that more than one in five electronic surveys did not reach the recipient's mailbox. All the above drawbacks provide an appearance of a poor quality study.

Despite these impediments, online survey technique is a useful data collection method and if it is well designed and administered it reduces the aforementioned drawbacks (Puleston, 2011; Roy and Berger, 2005). A number of statistical and methodological procedures have been recommended to not only improve the quantity of data but also to improve the quality of data collected through online survey technique. Roy and Berger's (2005) total design method was followed to improve the response rate. The emails were personalized and the link to the questionnaire was embedded in the body of the letter. A brief description of the study was included in the body to improve the response rate. No explicit incentive was provided. The questionnaire was designed by following the guidelines provided by Puleston (2011), which are further discussed in section 4.5.

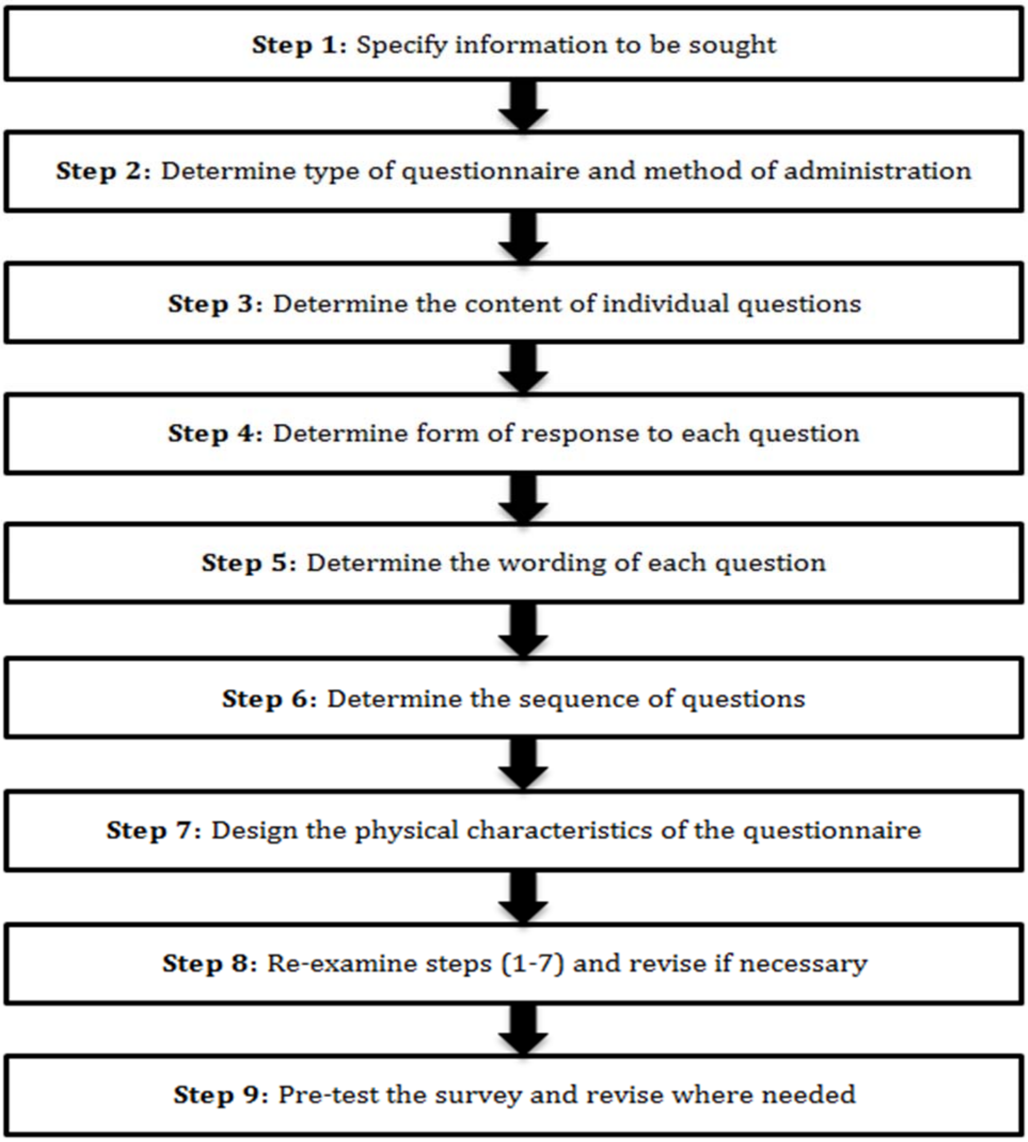
4. 4 Questionnaire Design

This section provides a detailed description of the questionnaire design process. As discussed in the previous section(s), the online survey design was selected as the process of collecting data for this study. There are three main objectives in designing a questionnaire. First, the utmost important objective is to collect accurate and relevant information, second, to maximise the proportion of respondents answering it (Leung and Kember 2005a), and third, reduce any concerns regarding common method variance be reduced (Podsakoff et al., 2003; Podsakoff and Organ, 1986). To achieve the above-mentioned objectives, Churchill and Iacobucci (2004) suggest a nine-step procedure. Figure 4.2 illustrates these nine steps, which are considered and implemented in this study.

4.4.1 Information to be sought

An in-depth literature review was conducted to locate acceptable measures of the key constructs of interest. A list of the key constructs is listed in Table 4.1, and the measure-searching task began by looking at the key construct (for e.g. ambidexterity, product advantages, and product innovativeness). The measures found in the existing literature were found to be reliable and valid, which were chosen in the current study. In addition, 12 structured interviews were held with new product development managers with the intent of incorporating their views into the wording of the questions in the questionnaire. The following sections provide detailed information on the proposed measures of these constructs. Construct measures were derived fundamentally from existing research but the measures were refined and validated as presented in Chapter 5 and 6.

Figure 4.2 Questionnaire Development Process



(Source: Adapted from Churchill and Iacobucci, 2004)

4.4.1.1 Ambidextrous Market Learning (AML)

The aims and proposed contribution of this research are mainly twofold. First, it is to examine the consequences of Ambidextrous Market Learning (AML) on product advantage, and second, to investigate the relationship between product innovativeness and product performance. To achieve these goals it was necessary to have specific measures for ambidextrous market learning.

Table 4.1 List of information

Ambidextrous Market Learning (AML) 1. *Exploration market learning* – whether firms have experimented and targeted a new group of customers. 2. *Exploitation market learning* – whether firms have focused on understanding the current needs and wants of the customers
Product Innovativeness (from the firm's perspective) 1. *Marketing Discontinuity* – products aimed at new customers 2. *Technological Discontinuity* – new or different technology involved in developing the new product(s)
Product Innovativeness (from the customers' perspective) 1. *Customer Discontinuity* – perceived learning/changeover cost required by the customer
New Product Financial Performance 1. Perceived satisfaction with *financial performance* of the product(s) introduced in the last three years by the firm.
Product Advantage 1. *Product Superiority* – Relative to the key competitors perceived superiority of the product(s) introduced in the last three years. 2. *Product Meaningfulness* – Relative to the key competitors, perceived meaningfulness (satisfying the needs/wants of the customers) of the product(s) introduced in the last three years.
Firm Profile Information 1. Business Experience 2. Industry characteristics 3. Business Type 4. Number of new products introduced in the last 3 years 5. Number of patents 6. Total annual turnover 7. Total number of employees 8. Number of employees in the new product development department 9. Percentage of turnover spent on R&D

There are several scales for measuring exploration and exploitation activities (e.g., He and Wong, 2004; Atuahene-Gima, 2005; Atuahene-Gima, 2003; Kim and Atuahene-Gima, 2010). There is a broad agreement that ambidexterity is pursuing of exploration and exploitation activities, but there exists a conceptual obscurity regarding the combined magnitude of these two complementary activities. The primary reason for this is the inconsistent measure of exploration and exploitation. For example, Ebben and Johnson (2005) conceptualise exploration and exploitation with a single variable that ranges from organisational efficiency to flexibility. On the other hand, He and Wong (2004) operationalize exploration and exploitation as different extents of innovation (radical and incremental innovation). Lavie et al., (2010) contend that *"in the future, scholars who employ the exploration and exploitation framework should conceptually relate their constructs back to March's (1991) original definition"* (p.520).

Based on March's (1991) definition, Kim and Atuahene-Gima (2010) define exploratory market learning as *"the acquisition and use of knowledge from outside the organisation's current customers and competitor boundaries"*, and exploitative market learning is *"specific information that provides a deeper understanding of current customers and competitors to ensure efficiency of organisational actions"* (p. 520). The scale developed to measure exploratory and exploitative market learning was based on relevant studies such as Clegg (1999), McGrath (2001), March (1991), Levinthal and March (1993). Kim and Atuahene-Gima (2010) define exploration and exploitation activities as two forms of organisational (market) learning.

The existing literature suggests that organisational learning is an important source of competitive advantage (for e.g., Hurley and Hult, 1998). In the recent years researchers, managers, and scholars have observed that for good manufacturing plan, good product design, better product innovative performance, and better product advantages, the need for the top managers to learn assumes a new urgency. This is mainly because as researchers agree that, the ability to learn faster than competitors may be the only source of sustainable competitive advantage (DeGeus, 1988; Dickson, 1992). There is a growing body of literature on the importance of organisational learning in new product development, but in its infancy the focus has been on the manifestation of the organisation's propensity to learn and adapt accordingly, rather than understanding the combined impact of two types of market learning on new product performance.

All items comprising exploratory and exploitative market learning scale were adapted from the scale developed by Kim and Atuahene-Gima (2010). The primary reason for adapting the scale developed by Kim and Atuahene-Gima (2010) study was that the items used by Kim and Atuahene-Gima's (2010) study to measure exploratory market learning and exploitative market learning resulted in a reliable result (composite reliability of 0.81 and 0.71). The items were measured on a 7-point Likert scale, with anchors at 1 = "Strongly Disagree" and 7 = "Strongly Agree". Four items were used to measure exploratory market learning and four items were used to measure exploitative market learning (see Table 4.2).

Table 4.2 Scale items for exploratory and exploitative market learning

Constructs	**Measurement Items**	**Item Source**
Exploitative Market Learning 1 = "*Strongly Disagree"; 7 = "Strongly Agree"*	How far do you agree/disagree with the following statements? We… 1. Use new ideas that are consistent with our current product – market experiences by analysing current customers' needs and competitor products. 2. Emphasis on using proven ideas for solutions to marketing problems by surveying current customers. 3. Use market information and ideas that may contribute to the firm's existing product markets through analysis of experience with prior projects, current competitors and technologies. 4. Undertake activities that help to utilise or integrate the firm's current market experience.	Kim and Atuahene-Gima (2010)
Exploratory Market Learning 1 = "Strongly Disagree"; 7 = "Strong Agree"	How far do you agree/disagree with the following statements? We… 1. Use market information that takes the company/business unit beyond its current product market experience through market experiments. 2. Use novel products or services that may not necessarily be successful in the current market through contact with non-customers, studying of emerging competitors and technologies. 3. Aim to collect new information that enables us to learn new things in our market. 4. Use market information and generate new ideas involving experimentation and high risk.	Kim and Atuahene-Gima (2010)

4.4.1.2 Marketing Discontinuity (MD)

Marketing discontinuity indicates the perceived degree of change required in targeting new customers, competitors, distribution channels or product category. Marketing discontinuity is one of the variables used in this study to measure product innovativeness from the firm's perspective. Danneels and Kleinshcmidt (2001) argue that product innovativeness viewed from the customers' perspective and from the firm's perspective is two different things. They conceptualise product innovativeness as marketing and technological discontinuity. In line with the aim of this study, it is essential to differentiate different dimensions of product innovativeness and analyse how each dimension of product innovativeness impacts new product financial performance. To capture the marketing discontinuity construct, the scale developed by Danneels and Kleinschmidt (2001) was adapted for this study. As mentioned in the previous chapter, a small group of researchers (for example, Calantone, Chan, and Cui, 2006; Danneels and Kleinschmidt, 2001; Garcia and Calantone, 2002; McNally, Cavusgil, and Calantone, 2010) illustrate the importance of differentiating between product innovativeness from the firm's perspective and product innovativeness from the customers' perspective. In the existing literature, the scale used to measure marketing discontinuity and technological discontinuity was developed by Danneels and Kleinschmidt (2001). In addition, the results of the reliability and validity of the items used to measure indicate that this scale could provide good reliable results in the current study (composite reliability of 0.78). Therefore, to measure the marketing discontinuity and technological discontinuity construct was adapted from the Dannels and Kleinschmidt (2001) study. All items were measured on a 7-point Likert scale, asking the respondents to indicate the extent to which a series of statements applied to the products/services introduced by their company/business unit in the last three years. The threshold was set as 1 = "Never" and 7 = "All the time". The marketing discontinuity scale items are presented in Table 4.3.

4.4.1.3 Technological Discontinuity (TD)

The other dimension of product innovativeness from the firm's perspective used in this study is technological discontinuity. Technological discontinuity is the degree of change in the processes or technologies associated with innovation. This could be new manufacturing equipment, new processes (for e.g., new software like Java), a new manufacturing process, or a new product development process.

Table 4.3 Scale items for Marketing Discontinuity

Constructs	Measurement Items	Item source
Marketing Discontinuity 1 = "Never"; 7 = "All the time"	How far do the following statements describe the products/services introduced by your company/business unit in the last three years? 1. To what extent were the products or services aimed at new customers to your company/business unit? 2. To what extent did these products or services take you up against new competitors? 3. To what extent did these products or services cater to new customer needs/wants? 4. To what extent did these products or services represent a new product or service category? 5. To what extent was the market for these products or services new or different for your firm?	Danneels and Kleinschmidt (2001)

Danneels and Kleinshcmidt (2001) suggest that the variety of resources used in product development can be segregated into technological resources and customer/market resources. Firms operate in new technological domains mainly to develop new products with high product advantages compared to other products available in the market. At times firms have to change the manufacturing processes, as these may not be efficient and effective. Some firms adapt to new technology as the needs/wants of the customers change and hence they have to develop new products using new technology. Danneels and Kleinschmdit (2001) develop a scale to measure technological familiarity to measure what extent the firms use new technology to develop new products. McNally, Cavusgil and Calantone (2010) adapt this scale to measure technological discontinuity. The reliability and validity results of the scale used in Danneels and Kleinschmidt (2001) study provided evidence of a good scale to use (composite reliability of 0.82). To capture the technological discontinuity construct, the scale developed by Danneels and Kleinschmidt (2001) was used in this study. All items were measured on a 7-point Likert scale, asking the respondents to indicate the extent to which a series of statements applied to the products/services introduced by their company/business unit in the last three years. The threshold was set as 1 = "Never" and 7 = "All the time". The technological discontinuity scale items are presented in Table 4.4.

Table 4.4 Scale items for Technological Discontinuity

Constructs	Measurement Items	Item Source
Technological Discontinuity 1 = "Never" and 7 = "All the time"	How far do the following statements describe the products/services introduced by your company/business unit in the last three years? 1. To what extent did the technology involved in the development of these products or services represent new or different technology for your firm? 2. To what extent did the engineering and design work involved in these new products or services project represent new or different work for your firm/business unit? 3. To what extent did the production technology and production process represent a new and different one for your firm/business unit?	Danneels and Kleinschmidt (2001)

4.4.1.4 Customer Discontinuity (CD)

Customer discontinuity (CD) is the perceived degree of change required from the customers in order to use the new product or service. Customer discontinuity indicates the behavioural change required by the customers to adapt new products (Atuahene-Gima, 1996; Lawton and Parasuraman, 1980). CD reflects product innovativeness from the customers' perspective. The more innovative the product is, the higher the learning effort and more behavioural change required by the customers. McNally Cavusgil and Calantone (2010) argue that, when considering product innovativeness from the customers' perspective, it is important to examine the various product innovation attributes (for e.g., relative product advantages, behavioural changes required, complexity, product superiority and risk associated with adoption). Therefore, in this study the CD construct focuses on the learning effort, behavioural changes required, and complexity of new products when customers adopt new innovative products. In this study product advantage is conceptualised as a higher order construct consisting of product meaningfulness and product superiority as a separate construct from CD to examine the relationships between product innovativeness from the customers' perspective and product advantage constructs. Many products fail in the market primarily because customers do not understand the benefits of using the product and that is why in this study, product advantage construct is examined separately from CD.

To capture the customer discontinuity construct, the 'product newness to customers' scale developed by Atuahene-Gima (1995) was adapted for the current study. In the existing literature, Atuahene-Gima (1995) adapt the degree of product newness from the customers' perspective from Eliashberg and Robertson's (1988) 'customer switching cost' construct. Though in the existing literature, recent studies measuring product innovativeness/product newness from the customer's perspective (for example, McNally, Cauvsgil, Calantone, 2010;

Calantone, Chan, Cui, 2006; Danneels and Kleinschmidt, 2001) adapt the Atuahene-Gima's (1995) primarily because Atuahene-Gima's (1995) provides more reliable measures (composite reliability of 0.78) in comparison to Eliashberg and Robertson's (1988) scale which resulted in a composite reliability of 0.71. Therefore, the customer discontinuity construct used in this study is adapted from the Atuahene-Gima's (1995) scale. All items were measured on a 7-point Likert scale, asking the respondents to indicate the extent to which they agree/disagree with a series of statements applied to the products/services introduced by their company/business unit in the last three years. The threshold was set as 1 = "Strongly Disagree" and 7 = "Strongly Agree". The learning cost scale items are presented in Table 4.5.

Table 4.5 Scale items for Customer Discontinuity

Constructs	**Measurement Items**	**Item source**
Customer Discontinuity 1 = "Strongly Disagree"; 7 = "Strongly Agree"	How far do you agree/disagree with the following statements that describe the products or services introduced by your company/business unit in the last three years? 1. Our products or services required a major learning effort by the customer. 2. It took a long time before the customer could understand the products' or services' full advantages. 3. Product or service concept was difficult for customers to evaluate or understand. 4. Products or services were more complex than what we had introduced before in the same market. 5. Our products or services involved high changeover costs for the customers. 6. Our products or services required considerable advance planning by the customer before use.	Atuahene-Gima (1995)

4.4.1.5 Product advantage

The product advantage construct was operationalized, as a higher order construct comprised of non-substitutable combination of product meaningfulness and product superiority. Product meaningfulness is defined as the perceived attributes and functionalities that are beneficial to the customers (Im, Hussain and Sengupta, 2008; Rijsdijk, Langerak, and Hultink, 2011). On the other hand, product superiority captures the perceived extent to which the products' attributes and functionalities outperform competing products (Day and Wensley, 1988). Product advantage construct indicate the product's superiority over other products based on quality, delivered benefits, and economic advantage (Cooper and Kleinschmidt, 1986; McNally, Cavusgil, and Calantone, 2010).

Prior research has captured product advantage as a single-order factor (Atuahene-Gima, 1995; Li and Calantone, 1998). This operationalization of product advantage construct leads to misalignment between the conceptualisation and operationalization, and introduces bias and loss of information. In the next chapter a detailed plan is presented, explaining the various stages involved in operationalizing product advantage as a higher order construct. As explained in the previous chapter, the product advantage construct has been misapplied in the existing literature. That is, many studies (for example, Li and Calantone, 1998; Atuahene-Gima, 1995; Langerak, Hultink, and Robben, 2004) have measured product innovativeness and applied it as a product advantage construct in their studies. In 2006, Calantone, Chan and Cui argue that this misapplied measures of product advantage have resulted in misleading information and has been a major factor for not fully understanding the relationship between product performance, product advantage and product innovativeness. In 2011, Rijsdijk, Langerak and Hultink adapt the scale used by Cooper and Kleinschmidt (1987) and added newly generated items to measure product meaningfulness and product superiority. The resulting scale provided excellent reliability and validity test. The product meaningfulness and product superiority scales resulted in a composite reliability of 0.92 and 0.91 respectively. The factor loading of all items was greater than 0.84 and the t-values for the factor loading was greater than 13.

Hence, all items comprising product meaningfulness and product superiority were based on scale were adapted from the scale used by Rijsdijk, Langerak, and Hultink (2011), and measured on a 7-point Likert scale. Since, product meaningfulness and product superiority are constructs that measure the attributes and functionalities of the product in comparison with the other products available in the market, hence the anchors used were 1 = "Much less than our key competitors" and 7 = "Much more than our key competitors". Three items were used to measure product meaningfulness and three items were used to measure product superiority (see Table 4.6).

Table 4.6 Scale items for Product advantage

Constructs	Measurement Items	Item source
Product Meaningfulness 1 = "Much less than our key competitors"; 7 = "Much more than our key competitors"	How far do the following statements describe the products/services introduced by your company/business unit in the last three years? Relative to our key market competitors, the products/services we offer in our market(s) are: 1. Products or services that provide many benefits to the customer. 2. Products or services that offer much value to the customer. 3. Products or services that offer many advantages.	Rijsdijk et al., (2011)
Product Superiority 1 = "Much less than our key competitors"; 7 = "Much more than our key competitors"	How far do the following statements describe the products/services introduced by your company/business unit in the last three years? Relative to our key market competitors, the products/services we offer in our market(s) are: 1. Products or services are superior to the competing products available in the market. 2. Products or services are the best of its kind in the market. 3. Products or services are superior in its category.	Rijsdijk et al., (2011)

4.4.1.6 New Product Financial Performance

In the existing literature, product performance has been measured as a multi-dimensional construct comprising of market, technical, and financial performance. This can be classified as economic and non-economic dimensions. Using the guidelines provided by Griffin and Page (1996), this study measured the financial aspects of the product performance. As mentioned in the previous chapter, one of the primary goals of this study is to measure whether the benefits of ambidextrous market learning culture outweigh the implementation cost. Hence, in this study, the product performance construct focuses on the financial dimension.

The literature suggests that objective and subjective measures can be used to measure product performance (for e.g. Moorman, 1995). In the existing literature, there is a broad agreement that product performance can be measured on economic and non-economic aspects. Table 4.7 illustrates the various items used under different dimensions to measure product performance. But there exists a lack of conceptual clarity regarding using subjective or objective measures. Gatignon and Xuereb (1997) measure product performance relative to their competitors. They suggest that if product advantage is measured in comparison to the competitors' products, then product performance should be measured relative to their competitors. On the other hand, Moorman (1995) argue that many products are developed to enter a new market or cater to the needs/wants of few customers, and then measuring product performance relative to their competitors is not an appropriate technique. Therefore, product performance should be measured in comparison to the firm's objectives. However, Pelham and Wilson (1996) argue that product performance should be a subjective measure. They argue that scholars and researchers should focus on the profitability aspect, as this dimension covers market and technical performance of the product.

Table 4.7 Product performance measures

Customer-based	**Financial**	**Technical**
1. Customer satisfaction 2. Customer acceptance 3. Market share goals 4. Revenue goals 5. Revenue growth goals 6. Unit volume goals 7. Number of customers	1. Met profit goals 2. Met margin goals 3. Return on investment (ROI) 4. Break-even time	1. Competitive advantage 2. Met performance specification 3. Speed to market 4. Development cost 5. Met quality specification 6. Launch on time 7. Innovativeness

(Source: Adapted from Griffin and Page, 1996)

In using objective measures relative to competitor can be reliable indicators of performance, nonetheless, their operationalization can pose considerable problems in this study, such as, data is collected from different industries, and the problem of differentiating between performance of product and services. The concern of using objective measures of product performance is concern over the quality of the data. In using subjective measures of product performance, scholars recommend the adoption of multi-item scales (for e.g., Griffin and Page, 1996). Accordingly, the product performance scale used in this study comprised of variables that captured managers' perceived satisfaction with market share, sales-volume, revenue, profitability, and return on investment. In the existing literature, studies have found subjective measures to provide reliable and valid measures of product performance (for e.g., Langerak et al., 2004; Atuahene-Gima, 2005).

All items were measured on a 7-point Likert scale, asking the respondents to indicate how satisfied they were with the performance of products/services introduced by their company/business unit in the last three years. All the items were sourced from Rijsdijk, Langerak, and Hultink (2011) study, primarily because these items were adopted from Griffin and Page (1996) study and resulted in a strong reliable and valid items to measure new product financial performance (composite reliability of 0.90 and t-value for all the factor loading was greater than 9). All items used were subjective measures and the threshold was set as 1 = "Very dissatisfied" and 7 = "Very satisfied". The product performance scale items are presented in Table 4.8.

Table 4.8 Scale items for New Product Financial Performance

Construct	**Measurement Items**	**Item source**
Product Performance 1 = "Very Dissatisfied"; 7 = "Very Satisfied"	Over the past three years, how satisfied have you been with the performance of the product(s) or service(s) along the following dimensions? 1. Revenue 2. Profitability 3. Return on investment	Rijsdijk, Langerak, and Hultink (2011)

4.4.1.7 Firm Profile Information

There were a total of 8 questions used to profile the high-tech firms that were sampled in this study. In line with previous research, firm experience, industry type, and firm type were measured (Atuahene-Gima and Murray, 2007). The firms were profiled on the bases of products development department and this was measured by the number of employees in the R&D department, number of new products introduced by firm in the last three years, total number of patents obtained in the last three years, and the percentage of R&D expenditure over total annual turnover. Specifically the existing literature on ambidexterity (for e.g., He and Wong, 2004; Fernhaber and Patel, 2012; Wang and Rafiq, 2014) has profiled the firms in this way. The 8 profile questions are provided in Table 4.9.

Table 4.9 Profiling variables

1. Which industry does your firm operate in?
    - Automobile
    - Information Technology
    - Computers (hardware and software)
    - Chemicals
    - Electrical and Electronics
    - Biotechnology
    - Pharmaceuticals
    - Mechanical
    - Others, please specify
2. How many full-time/full-time equivalent staff is employed by your company/business unit in the UK?
3. Of these, how many work in the new product development department?
4. In the last three years, how many new products were introduced by your company/business unit in the UK?
5. In the last three years, how many new products are patented or will get a patent?
6. Approximately, what was your average ANNUAL TURNOVER for the company/business unit last three years?
7. On average, what percentage of your firm's/business unit's turnover invested in R&D, over the last three years?
8. What year was your company/business unit founded?

4.4.2 Form of response

Following the steps for designing a questionnaire (See figure 4.2), in the previous section(s) the information wanted to achieve of the aims of this study is listed. Based on the aim of this study and other factors, a computerised self-administrated questionnaire technique was chosen; and based on the existing literature; the content of each individual question is listed. The next four steps in designing a questionnaire are to decide the form of response and the physical characteristics of the questionnaire.

The next step was to decide the particular form of response. Churchill and Iacobucci (2002) suggest two response formats; these include open-ended answers and close-ended answers. In the questionnaire there was limited number of open-ended questions. There are three main benefits of using closed-ended questions. It saves time for the respondents as completing the questionnaire is merely circling or ticking the boxes. Two, it assist the respondents as they as they do not have to think of the responses, and, three data analysis is made easier (Hague, 1993). Closed-ended questions are divided into the following types:

1. Multiple choice questions
2. Dichotomous questions
3. Scales

(Churchill, 1999; Malhotra, 1999)

Multiple-choice questions are preferred when there are many possible answers to a single question. As most of the questions in this study were to measure the behaviour of the respondents, using multiple-choice questions seemed the least preferable option. On the other hand, Dichotomous type of questions is most preferred when questions have only two response alternatives (Churchill, 1999).

Most of the questions used in the questionnaire were scale type closed-ended questions. Scale type questions are commonly used in marketing literature. “Scales are questions which limit the choice of the respondents (Hague, 1993). Malhotra (1999) suggest that there is three commonly used itemised rating scales. These are:

1. Likert scale
2. Semantic differential scale
3. Staple scale

Likert scale is commonly used when the respondents indicate the degree to which they "agree" to "disagree" with statements. Semantic differential scale type is preferred when the end points are associated with bipolar labels (for example, Never – All the time). On the other hand, Staple scale is a unipolar rating scale that consists of single adjective to describe the middle point of an even-ranged of values. Most of the questions used in this study are Likert and semantic differential scale types. The primary reasons for using these types of closed-ended questions are, one, as they are easy to construct, administer, and understand. Two, there is also continuity because of the use of the same scale responses.

4.4.3 Common Method Bias

Podsakoff et al., (2003) suggest that there is a raising concerns regarding common method bias, since the dependent and independent variables were sourced from the same informant. This may create false internal consistency and may cause the results to be biased (for example, Podsakoff and Organ, 1986; Podsakoff et al., 2003; Rindfleisch et al., 2008). In order to reduce the raising concerns regarding common method bias, suggested steps were taken into consideration when the questionnaire was designed.

First, Podsakoff et al., (2003) suggest that there may be certain error(s) connected with the chosen scale format. Therefore, as it can be seen from the previous section, the questionnaire employed different format anchors, such as "*Very Dissatisfied*" and *"Very Satisfied"* to *"Much less than our key competitors"* and *"Much more than our key competitors"* (for example, Lindell and Whitney, 2001; Podsakoff et al., 2003). In addition, many reverse-coded questions were asked which may reduce the errors rising from common method bias (for example, Chang, van Witteloostuijn, and Eden, 2010). Further test for common method variance (CMV) will be discussed in section 6.6.1 of Chapter 6.

4.4.4 Physical Characteristics

The physical characteristics of the questionnaire have a significant impact on the respondent's cooperation, response rate and also the validity of the response (Churchill, 1995). The overall design, wording of each question and the sequence of the questions play an imperative role as the researcher's ability to send longer and more sophisticated questionnaires is restricted while conducting an online survey as compared to traditional mail surveys (Roy and Berger, 2005). It was, therefore, important to ensure an online questionnaire was well designed and looked presentable.

There are no hard and fast rules when determining the exact wordings of the questions (Churchill, 1999; Malhotra, 1999). It was made sure that the questions were kept simple and easily understood by the respondents. As the questionnaire was mainly developed from existing empirical studies it was believed the language was simple and the questions would yield reliable results. In addition the sequence of the questions plays a vital role. Following the guidelines offered by Churchill (1999) and Malhotra (1999); the questions were arranged in logical sets. For example, the most easily answered questions were measured initially leading to more essential and difficult questions. The latter stages of the questionnaire contained more sensitive and confidential questions for example, product performance.

The length of the questionnaire can have an impact on the response rate (DeVellis, 2003). The longer the questionnaire more likely it is that it may result in lower response rates. Not to mention, to undertake advanced statistical analyses researchers need the majority of the questionnaires returned fully complete. On the other hand, shorter questionnaires can yield more response rate but could reduce the reliability (DeVellis, 2003). Keeping this in mind, a 16 page online questionnaire was prepared, opting for a higher reliability and focusing on adequately capturing the constructs in the conceptual framework.

4.5 Sampling Frame

The population for this study was high-tech firms located in the United Kingdom. As this study focuses on the business unit level, it was important to develop a sample of high-tech business units from the list of high-tech firms. There were other criteria used to select the sample for this study. The following criteria to select the sample was applied: (a) firms must have been in operation for at least three years; (b) firms with at least 50 employees; (c) firms with greater than 2.5% research and development (R&D) to turnover ratio; (d) firms that operate in a high-tech industry, producing technologically sophisticated products and services. Table 4.10 presents the list of high-tech industries provided by Organisation of Economic Co-operation and Development (OECD, 1999).

Several database directories and companies that provide list of firms were available and could have been used for this study. Among these are Dun & Bradstreet, FAME, Kompass Register CD database and many others. The Pilkington library of Loughborough University made FAME database available for free and therefore for practical reasons FAME database was selected. The FAME database contained more than 100,000 companies along with their financial records for the last five years (minimum), names of the senior management (which includes CEOs, directors, and marketing managers).

Table 4.10 List of high-tech industries

Industry name	Total R&D-intensity (1999, in %)
High-Technology	
Pharmaceuticals	10.46
Aircraft & spacecraft	10.29
Medical, precision & optimal instruments	9.69
Radio, television & communication equipment	7.48
Office, accounting & computing machinery	7.21
Medium-High-Technology	
Electrical machinery & apparatus	3.60
Motor vehicles, trailers & semi-trailers	3.51
Railroad & transport equipment	3.11
Chemical & chemical products	2.85
Machinery & equipment	2.20

(Source: OECD, 1999)

There were about 65000 firms in the United Kingdom that operate in the above list of industries. However, after applying the above criteria the list was reduced to population sample of 1820 firms. Moreover, many of the firms were no longer in business. Further data cleaning was undertaken, which resulted in 207 firms being removed due to acquisition, and relocation. Thus in all, a total of 1613 high-tech firms were used for both the pre-test and the main survey.

The most critical factor in conducting a good email survey is to collect current and up to date information so that the questionnaire is sent to the right emailing address. It was important to not only to develop the list of target firms but also to prepare a list of the right respondent in each firm. The only criterion for this was based on intense research on the 1613 firms and searching for the respondents with the appropriate job responsibility. The research was done using the company website, Linkedin, and Google. Following similar studies (e.g., Atuahene-Gima and Murray, 2007; Yannopoulos, Auh, and Menguc, 2012) marketing and non-marketing managers were identified. Respondents included new product development managers, product-line managers, marketing managers, senior technical managers and R&D managers.

4.6 Pre-test

The first stage in conducting a research project is to conduct a pre-test. Pre-testing is an essential part of questionnaire development process. Pre-test is a study conducted on a small scale in which the results are only preliminary and is conducted to design the subsequent study. An adequate pre-test is primarily conducted to evaluate the face validity and content validity of the study (Churchill, 1999; Malhotra, 1999). Face validity basically reflects the degree to which a scale's items represent a sample of the theoretical content (Hair et al., 2006). Assessing face validity plays an essential role in a study when the items in a questionnaire are borrowed from previous studies (Hair et al., 2006). Content validity refers to the degree to which a measure represents all facets of the theoretical construct (Nunnally and Bernstein, 1994). Pre-test is conducted to improve the questionnaire by identifying and eliminating potential problems (Malhotra, 1996). In addition, to assessing the face validity and content validity of the questionnaire, the pilot study was conducted to estimate the potential response rate of conducting an online survey. This section illustrates how the pilot study was conducted.

According to Hunt et al., (1982) there are five rudimental issues pertaining to pretesting.

1. What specific questions/items need to be pretested?

This could be about testing the entire questionnaire itself, or about specific questions, or, the main constructs used in the data analysis. The fundamental items to be pretested were considered. In addition, it is important to check individual questions for understanding of any unrecognisable terminology, and ambiguous or leading questions.

2. What method should be used to conduct the pre-test?

The three most commonly used methods of pretesting of the study are personal interviews, telephone interviews and mail self-reports.

A panel of experts verified the scale instruments to ensure the content and face validity. A combination of three methods was used to improve the final questionnaire.

3. Who should conduct the pre-test?

Malhotra (1999) and Hunt et al., (1982) suggest that both experienced and new interviewers should carry out the pre-test. This will bring a new perspective and by bringing in new interviewers it would reduce the risk of any interviewer bias.

4. The subjects in the pre-test?

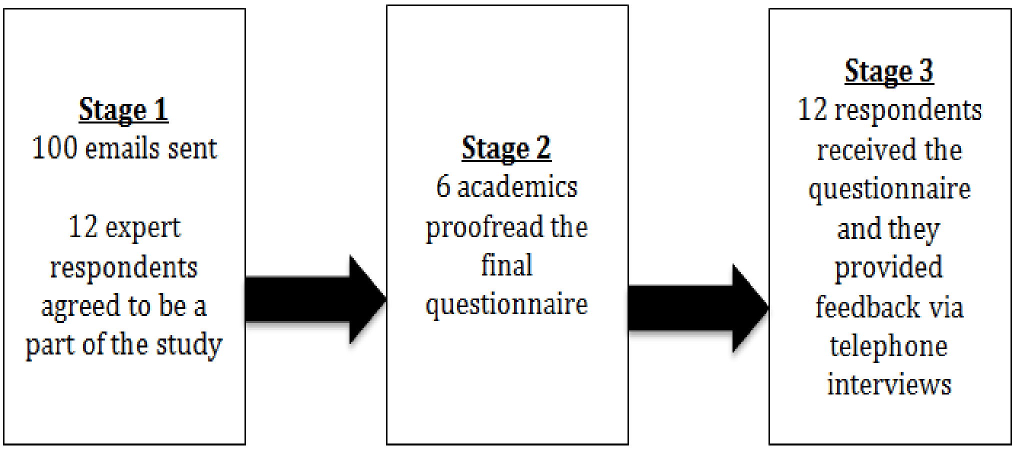
Churchill (1999) suggests that respondents who are similar to the sample should be used. The other reason for using subjects similar to the main study is their knowledge of the subject matter and thus using 'expert' pre-test subjects would provide an elaborate feedback and recommend strategies for eliminating any errors.

5. The size of the sample needed for the pre-test?

Finally, the size of the sample is a fundamental issue in pre-test. Hunt et al., (1982) argue that the sample size is a function of the target population and the instrument used to conduct the main study. They argue that as the size of the questionnaire increases, a bigger sample size is required. Malhotra (1999) recommend two procedures for conducting a pre-test. One, the respondents are asked to fill in the entire questionnaire and then asked for their feedback. Two, while the respondents fill in the questionnaire the interviewer makes careful observations.

Taking the above five rudimental issues in mind, the pre-test for this study was divided into three stages.

Figure 4.3 Three stages of Pre-testing



In the first stage emails were sent to a random sample of 100 firms. In the email a brief description of the study was mentioned and it asked them if they would like to be a part of the pre-test, which involved an interview stage followed by them filling up a questionnaire and in the final stage a small discussion regarding the questionnaire.

After two weeks and one reminder, 12 respondents from the target firms agreed to be a part of this study. 17 emails were returned undelivered due to wrong email address and 4 wrote back saying that it was against the firm policy to take part in surveys. In all, a total of 79 eligible firms did not respond to the emails constituting approximately 16-percentage response rate. Spector (1992) argues that in order to measure the validity and reliability of measures adequately, 100 to 200 responses are needed. The 16-percentage response rate obtained was acceptable because if the results from the pre-test are extended to the main study of remaining 1513 firms, it would provide approximately 229 responses.

The researcher conducted 12 short interviews to evaluate the face validity of the concepts in the research and to find how these firms used exploratory and exploitative market learning for their new product development projects. The findings from the qualitative fieldwork suggested that small and new firms tend not be ambidextrous as they do not have the essential resources to explore the market. The results provided a rough estimate of the response rate and helped improve the wording of the cover letter. The other finding from the interviews was that respondents were happy to receive email format of the questionnaire. They mentioned that they themselves used emails to get feedback from their customers they saw no harm in filling in an online questionnaire themselves, as long as the answers remained confidential and they were not identified individually in the results. This also helped in pre-qualifying the respondents.

In the second stage once the questionnaire was developed, the questionnaire was improved based on the feedback provided by 6 academic experts. They consisted of 6 academics and 16 managers from the sample population. The 6 academics were chosen mainly because (1) they were well versed and doing research in marketing, product development, marketing strategy, and (2) experts in questionnaire design and scaling.

The findings from the feedback provided by academic experts improved the overall physical characteristics of the questionnaire. First, in order to improve the response rate a light blue colour was used in the background of the questionnaire as this attracts the attention of the respondents. Second, it was suggested to change the order of a few of the items in order to not confuse the respondents. Finally, it was recommended by the academic experts to upload a picture of the researcher in order to build trust with the respondents and hence improve the response rate.

In the final stage the 12 expert respondents were emailed the questionnaire as a web link and not as an attached file. Once the respondents finished the questionnaire, a telephone interview was held. The main interest was questionnaire length, terminologies used, structure, space, and wording. It was advised by the respondents that few of the terms used were vague and needed proper definition. Two, instead of having to scroll down each page why not try to fit in enough questions to fit the size of the screen. Three, the length of the questionnaire was their biggest concern. To sum up, the respondents offered a number of observations.

After conducting the three stages of pre-tests the following changes were introduced to the questionnaire. In regards to the text within the questionnaire, since all the questions were taken from previous studies it was made certain that these questions were worded properly and were double checked by the researcher. In regards to the outline and overall design of the questionnaire, the main comment from all the respondents and the six academicians was that the length of the questionnaire. However, this was not an option but since this was no option, none of the questions were removed. In addition, the following changes were implemented:

1. The background colour of the questionnaire was changed and a clear visible difference could be noticed. The questionnaire looked far more appealing compared to before. The initial background colour of the questionnaire was a darker shade of blue. This was later changed to a lighter shade of blue which was not strenuous on the eyes.
2. In order to increase the response rate and personalise the process of survey, the initial page of the questionnaire contacted contact information of the researcher and in addition a photograph was inserted as well.
3. Additional reminders of confidentiality were added especially just before any question pertaining to sensitive information (for example, firm turnover, and performance objective)
4. As per some of the respondents' suggestion, a progress bar at the top of each page was added, as this may motivate the respondents to complete the entire questionnaire.
5. The number of questions on every page was reduced so that all the questions on each page could fit the screen and the respondents would not have to scroll down. This was a helpful observation, as the respondents would not change their answers

by looking at the next set of questions. Even though this made the questionnaire a bit longer but the advantages of doing so were far more superior.

4.7 Main Survey

The implementation of the fieldwork for the main survey was aligned with the observations from the expert and non-expert respondents in the pre-test study. The insights gathered from the pre-test stage helped greatly to improve the questionnaire quality. In the following sections, issues relating to characteristics of the respondents contacted; steps taken to ensure high response rate; survey bias assessment are discussed in detail.

4.7.1 Characteristics of the respondents contacted

The integrity of the results relies mostly on the source of the responses (Dillman, 2000). The list of 1513 high-tech firms in the United Kingdom was selected based on the criteria mentioned earlier, but it was difficult to be sure if the respondents would provide reliable and valid answers. Not all marketing managers/directors have job responsibilities related to product innovation and not necessarily all technical directors/managers have anything to do with the business unit's marketing strategy. Following similar studies (e.g., Atuahene-Gima and Murray, 2007; Yannopoulos, Auh, and Menguc, 2012) marketing and non-marketing managers of 1500 highly innovative SBUs operating in high-tech industries. The following table provides the characteristics of the respondents.

Table 4.11: Characteristics of the respondents contacted

Job Title	Total Number	Percentage
Product Development Director/Manager	480	32
Marketing manager/director	297	19.8
Chief Executive Officer	83	5.5
Chief Technical Officer/Director/manager	282	18.6
R&D director/manager	173	11.4
Product Strategic Director/manager	125	8.3
Business & Department Directors	83	5.5

To gather the contact details of the respondents; initially various Internet tools such as Linkedin, Google, company website, company financial annual reports, FAME and government websites were used. In the second stage, a pre-screening telephone calls were carried out to a small list of firms to find out the most appropriate and competent respondent who could fill in the questionnaire. To make sure that the respondents had considerable experience and knowledge regarding product innovation, each respondent was asked to indicate their experience, the number of products/service they have co-developed/developed. Results shown in the next section indicate that majority of the respondents had considerable experience and knowledge to complete the questionnaire. It was of the utmost importance to find the most ideal respondent from each business unit and to develop this list of the most appropriate respondents from 1513 high-tech firms took around five months.

4.7.3 Ensuring high response rate

Roy and Berger's (2005) total design method was followed to improve the response rate of email surveys (see the final questionnaire in Appendix 4A). The emails were personalised and the link to the questionnaire was embedded in the body of the email letter. A brief description of the study was included in the body to improve the response rate. No explicit incentive was provided. The only incentive provided was, each responding business unit was promised a summary report of the research results. It was decided not to provide any additional incentive as this may hinder the credibility of the response. The first page of the questionnaire contained information about the researcher and the university. It also provided few guidelines for completing the questionnaire and a photograph of the researcher was attached, as this would help the respondents to make a connection with the researcher. An indicator was provided on every page stating what percentage of the questionnaire had been completed so that the respondents got a more clear picture on how much more time will they need to complete the questionnaire. The respondents were reassured that any information they provided will be treated in confidence and at no time will a participating individual will be identified in the results.

In addition, two key steps were included to the final questionnaire. First, every respondent contacted was given a unique username and password. The benefit of providing a unique username and password to each respondent was two-fold. First, the respondents could restart completing the questionnaire from where they left it. Understanding that the questionnaire was lengthy and the results of the pre-test survey confirmed that it would roughly take around 25-30 minutes to complete the questionnaire and most respondents may not be able to complete it at one go. This meant that the respondents would be more inclined and encouraged to fill up the questionnaire and hence improving the response rate. Two, by providing a unique username and password, Qualtrics (the survey software used) created a unique Internet Protocol (IP) address for each respondent and gave an in-depth analysis of how many had completed the questionnaire and what percentage of the questionnaire they had completed. The other step taken to maximise the response rate at this stage was in the cover page the contact telephone number and email ID of the thesis supervisor Dr. Mohammed Rafiq was provided, thus lending credibility to the study.

Similar to the pre-test study, several steps were taken to ensure a high response rate for the main survey. For example, seven days after the first questionnaire emailing, a first round of reminder email was sent to all non-respondents. The reminder email can be seen in Appendix 4B. Fourteen days after the initial questionnaire and seven days after the first reminder was sent, a second and a final round of reminder dispatched to the non-respondents.

4.7.4 Main Study Response rate analysis

At the end of 28 days from the first wave of emails sent, the online questionnaire was removed. Following two email reminders and 28 days later, a total of 227 responses were received. Response rate is briefly defined as "the percentage of the total attempted interviews that are completed" (Malhotra, 1999, p. 192). Nonetheless, there is a lack of agreement on the interpretation of this definition. To overcome this complication, the definition by the Council of American Survey Research Organisations (CASRO) was used as a standard definition. They define response rate as:

$$\frac{Number\ of\ completed\ interviews\ with\ reporting\ units}{Number\ of\ eligible\ reporting\ units\ in\ sample}$$

With this definition, the key requirement is to measure the amount of information supplied that forms a completed interview, to calculate the response rate. For this research completed questionnaires were defined as, the ones in which 80% or more of the questions were answered. Out of the 227 responses received 49 responses did not qualify as completed questionnaires as these had less than 80% of the questions answered. In the end, a total of 178 responses were eligible to be defined as completed questionnaires. The next step to calculate response rate is to properly handle eligible respondents (Churchill 1999). For this research eligible respondents were defined as those capable of completing the questionnaire. By this definition, the sample frame dropped and Table 4.12 provides analysis of the response pattern of the sample frame that was finally used for this study.

The effective response rate calculated using the above definition by CASRO was:

$$\frac{178}{1285} \times 100 \ = 13.85$$

Thus, the 13.9 percentage response rate achieved for this study was satisfactory. Ibeh, Brock, and Zhou (2004) argue that generally UK managers have an adverse attitude towards mail surveys. This probably explains the high number of unusable surveys and also why some companies have a policy not to participate in surveys.

Table 4.12 Response Pattern Analysis

Sampling Issues	**Subtotal**	**Total**
Initial sample frame		1513
Undeliverable		196
Total responses		227
Non-useable responses		49
Final Sample Frame		1285
First wave	105	
First reminder	50	
Second reminder	23	
Total useable responses	178	

4.7.5 Non-response bias assessment

In academic research, especially research conducted in social sciences there is a chief concern of generalizability and the quality of results is affected by non-response (Yu and Cooper, 1983). Non-response bias is defined as the potential difference between the answers provided by the respondents to the possible answers of those who did not participate in the research. The impact of non-response on the results of a study is basically two fold. First, "the non-respondents may be significantly different from the ones included for the study" (Parasuraman 1982, p.267) and two, response from the non-respondents would have affected the conclusion of the various variables in the study (Yu and Cooper, 1983). Therefore, it is crucial to eliminate non-response bias and if there is a bias it is necessary to test for the non-response bias.

Non-response bias can be reduced by, either sampling the non-respondents, or estimating if there is any non-response bias in the results or by minimising non-response in the beginning of the study by carefully designing the study. Given the response rate of this study it was imperative to check for the non-response bias. The first step in testing for non-response bias it is important to locate the early and late respondents. As the main survey was an online survey all the emails were sent using various tools such as Microsoft word and Microsoft outlook. Hence all the questionnaires were delivered uniformly and the only way to locate the early and late respondents is by dividing the responses provided after the first emails compared to responses received after the first reminder and second reminder. This means that early responses (105 responses) were compared with responses received after the first reminder (50 responses) and second reminder (23 responses).

Early versus late responses were compared using the test specified by Armstrong and Overton, 1977. T-tests were performed for three groups on the key variables used for this study. The presumption is that “firms that respond less readily are more like non-respondents” (Armstrong and Overton 1977, p. 397). The results as shown in Table 4.14 indicate that the differences between the three groups of responses were not significant at five per cent significant level.

In addition, to testing for non-response bias using subjective data, objective measures were used. In line with Morgan, Vorhies and Mason (2009); Morgan and Vorhies (2001); and Morgan, Slotegraaf and Vorhies (2009), the t-test was conducted on firm/business unit annual turnover and firm age for the year the survey was conducted. The secondary was collected using FAME database. The objective measures were then divided into scales as show in Table 4.13. After analysing the mean score differences using paired t-tests, the results indicate that there is no difference at five per cent significance level, indicating that non-response bias is highly unlikely to be present in the dataset.

Table 4.13 Secondary data

Annual Turnover (Secondary data)	Label	Firm Age (Secondary data)	Label
0 – 10 Million Pounds	1	2000 – 2009	1
11 – 20 Million Pounds	2	1990 – 1999	2
21 – 50 Million Pounds	3	1980 – 1989	3
51 – 75 Million Pounds	4	1970 – 1979	4
76 – 125 Million Pounds	5	1960 – 1969	5
126 – 250 Million Pounds	6	1950 – 1959	6
251 – 500 Million Pounds	7	1940 – 1949	7
501 – 1000 Million Pounds	8	1930 – 1939	8
>1000 Million Pounds	9	Before 1929	9

Table 4.14 Non-response bias assessment

Response Bias Assessment			
Variables	First Wave Mean (105)	Second Wave Mean (73)	Sig. of t-values
Exploitative Market Learning	5.04	4.94	p = 0.64
Exploratory Market Learning	4.02	4.05	p = 0.76
Customer Discontinuity	3.64	3.52	p = 0.57
Technological Discontinuity	4.57	4.62	p = 0.24
Marketing Discontinuity	4.55	4.52	p = 0.87
Product Meaningfulness	5.46	5.59	p = 0.73
Product Superiority	5.52	5.76	p = 0.25
Annual Turnover (Secondary data)	4.42	4.36	p = 0.45
Firm Age (Secondary data)	3.46	3.58	p = 0.22

Another way to test non-response bias is by finding the reasons for not completing the questionnaire. In the end, a total of 227 responses were received out of which 49 were not useable as shown in Table 4.12. After four weeks of sending the first email, an email was sent to the non-respondents and the respondents who started the questionnaire but did not complete it. In total 1090 emails were sent and the reasons for non-response are presented in Table 4.15.

Table 4.15 Reasons for non-response

Reason	**Number of respondents**
No time to fill	18
It's company policy to not fill in questionnaires	32
Not interested	8
They do not trust the online survey software (Qualtrics) ethical policy	6

Thus, these tests suggest that there were no significant difference between the responding and non-responding participants in this study. Therefore, it is considered that non-response bias did not create any considerable impact on the variables used in this study.

4.8 Chapter Summary

The five objectives that guided this chapter were: discuss the research design used for this study; justify the methodology that suited best for the research questions answered in this study; discuss the survey administration process; discuss the steps taken in conducting a pre-test study and how the results from pre-test helped design a superior main survey; and explanation of the issues and challenges faced during the main survey.

In short, it was argued how cross-sectional research design suited well for this study and how it was the foremost design to answer the research questions. Rather than conducting mail survey or face-to-face interviews, this study chose an email/online survey administration process as it ensured faster response. In total, 1513 high-tech business units were contacted for this study and a total of 178 useable responses were received providing roughly a 14 per cent response rate. Marketing and non-marketing managers of 1513 highly innovative SBUs operating in high-tech industries, including computers (hardware and software), electrical and electronics, medical devices, aerospace, automobile and biotechnology, were identified. Finally, efforts were made to reduce non-response bias and comparison of early versus late respondents showed no concern for any effect of non-response bias on the results. In the next chapter, descriptive profile of the business unit that participated is provided and the measurement development strategy is outlined.

Chapter Five: Data Preparation and Descriptive Analysis

5.1 Introduction

This chapter is divided into two parts: the first part of the chapter presents the results of the preliminary analysis conducted (that is the descriptive analysis of the sample, initial data cleaning and preparation of the data) and in the second part of this chapter the results of the exploratory factor analysis is presented. Finally, a summary is provided to conclude the chapter.

5.2 Preliminary Analysis

The initial analysis of the data collected is to provide general characteristics of the firms that provided information for this study. The data was collected using Qualtrics, an online survey tool, which provides the raw data in excel, or CSV format (Comma Separated Values). CSV format is used in SPSS and AMOS. Hence, there are no human coding errors, that is, the error incurred if the variables have not been recoded properly. The purpose of conducting a preliminary analysis is to develop a fundamental understanding of the respondents and business unit that are studied. This is because the business units under observation are of different sizes, business experience and in different industries. The other purpose for conducting an initial analysis is to ensure that the data collected is of sufficient quality to produce reliable and valid results.

To achieve the above-mentioned goals, the preliminary analysis was divided into two sections. First, data editing was performed to ensure the accuracy of data. The various steps involved in this stage are explained in-detail in the next section. Second, a profile analysis of the sample was cultivated and later an analysis on the respondents was conducted to evaluate the characteristics of the key respondents.

5.2.1 Data Preparation and Screening

The objective of this section is to check and screen the data essentially to ensure that the raw data will provide valid and reliable results. To perform statistical analysis, structural equation modelling, there should be no missing values (Hair et al., 2006). The other requirement to conduct structural equation modelling, all variables are required to meet the assumptions of multivariate normality (Bentler and Chou, 1987). In this section, the results of preliminary examination of the data for missing values and assumptions of normality are presented, which enabled statistical analysis to be performed accurately.

5.2.1.1 Missing Values

The objective of this section is to provide the initial data editing performed to determine if the data is accurate, and to check that the data is not missing any values for statistical analysis. Missing values may occur due to omission of answers by the respondents or due to errors in data entry (Hair et al., 2006). As mentioned, the data was collected using Qualtrics, an online survey tool and therefore there was no manual data entry conducted. Hence, the primary reason for any missing data was due to omission of answers by the respondents. As mentioned in section 4.6.5, a number of respondents started completing the questionnaire and did not finish it. Since data was collected online it was easy to track the respondents who had given incomplete data. They were emailed again and asked to revisit their questionnaire. Yet there remained few incomplete questionnaires that remained to be dealt with.

The first step in handling missing values it is essential to check what per cent of the data is missing. Missing value analysis (MVA) is conducted in two steps. First, to determine the amount of missing data, it is important to check for the overall missing data, and second, to check the total missing data for each variable (Little, 1988; Little and Rubin, 1989). Results of MVA showed that the largest missing value was 2.1 per cent for annual turnover and 3.2 per cent for R&D expenditure over turnover per cent. Since the data was collected using an online questionnaire, the respondent could not answer the next question without answering the previous questions, the overall amount of missing data was less than 1 per cent. Hair et al., (2006) suggest that in a large dataset if the total missing data is less than 5 per cent than it poses no potential threat.

Replacing missing values was conducted in two stages. First, the data collected was divided into two sections, i.e., profile variables and key variables. In case of any missing profile variables, a secondary research (for example, internet research, firm websites, and annual report) was conducted to answers questions that are related to firm size, industry analysis, and respondent characteristics. In case of any missing key variables, statistical analysis package provides several method of dealing with missing values. Missing value analysis was undertaken using Expected – Maximization (EM) algorithm. Expected – Maximization (EM) technique was chosen over the other imputation techniques primarily because it introduces the least bias, is the best algorithm for missing values when the dataset is not too large, and this method is based on maximum likelihood, that implies minimum variance (Little and Rubin, 2002). In addition, EM method was chosen due to its availability in SPSS. Following imputation using EM, the dataset contained 178 complete sets.

5.2.1.2 Assumptions of Normality

In case of performing structural equation modelling, it is crucial that all variables meet the assumptions of normality (Bentler and Chou, 1987). Non-normality affects the power of statistical analysis and non-normality can be the underlying cause to distinguish between good and bad models. Non-normality can occur on two levels, univariate and multivariate. Normality can be assessed using graphical or statistical methods (Tabachnick and Fidell, 2007). Univariate normality is concerned with the distribution of each variable, and can be inspected from the skew and kurtosis values. The value of kurtosis is the measure of the "peakedness" of the probability distribution (i.e., it describes the shape of the curve and checks if the shape forms a normally distributed bell curve). On the other hand, the value of skew provides insight into the asymmetry of the curve.

In addition, Kolmogorov-Smirnoff (KS) test was conducted on each item in all the variables to test for normality. A non-significant KS result (i.e., the probability (p) were less than 0.001) would mean that the distribution approximated to normality (Hair et al., 2006). The results of the KS test and the skew and kurtosis values are presented in Table 5.1. The general rule of skewness and kurtosis value is, if the value is within +/- 1.0 (Hair et al., 2006) it shows that the data is normally distributed. However, it is suggested by Kline (1998a) that a skewness value greater than +/- 3 and the value of kurtosis greater than +/- 10 is problematic and this must be considered as non-normal distributed data. Therefore, to test the data for univariate normality, the data should meet the requirements of three conditions. The skewness values in Table 5.1 suggested that all the items are in the range of +/- 1.0, and the value of kurtosis suggested that most of the items are in the range of +/- 1.0 but as expected a few items are slightly non-normal distributed. The results of the KS test suggested that all items are distributed normally.

According to Kline (1998a, p.62), univariate normality is the first level of normality. To check for multivariate normality, the data should meet three conditions.

1. All univariate distributions are normal,
2. The joint distribution of any combination of the variables are normal, and
3. All bivariate scatterplots are linear and homoscedastic.

From the table below it is evident that the first of the three conditions are met.

5.2.2 Profile Analysis

The objective of this section is to provide general characteristics of the high-tech firms/business units that provided information for this study. Analysing the general characteristics of the firms helps in interpreting the results of the data analysis. This section also provides an opportunity to develop an initial impression of the source of information. In addition, this section shows the characteristics of the key informants that provided the information. This is to ensure that the information collected is of acceptable quality to provide valid and reliable results.

Table 5.1 Normality test result

Normality test results				
Variable	**Item Number**	**Skewness**	**Kurtosis**	**Kolmogorov-Smirnov Test**
Exploitative Market Learning	Q1	-0.598	1.044	<0.001
	Q2	-0.713	0.519	<0.001
	Q3	-0.794	0.77	<0.001
	Q4	-0.324	-0.709	<0.001
Exploratory Market Learning	Q1	0.076	-0.687	<0.001
	Q2	0.123	-0.685	<0.001
	Q3	-0.803	-0.374	<0.001
	Q4	0.058	-0.915	<0.001
Product Superiority	Q1	-0.74	0.593	<0.001
	Q2	-0.809	0.635	<0.001
	Q3	-0.826	0.913	<0.001
Product Meaningfulness	Q1	-0.529	0.446	<0.001
	Q2	-0.552	0.427	<0.001
	Q3	-0.543	0.469	<0.001
New Product Financial Performance	Q1	-0.194	-0.621	<0.001
	Q2	-0.008	0.063	<0.001
	Q3	-0.03	-0.326	<0.001
Technological Discontinuity	Q1	-0.441	0.239	<0.001
	Q2	-0.556	0.292	<0.001
	Q3	-0.362	-0.332	<0.001
Marketing Discontinuity	Q1	-0.238	-0.425	<0.001
	Q2	-0.208	-0.742	<0.001
	Q3	-0.684	0.324	<0.001
	Q4	-0.08	-0.743	<0.001
	Q5	-0.496	-0.374	<0.001
Customer Discontinuity	Q1	0.029	-1.082	<0.001
	Q2	0.074	-0.984	<0.001
	Q3	0.469	-0.472	<0.001
	Q4	0.161	-0.953	<0.001
	Q5	0.513	-0.653	<0.001
	Q6	0.198	-1.06	<0.001

5.2.2.1 Industry Profiling

The objective of conducting a preliminary analysis is to develop a fundamental understanding of the respondents and business unit that are studied. This is because the business units under observation are of different sizes, business experience and overall in different industries. Table 5.2 presents the distribution of firms/business unit in terms of the industries they operate in. From Table 5.2 it can be seen that almost 26 per cent of the respondents operate in the electrical and electronics industry and only 8 firms/business units out of 178 (adding up to 4.5 per cent) of the respondents fall under the chemicals industry. All the respondents operate in the high-tech industries and this ensures that the data collected is valid and reliable.

Table 5.2 Industry Profiling

Characteristics of the firm/business unit		
Industry Profiling		
Industry Name	**Frequency**	**Percentage**
Automobile	25	14.0
Information Technology	23	12.9
Chemicals	8	4.5
Computers (Hardware and Software)	32	18.0
Electrical and Electronics	46	25.8
Biotechnology	7	3.9
Pharmaceuticals	8	4.5
Mechanical	12	6.7
Others	17	9.6
Total	178	100

5.2.2.2 Firm Size

In the existing literature, firm size is examined by assessing two variables: number of full-time employees and total annual revenue (Cooper and Kleinschmidt, 1985). In line with the existing literature, this study assesses firm size on total revenue generated and number of full-time employees. In addition, drawing from the existing literature on new product development, this study also assessed the number of full-time employees in the new product development unit.

Table 5.3 presents the distribution of firm size in terms of full-time employees in the business unit/firm in the UK. This distribution was positively skewed and a mean of 101 – 250 full-time employees. From table 5.3 it can be seen that more than half of the respondents were medium and large firms. In the first quartile (i.e., 25 per cent) of the high-tech firms/business unit employed less than 100 employees, and 75 per cent employing fewer than 500 employees.

Table 5.3 Firm Size (Number of full-time employees)

Characteristics of the firm/business unit	
Full-time staff in the firm/business unit in United Kingdom	
Full-time staff	**Frequency (in %)**
1 to 25	5.61
26 to 50	6.74
51 to 100	16.85
101 to 250	30.89
251 to 500	20.22
501 to 1000	11.23
Greater than 1000	8.42
Total	100

The distribution of firm size in terms of total number of full-time employees or their equivalent working in the new product development department was positively skewed. The distribution covered a wide range from 10 to greater than 250 employees with a mean of 21 to 50 full-time employees. Table 5.4 provides detailed information on the firm's total number of full-time employees and their equivalent working in the new product development department. The first quartile of the high-tech firms/business units employed fewer than 10 full-time employees in the new product development department, and 75 per cent employed fewer than 50 employees in the new product development unit.

The other variable most commonly used to analyse the firm size in the existing literature is the annual turnover. The distribution of the firm size in terms of the annual turnover (in million £) is positively skewed. Table 5.5 provides detailed information on the firm's average annual turnover over the last three years. The distribution covered over a wide range from an annual turnover of less than 10 million pounds to greater than billion pounds turnover. From Table 5.5 it can be seen that the first quartile of high-tech firms had an average annual turnover of lesser than 20 million pounds, and 75 per cent had an average annual turnover of lesser than 250 million pounds. The definition of Small and Medium Enterprise (SME) by the Department of Trade & Industry (DTI) in terms of annual turnover is "a firm with a turnover not more than 11.2 million pounds" (DTI website). According to this definition, only the first 20 per cent of the respondents could be classed as SMEs. Therefore, in terms of turnover most of the firms in this study can be defined as large high-tech firms.

Table 5.4 Firm size (number of full-time employees in the new product development unit)

Characteristics of the firm/business unit		
Full-time staff in the new product development department		
Full-time staff	**Frequency**	**Frequency in (%)**
1 to 10	45	25.28
11 to 20	40	22.47
21 to 50	43	24.15
51 to 75	21	11.79
76 to 125	11	6.17
126 to 250	8	4.49
Greater than 250	10	5.61
Total	178	100

5.2.2.3 New product development performance

Easingwood (1986) argues that firm's scale of new product development activities could be examined by assessing the number of products/services introduced in the last three years and the average (R&D) expenditure over turnover percentage. In line with Easingwood's assessment, this study examines the new product development activities on the bases of number of products introduced by the firms in the last three years and the average R&D expenditure over turnover percentage.

Table 5.5 Firm size (Annual turnover)

Characteristics of the firm/business unit		
Annual Turnover for the business unit/firm in million £		
Million £	**Frequency**	**Frequency (in %)**
0 to 10	39	21.91
11 to 20	31	17.41
21 to 50	32	17.97
51 to 75	10	5.61
76 to 125	8	4.49
126 to 250	18	10.11
251 to 500	16	8.98
501 to 1000	15	8.42
Greater than 1000	9	5.05
Total	178	100

Table 5.6 presents the distribution of new product development activities in terms of number of new products/services introduced in the last 3 years in the United Kingdom. The distribution covered over a wide range from less than 5 products to greater than 30 new products/services introduced in the last three years. From Table 5.6 it can be seen that the first quartile of high-tech firms had fewer than 5 new products introduced in the last three years, and 75 per cent had fewer than 15 new products introduced in the last three years. According to the Department for Business Innovation & Skills, United Kingdom (DBIS), the number of new products and services introduced has declined significantly since 2010, roughly by four per cent. On average, across the various high-tech industries, only 43% (1018

firms out of a sample of 2367) of firms introduced new products or services in 2012 compared to a 47% (895 firms out of a sample of 1904). In line with the statistics provided by DBIS, it can be seen that the number of new products introduced by firms has reduced and the respondents are a perfect fit.

Table 5.6 New product development performances - I

Characteristics of the firm/business unit		
Number of new products/services introduced in last 3 years		
Number of products/services	**Frequency**	**Frequency in (%)**
1 to 5	68	38.20
6 to 10	39	21.91
11 to 15	22	12.35
16 to 20	10	5.61
21 to 25	13	7.30
26 to 30	5	2.80
Greater than 30	21	11.79
Total	178	100

In line with the existing literature, the other way to measure the new product development activities is by measuring and analysing the average per cent of R&D expenditure over turnover. Table 5.7 provides detailed information on the firm's average R&D expenditure over annual turnover over the last three years. The distribution covered over a wide range from less than 2% to greater than 20%, and is positively skewed. From Table 5.7 it can be seen that the first quartile of high-tech firms had an average R&D expenditure over annual turnover of lesser than 8%, and 75 per cent had an average annual turnover of less than 16%. According to the Department for Business Innovation & Skills (BIS), in 2010 the average per cent of R&D expenditure over sales in high-tech firms in the United Kingdom was around 7%. Therefore, the average per cent of R&D expenditure over turnover of the respondents was in line with the statistics provided by BIS.

Table 5.7 New product development performances - II

Characteristics of the firm/business unit		
Average percentage of the turnover invested in R&D in last 3 years		
Percentage	**Frequency**	**Frequency in (%)**
0 to less than 2%	4	2.24
2 to less than 4%	18	10.11
4 to less than 6%	15	8.42
6 to less than 8%	27	15.16
8 to less than 10%	28	15.73
10 to less than 12%	32	17.97
12 to less than 16%	18	10.11
16 to less than 20%	17	9.55
Greater than 20%	19	10.67
Total	178	100

This study also measured the number of products or services introduced in the last three years that were patented. In addition to the number of new products/services introduced and the average R&D expenditure over turnover per cent, this measure provides an exhaustive understanding of the new product development activities of the firms/business units.

Table 5.8 New product development performances - III

Characteristics of the firm/business unit		
Number of products introduced in the last 3 years that are patented		
Number of patents	**Frequency**	**Frequency in (%)**
0	43	24.15
1 to 3	70	39.32
4 to 7	35	19.66
8 to 10	11	6.17
11 to 14	5	2.80
Greater than 15	14	7.86
Total	178	100

Table 5.8 presents the distribution of new product development activities in terms of number of new products/services introduced in the last 3 years that were patented in the United Kingdom. The distribution covered over a wide range from nil to greater than 15 patents in the last three years. From Table 5.8 it can be seen that the first quartile of high-tech firms had zero new products introduced in the last three years that were patented, and 75 per cent had fewer than 7 patents for the new products introduced in the last three years.

5.2.2.4 Respondent Profiling

The second objective of conducting a preliminary analysis is to check how reliable the data is and if the information provided is acceptable. To achieve this goal, a respondent profiling was conducted to analyse if the respondents' had sufficient experience and are suited to completing the questionnaire. This section accounts for the characteristics of the respondents that represented the firm/business unit in this sample.

To achieve this objective, this study measured the number of years of experience that the respondents had and the number of new product/service development projects that they have worked on so far. In addition, the key respondents were asked to state their current job title which provided a sense of reliability. This analysis provides a distribution of the respondents' work experience and measure of whether they had sufficient experience. Table 5.9 presents the characteristics of the respondent in terms of number of new products/services development projects they have worked on. The distribution covered over a wide range from one to greater than 30. From Table 5.9 it can be seen that the highest proportion of the informants had experience of working on greater than 30 new product development projects.

Table 5.9 Respondent Profiling (Number of NPD projects)

Characteristics of the Respondents		
Number of new product development projects worked		
Number of products/services	**Frequency**	**Frequency (in %)**
1 to 5	29	16.29
6 to 10	30	16.85
11 to 15	23	12.92
16 to 20	27	15.16
21 to 25	12	6.74
26 to 30	12	6.74
Greater than 30	45	25.28
Total	178	100

Table 5.10 presents the characteristics of the respondents in terms of the number of years of experience in new product development. The distribution covered a wide range from less than two years to greater than 10 years. From Table 5.10 it can be seen that the highest proportion (roughly 60 per cent) of the informants had greater than 10 years of experience in new product development.

Table 5.10 Respondent Profiling (Number of years in NPD)

Characteristics of the Respondents		
Number of years of experience in New Product Development		
Number of years	**Frequency**	**Frequency in (%)**
Less than 2 years	11	6.17
2 to <4 years	9	5.05
4 to <6 years	15	8.42
6 to <8 years	8	4.49
8 to <10 years	23	12.92
Greater than 10 years	112	62.92
Total	178	100

Table 5.11 presents the function/department in which the key respondents work. The responses came from respondents working in the marketing department, strategy, technical, New Product Development (NPD) department. As indicated in the previous chapter (see Chapter 4.5), that various online resources were used (such as the company website, LinkedIn, Google, conference guests list and FAME database) to appropriately match the job responsibility with the current study. As seen from the table below, the most number of respondents are from the NPD department, functions such as, product portfolio director, product/process technology manager, New Product Innovation leader, and Senior Scientist.

Table 5.11 Respondent Profiling (Function/Department)

Characteristics of the Respondents		
Function/Department		
	Frequency	**Frequency in (%)**
CEO/Board Member	32	17.97
Marketing	37	20.78
R&D	34	19.06
Technical/Engineering	8	4.49
Strategy	23	12.92
New Product Development (NPD)	38	21.23
Other	6	3.37
Total	178	100

Table 5.12 below presents the level of seniority of the respondents. As it can be seen that, more than half of the responses came from managers at a very senior level, for example, CEOs/Owners, marketing directors, lead scientist, Senior Product Development Engineers, Senior game designers, marketing and R&D directors. The lowest portion of the responses came from junior managers (only 2.24 per cent of the total respondents).

Table 5.12 Respondent Profiling (Hierarchical Level)

Characteristics of the Respondents		
Hierarchical Level		
	Frequency	**Frequency in (%)**
CEO/Board Member/Owner/Director	65	36.5
Senior Manager	68	38.20
Middle Manager	34	19.10
Junior Manager	7	3.93
Other	4	2.24
Total	178	100

This section of the chapter has provided information on how missing values were handled and the data was checked for its accuracy. In addition, this section provides evidence that the respondents' are more than qualified to complete the questionnaire and providing valid answers. The preliminary analysis revealed that most firms are medium to large firms. They are classified as high-tech firms and are highly involved in new product development. These firms are highly invested in R&D and a good sample of firms/business unit has patented products/services as well. In the next section, the results of the exploratory factor analysis will be presented.

5.3 Exploratory Factor Analysis

The primary reason for analysing the data using Exploratory Factor Analysis (EFA); is to measure the reliability, dimensionality and validity of the higher-order constructs used in this study. In addition, the preliminary validation of the items and their loading onto factors was conducted using EFA in SPSS v.22. The exploratory analysis of the variables also supplements the need to meet the minimum sample size to variable/parameter ratio (Hair et al., 2006). That is, the recommended sample size to conduct a single CFA is of at least five-to-one sample size to parameter ratio (Hair et al., 2006). In this study there are 8 first-order variables and two second-order variables that have 35 indicators, which would mean a large set of parameters would be estimated. Bearden, Sharma, and Teel (1982) found that the two things that can affect the model fit are model complexity and sample size. Therefore to carry out the aforementioned aims of conducting EFA, the constructs were divided into two subsets. The primary reason for dividing the constructs into two subsets is to meet the minimum requirement of ten cases per item for conducting a good quality exploratory factor analysis (Hair et al., 2006). First, a factor analysis was conducted on the four constructs (that is, exploratory market learning, exploitative market learning, product meaningfulness and product superiority) measuring the two higher-order constructs, and then a factor analysis was conducted on the remaining four constructs (that is, customer discontinuity, market discontinuity, technological discontinuity, and product performance). Factor analysis on the first and second subset was conducted as a data reduction technique. In addition, to measure the robustness of the complete model, a full measurement model is also analysed. Finally, in addition, to analysing the reliability, validity and dimensionality of the single-order constructs; a second-order exploratory factor analysis was conducted to analyse the reliability, validity and dimensionality of the higher-order constructs.

5.4 Data Reduction Technique using EFA

EFA is the most adapted statistical technique used for initial data reduction (Clark and Watson, 1995). In addition, exploratory factor analysis makes it possible to identify the relationships between the various variables to define a factor (Hair et al., 2006). In other words, factor analysis provides an insight into how various items load on the related factor by maximising the variance and hence serves as a data reduction technique. In addition, factor analysis underlines patterns and relationships between various items and factors (DeVellis, 2003).

Browne (2001) noted that many studies directly use the Modification Indices (MI) criteria in Confirmatory Factor Analysis (CFA) in an exploratory fashion in an attempt to improve the model fit. This procedure has been criticised, for example, Thompson (1997) argues that this procedure may neglect to analyse the patterns and structure that could lead to the omission of important information relevant to the item analysis. Over the years, there are two key sequences used by various researchers in selecting the items. The first procedure/sequence suggested by Anderson and Gerbing (1988), has three key steps starting with defining the preliminary scales through EFA; then, examining the dimensionality of these scales through CFA; and finally, using the internal-consistency techniques to assess the reliability measures of the scale and the overall model. The second procedure/sequence suggested by Willie (1997), has two key steps starting with internal-consistency analyses, and then analysing the data for the convergent and discriminant validity measures. This procedure may be more applicable when the scales have been formed through some method of scale development. In other words, this procedure may be more suitable in a study, which uses scales taken from previous studies. In this study, Willie's (1997) procedure will be incorporated. To begin with, internal-consistency will be examined using EFA and then the validity measures will be tested using EFA and CFA.

5.4.1 Item Analysis

Item analysis techniques produce an experimental analysis of the scale for a later assessment (DeVellis, 2003). In other words, item analysis provides information on the internal consistency and reliability measures of the scales, which in turn provides a better understanding of the items that contribute poorly to the reliability of the construct. Subsequently, items measuring the same construct should determine high-level of item-scale correlation, inter-item correlations, and reliability. In this study, reliability is measured using the Cronbach's alpha technique. At this stage, to eliminate the items that contributes poorly to the reliability of the scales, three measures were considered simultaneously, one, inter-item correlation, two, inter-scale correlation, and three, coefficient alpha values for each scale.

5.4.1.1 Inter-Item Correlation

A correlation matrix of all items is examined to establish the initial validity of the scales (DeVellis, 2003). Clark and Watson (1995) argue that a strong inter-item correlation reflects that the items share a common cause, and therefore are measuring the same construct. Items with low correlations may suggest that these items do not measure the construct and in essence can be considered for deletion. There is a general agreement in the literature that inter-item correlations in a range of 0.4 to 0.5 can be considered as valid measures of a construct (for example, Clark and Watson, 1995; DeVellis, 2003). On other hand, a small correlation value, that is, less than 0.2 or 0.3 indicates that the item is not a good measure of the construct and can be considered for elimination (Churchill, 1979).

5.4.1.2 Inter-Scale Correlation

A correlation matrix of all item-scale correlation can be considered as a measure to establish the unidimensionality of the scale. DeVills (1993) proposes two types of inter-scale correlation, that is, the corrected and the uncorrected item-scale correlation. The difference between the types of inter-scale correlation boils down to the argument whether or not to include the item in question with all the other items in the scale. The corrected item-scale correlation is one in which the item in question is included with all the other items in the scale. A high correlation value is more desirable and items with low inter-correlations can be considered for deletion (DeVellis, 2003). A minimum of 0.5 is considered as a strong recommendation for a threshold value (DeVellis, 2003). After establishing the items that may lead to elimination, the reliability of the scales is examined.

5.4.1.3 Reliability Assessment

Reliability assessment deals with the consistency of the repeated measures over time (Bagozzi and Foxall, 1996). Cronbach's alpha calculates the "ratio of the variance of the true score to the variance of the observed score" (Nunnally, 1978). The value of cronbach's alpha can be used to analyse the internal-consistency (Schmitt, 1996). Reliability values generally predict the dependability and stability of the scale used. The value of cronbach's alpha is measured on a scale of 0 to 1. The greater the coefficient alpha value provides evidence of a good reliable scale. The coefficient value increases as the inter-correlations between the items increases. In the literature, it is widely believed that cronbach's alpha indirectly provides evidence of uni-dimensionality (Nunnally, 1978). A general agreement in the literature (for example, Kline, 2000) suggests that scales with a coefficient alpha of greater than 0.9 reflects excellent internal-consistency. Values between 0.7 and 0.9 provide evidence of a good internal-consistency scale. Coefficient values between 0.6 and 0.7 are acceptable but may cause concerns but scales with coefficient values below 0.5 should be avoided. Nunnally and Bernstein (1994) argue that 0.7 should be set as a threshold criterion. However, Cortina (1993) argues that a scale with large number of items can artificially exaggerate the value of alpha. The general agreement is that a scale with a larger number of items provides a more dependable and accurate results. Therefore, in this study, a minimum of three items per scale was considered as a threshold. Constructs with two items tend to have a small coefficient alpha value (Cortina, 1993). Further reliability assessment is conducted using CFA (see section 6.2).

5.4.2 Scale Purification and Item Selection

As stated in the previous section, due to the sample size restriction, exploratory factor analysis was divided into two subsets. The first subset includes all items measuring the higher-order constructs, that is, exploratory market learning, exploitative market learning, product meaningfulness and product superiority. The primary reason for including these items in the first subset was to conduct a second-order factor analysis on these items. In addition, it was justifiable to analyse these items together as they are conceptually similar (Kim and Atuahene-Gima, 2010). The second subset includes all items measuring product innovativeness (from the customer's and firm's perspective) and product performance. Again, it was justifiable to analyse these items together as they are conceptually similar (Dannels and Kleinschmidt, 2001). Finally, for the completeness and robustness all items (involving good items) involved in this study analysed as one measurement model was also planned. Table 5.13 and 5.14 provides a list of items entered in SPSS as subset1 and subset 2 respectively.

Table 5.13 Items entered into Subset 1

Construct	Item Label	Item Wording
Exploitative Market Learning 1 = Not at all 7 = To a very great extent	exi1	Use new ideas that are consistent with our current product-market experiences by analysing current customer's needs and competitor products.
	exi2	Undertake activities that help to utilise or integrate the firm's current market experience.
	exi3	Use market information and ideas that may contribute to the firm's existing product market (for example, through analysis of experience with prior projects, current competitors and technologies).
	exi4	Emphasis on using proven ideas for solutions to marketing problems by surveying current customers.
Exploratory Market Learning 1 = Strongly Disagree 7 = Strongly Agree	exr1	Use market information that takes the firm/business unit beyond its current product market experience through market experiments
	exr2	Use novel products or services that may not necessarily be successful in the current market through contact with non-customers, studying of emerging competitors and technologies
	exr3	Aim to collect new information that enables us to learn new things in our market
	exr4	Use market information and generate new ideas involving experimentation and high risk.
Product Meaningfulness 1 = Much less than our key competitors 7 = Much more than our key competitors	npa1	New products or services that provide many benefits to the customer
	npa2	New products or services that offer much value to the customer.
	npa3	New products or services that offer many advantages.
Product Superiority 1 = Much less than our key competitor 7 = Much more than our key competitors	npa4	New products or services that is superior to the competing products.
	npa5	New products or services that are the best of its kind in the market.
	npa6	New products or services that is superior in its category.

Table 5.14 Items entered into Subset 2

Construct	**Item Label**	**Item Wording**
Customer Discontinuity 1 = Strongly Disagree 7 = Strongly Agree	cf1	Our products or services required a major learning effort by the customer.
	cf2	It took a long time before customers could understand the products' or services' full advantage.
	cf3	Product or service concept was difficult for customers to evaluate or understand.
	cf4	Products or services were more complex than what we have introduced before in the same market.
	cf5	Our products or services involved high changeover costs for the customers.
	cf6	Our products or services required considerable advance planning by the customer before use.
Marketing Discontinuity 1 = Never 7 = All the time	md1	To what extent were the products or services aimed to new customers to your firm/business unit?
	md2	To what extent did these products or services take you up against new competitors?
	md3	To what extent did these products or services cater to new customer needs?
	md4	To what extent was the market for these products or services new or different for your firm/business unit?
	md5	To what extent did these products or services represent a new product or service category?
Technological Discontinuity 1 = Never 7 = All the time	td1	To what extent did the technology involved in the development of these products or services represent new or different technology for your firm/business unit?
	td2	To what extent did the engineering and design work involved in these products or services project represent new or different work for your firm/business unit?
	td3	To what extent did the production technology and production process represent a new and different one for your firm/business unit?
New Product Financial Performance 1 = Very Dissatisfied 7 = Very Satisfied	npp3	The revenue goals
	npp4	The profitability goals
	npp5	The return on investment goals

The inter-item correlations were first analysed to test the internal consistency of all scales. As stated in the previous section, a threshold of 0.4 was considered as a good measure of an item. Items measuring product meaningfulness (ranging between 0.630 and 0.773), product superiority (ranging between 0.803 and 0.840), product performance (ranging between 0.600 and 0.874) and technological discontinuity (ranging between 0.545 and 0.751) showed strong and positive inter-item correlations with other items. Some of the items measuring other constructs were a source of concern. Items measuring exploitative market learning showed positive and strong inter-item correlations with all other items, except for item 'exi3'. This item had a weak correlation with exi1 (0.304) and correlation with other items was stronger than but not as strong as the correlation values between the other items. The reason behind this finding is unclear; although one explanation could be that the other items were more related to measuring the product-market factors and not just market factors. This could be a source of concern and the results of reliability assessment and factor analysis would provide more evidence into whether or not this item needs to be included. The reliability assessment of exploitative market learning did not provide any evidence of 'exi3' of being a poor measure. The reliability (Cronbach's coefficient value) assessment results for all scales are provided in Appendix 5A. The coefficient values of all constructs (ranging between 0.780 and 0.951) provided enough evidence for a good internal-consistency scale.

Items measuring the exploratory market-learning construct had similar concerns. Most items had a strong and positive correlation (ranging between 0.437 and 0.559) except for item 'exr3'. The correlation between 'exr3' and its counterpart was lower than the average (ranging between 0.310 and 0.439). A similar explanation may justify the reason behind this result. The remaining items were more related to measuring the product-market factors and not just market factors.

For the marketing discontinuity construct, most items were strongly correlated (ranging between 0.48 and 0.620), except for items 'md2' and 'md3'. The correlation between the two items and its remaining items was lower than the average and below the threshold value of 0.4 (ranging between 0.336 and 0.486). These items measured the possibility of facing new competition when a new product is developed. This may suggest that firms in the same industry tend to face each other even if the product is made for a new market.

The customer discontinuity construct items showed good and positive correlation (ranging between 0.41 and 0.831). However, the first three items 'cf1', 'cf2', 'cf3' were highly correlated with each other (ranging between 0.728 and 0.831), while the other three items 'cf4', 'cf5', 'cf6' were lower than the average (ranging between 0.41 and 0.563). This result indicated that these three items might not be closely tied with the other three items. A plausible explanation could be that the first three items measure the learning cost paid by the customer when they use the new product and the last three items measure the behavioural change incurred by the customer when they use the new product. This result may indicate that these items result in two factors. This could be a source of concern and the results of the factor analysis would provide more evidence into whether or not these items can be included.

The first subset that includes 14 items was entered into SPSS and by using principal component analysis and direct oblimin rotation; a solution of four factors was obtained. The cumulative variance extracted was 71.92% (See Appendix 5B). As stated in the previous section, factor loadings of above 0.5 were reported as a minimum requirement for a well-defined factor structure. One item from exploitative market learning (exi3) and exploratory market learning (exr3) loaded poorly (less than 0.4) on their respective factors. Moreover, these two items had a huge (greater than 0.4) loading on other factors. Taking the inter-item correlation results into consideration, these two items can be removed and not added to the subsequent measurement models.

The second subset that includes 20 items was analysed and a solution of four factors was obtained. A total of 68.251% cumulative extracted variance was obtained. All items loaded well (greater than 0.5) on to their respective constructs, as expected. But few of the items measuring the customer discontinuity construct, that is, ‘cf5’ and ‘cf6’ had huge cross-loadings (greater than 0.3) onto other factors. Taking into consideration, the inter-item correlation results and the factor analysis results, there is enough evidence to show that items ‘cf5’, and ‘cf6’ can be considered as poorly performing measures of customer discontinuity construct.

Having selected the good items for all the scales by assessing these scales individually and in subsets, it is now time to analyse all constructs in one measurement model. In total, 24 items measuring eight constructs were analysed simultaneously in EFA. Using principal component analysis and direct oblimin rotation, a solution of eight factors was obtained with a total of 79.464% cumulative extracted variance. All items loaded well (greater than 0.5) on to their respective factors (see Appendix 5C). Overall, result of the measurement model was a decent fit, with KMO measure of 0.829 and strong alpha coefficient value further demonstrating a good reliability of all the scales. Before, entering this measurement model into CFA for further examination, it is important to test the higher-order constructs and check for the validity and reliability of these constructs.

5.5 Higher-order Exploratory Factor Analysis

The use of higher-order multidimensional constructs in the management theory has grown in the recent years but this requires further analysis of these constructs to justify the use of these constructs in a study (Johnson, Rosen, and Chang, 2011). Analysing constructs that have a high correlation may reveal some evidence of a common factor running through the items or it may also lead to concerns with dimensionality assessment (Gall, Borg, and Gall, 1996). In this study, unidimensionality measures were indirectly analysed using the Cronbach's alpha. The other explanation is to check for enough evidence of these constructs having a common factor. It is essential to conduct a higher-order exploratory factor analysis to test the reliability, validity and dimensionality of the higher-order constructs. Therefore, in this study, the dimensionality of the higher-order constructs is measured using both EFA and CFA analytic techniques.

The high correlation between the constructs (between exploratory market learning and exploitative market learning; and product meaningfulness and product superiority) in subset1 does not provide enough evidence that these constructs may lead to higher common factors. A higher-order exploratory factor analysis was conducted. The regression factor scores for all the constructs were saved while conducting the single-order full measurement model factor analysis. The four constructs (exploratory market learning, exploitative market learning, product meaningfulness, and product superiority) were further analysed. Using principal component factor analysis and direct oblimin rotation, a solution of two factors was obtained, with a 69.404% cumulative variance extracted (see Appendix 5C). All items loaded well (greater than 0.5) on to their respective constructs, as expected (see Table 5.15). In Table 5.15, Item1 is the regression factor score for exploitative market learning, Item2 for exploratory market learning, Item3 for product meaningfulness and Item4 for product superiority. This provides enough evidence that these single-order factors lead to higher-order common factors.

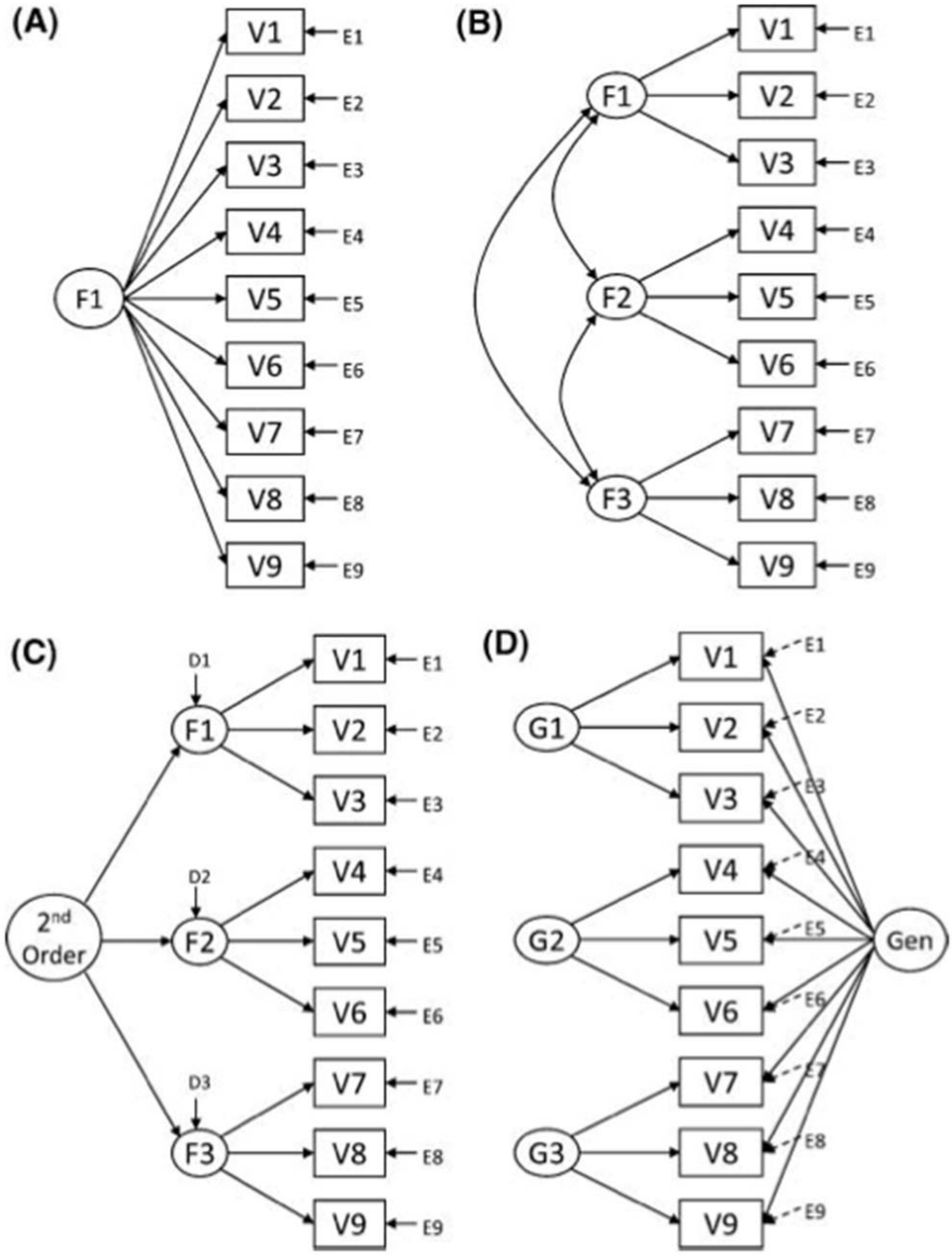
Table 5.15 Pattern Matrix for the higher-order constructs

Factor Loading		
Items	**Ambidextrous Market Learning**	**Product Advantage**
Item1 (ExiML)	0.524	
Item2 (ExrML)	0.546	
Item3 (PM)		0.510
Item4 (PS)		0.535

In addition, there is enough evidence from the existing literature that ambidextrous market learning and product advantage are higher-order constructs and the higher-order exploratory factor analysis conducted on the data supports this. There are four ways to model a structural model (see Figure 5.3). The most basic way to model a structural model is represented as Model A in this figure. This represents a unidimensional model, which has all the items measuring a single construct. Model B in this figure represents single-order factor or also known as "correlated traits" model. Model B is not a higher-order model per se. This model represents single-order constructs that have a high correlation between these factors and there is no common factor or common variance explained. The third way to model a structural model as represented by Model C in the figure is a higher-order construct with three single-order factors contributing to a common variance. The final way to model a measurement model with higher-order constructs is represented as Model D. This model is also known as a "bi-factor" model. As it can be noted that the difference between the Model

C and Model D is, in Model D there is a direct relationship between the item and higher-order construct.

Figure 5.3 Examples of four alternative structural models



(Adapted from Reise, Moore, and Haviland, 2010, p.546)

It is important to check if the items directly load well (as mentioned in the previous section, a minimum of 0.5 is set as a threshold for this study) on a single common factor and also loads on the single-order factor that leads to higher-order constructs. If this turns to be the case, then this result may provide evidence of multi-dimensionality and these factors can be discarded as poor measures.

It is not straightforward to analyse a bi-factor model, as most of the software available today do not provide packages to test a bi-factor model. The best way to analyse a bi-factor model is by using Schmid-Leiman Solution (SLS) for a “restricted bi-factor” analysis. A restricted bi-factor model in which, each item in the model is restricted to load on one single common factor and at most, one additional orthogonal group factor (Gibbons and Hedeker, 1992). The basic explanation of calculating the SLS model is to simultaneously load the items on the single-order factor and the higher-order factor. The result of this test provides information on whether the items have a larger factor loading on the higher-order construct directly or on its orthogonal group factor. The results of this test also checks for the variance extracted for the higher-order construct when the variance is extracted from the items directly or via the single-order factors. The syntax used in SPSS v.22 was adapted from Wolff and Preising (2005) is provided in Appendix 5D.

The result of the higher-order SLS model for ambidextrous market learning is provided in Table 5.16. The two first-order factors (that is, exploitative market learning and exploratory market learning) are labelled as ‘ExiML’ and ‘ExrML’ in the table below. The higher-order factor (Ambidextrous Market Learning) is labelled as ‘AML’; the items measuring ‘ExiML’ are ‘exi1’, ‘exi2’, and ‘exi4’; and the items measuring ‘ExrML’ are ‘exr1’, ‘exr2’, and ‘exr4’. As it can be seen from the results (Table 5.14), all the items are simultaneously loading on their respective single-factor (that is, ExiML and ExrML) and the higher-order factor (‘AML’). The factor loadings of all the items are stronger on their respective factor in comparison to the higher-order factors. In addition, except the factor loading of item ‘exr4’ on ‘ExrML’ all other item loading is above 0.5. This results show that all item in this list are a better measure of their first-order factor than of AML. In addition, the variance extracted for AML is higher (70.6%) when the variance extracted is explained by the first-order factors in comparison to 29.4% extracted variance explained by all the items. In addition, the item loadings (ranging between 0.026 and 0.123) on additional factors are mostly small, which provides enough evidence to support that ambidextrous market learning (AML) in this study can be measured as a higher-order construct.

Table 5.16 Factor Loading of Schmid-Leiman Solution for Ambidextrous Market Learning

```
       ExiML ExrML
exi1   .680   .031
exi2   .835 -.078
exi4   .737   .121
exr1   .069   .766
exr2 -.093   .743
exr4   .145   .575

F2
        AML
ExiML  .524
ExrML  .536

factor loadings of Schmid-Leiman Solution and h²
         AML     ExiML     ExrML H² tota     H² G  H² 1st
exi1     .373     .579      .026     .475     .139     .336
exi2     .396     .711    -.066     .667     .157     .510
exi4     .451     .628      .102     .608     .203     .404
exr1     .447     .059      .647     .621     .200     .422
exr2     .350    -.079      .627     .522     .122     .400
exr4     .384     .123      .485     .398     .148     .251

sum of squared loadings
      AML ExiML ExrML total
H²   .968 1.260 1.063 3.291
%     .294  .383  .323 1.000

percentage of exracted variance explained by general factors (%)
  .294

percentage of extracted variance explained by first order factors (%)
  .706

------ END MATRIX -----
```

The result of the higher-order SLS model for product advantage is provided in Table 5.17. The two first-order factors (that is, product meaningfulness and product superiority) are labelled as ‘ProdMean’ and ‘ProdSup’ in the table below. The higher-order factor (Product Advantage) is labelled as ‘ProdAdv’; the items measuring ‘ProdMean’ are ‘npa1’, ‘npa2’, and ‘npa3’; and the items measuring ‘ProdSup’ are ‘npa4’, ‘npa5’, and ‘npa6’. As it can be seen from the results, all the items are simultaneously loading on their respective single-factor (that is, Product Meaningfulness and Product Superiority) and the higher-order factor (Product Advantage). The factor loadings of all the items are stronger on their respective factor in comparison to the higher-order factors. In addition, each item loading on their respective first-order factor is above 0.5. This results show that all item in this list are a better measure of their first-order factor than of Product Advantage. In addition, the variance extracted for AML is higher (72.2%) when the variance extracted is explained by the first-order factors in comparison to 27.8% extracted variance explained by all the items. In addition, the item loadings (ranging between 0.009 and 0.249) on additional factors are mostly small, which provides enough evidence to support that product advantage construct in this study can be operationalised as a higher-order construct.

Table 5.15 Factor Loadings of Schmid-Leiman solution for Product Advantage

factor loadings of Schmid-Leiman Solution and h²

	ProdAdv	ProdSup	ProdMean	H² tota	H² G	H² 1st
npa1	.458	.043	.754	.780	.209	.571
npa2	-.462	-.061	-.743	.769	.213	.556
npa3	.437	.249	.513	.515	.191	.325
npa4	.459	.725	.079	.743	.211	.532
npa5	.446	.772	.009	.795	.199	.596
npa6	-.478	-.819	-.017	.899	.228	.671

sum of squared loadings

	ProdAdv	ProdSup	ProdMean	total
H²	1.251	1.860	1.391	4.502
%	.278	.413	.309	1.000

percentage of exracted variance explained by general factors (%)
.278

percentage of extracted variance explained by first order factors (%)
.722

Overall, the reliability, validity and dimensionality assessments of all the higher-order and single-order constructs are undertaken using EFA**.** Further assessment of these constructs and the measurement model is undertaken in Confirmatory Factor Analysis (CFA). In evaluating the measurement model, this study calculates the overall fit in AMOS v.21 software package.

5.3 Chapter Summary

The current chapter has provided two purposes: first to present the results of the descriptive analysis conducted which helps to provide general characteristics of the respondents and their firms. With respects to the descriptive analysis this chapter specifically focuses on size in terms of the number of staff and the annual turnover, number of products that were patented by the firm, and the percentage of the annual turnover employed in R&D expenditure. In addition, this chapter also provides general characteristics regarding the NPD departments in the firm and this focuses primarily on the size of the department in terms of the number of employees in the department and the number of products introduced in the last three years. This profile helped to develop an initial impression about the characteristics of the firm and the respondents that participated in the study. In addition, the results of the exploratory factor analysis (EFA) were presented. The EFA was further used to test if the two constructs that are operationalised as higher-order constructs can be operationalised as higher-order constructs, via using the SLS technique. In addition, scale purification procedures were conducted to improve the overall fit of the measurement model. In the next chapter, results of the Confirmatory Factor Analysis (CFA) are outlined.

Chapter Six: Measurement Model and Confirmatory Factor Analysis

6.1 Introduction

In this chapter the steps taken to obtain valid measures to test the hypothesised relationships are presented. At this stage, it is not just important to assess the validity and reliability of the items used to measure the constructs in this research, but it is essential to assess the measurement model as one. Following the initial assessment of the measures used in the previous chapter, Structural Equation Modelling (SEM) was chosen as the statistical analysis method to assess the measurement and hypothesised model. This chapter illustrates the proposed measurement development strategy that could be used, following the guidelines from the literature (for example, Anderson and Gerbing, 1988; Bollen and Long, 1993; Byrne, 2010; Churchill, 1979; Churchill and Brown, 1993; Hair et al., 2006).

Since the items used to measure the latent variables in this study have been drawn from the existing literature, the reliability of the scales can be directly assessed through Confirmatory Factor Analysis (CFA). Therefore, this chapter is divided into two parts: In the first part of this chapter, an overview of how to conduct confirmatory factor analysis is discussed and in the second part, specific Confirmatory Factor Analysis (CFA) techniques used to analyse the fitness of the measurement model is presented. Finally, a summary is provided to conclude the chapter.

Structural equation modelling (SEM) was primarily chosen because of its advantages over other multivariate analysis techniques. Firstly, with SEM, researchers can simultaneously analyse multiple and complex relationships between variables. Though these complex relationships could be tested using multiple regression equations but SEM provides additional results regarding the overall fit of the model. In addition, researchers can measure latent variables using SEM. Latent variables are abstract variables that cannot be directly measured, such as perceptions, beliefs or attitudes. Latent variables are measured indirectly by using scale(s) that contain observed indicators which indirectly measure the latent variable (Byrne, 2010; Hair et al., 2006. In this study, all the single-order factors are latent variables and in addition, the higher-order factors are measured as latent variables that are indirectly measured using the first-order factors (Doll, Xia, and Torkzadeh, 1994). In case of the higher-order factors, the structural coefficients of the first-order factors can be interpreted as factor loadings (Doll, Xia, and Torkzadeh, 1994). Hence, taking the advantages into consideration, SEM is the preferred choice of analysis technique. The advantages of SEM in comparison to the other multivariate analysis techniques are discussed in-detail in Chapter 7.

6.2 An overview of Confirmatory Factor Analysis (CFA)

The inception of factor analysis (Spearman, 1904; 1927) was to determine the number of factors/constructs that account for the variation among the various observed variables/items. Fundamentally, both EFA and CFA aim to observe the relationships between a group of items and a smaller set of latent variables, but the key difference is that EFA is a data-driven approach and there are no prior specifications made on the factor model (Hair et al., 2006). Since, in CFA the number of factors and the pattern of item factor loading are specified in advance, this technique is far more rigorous and parsimonious in comparison to EFA (Kelloway, 1998). In addition, the significant difference between EFA and CFA is that CFA accounts for external consistency as the specificity of the measurement model is described in CFA (Gerbing and Anderson, 1981). Therefore, the test conducted on dimensionality, reliability and validity measures of the factors and the measurement model as a whole are more adequately measured in CFA in comparison to EFA.

Confirmatory Factor Analysis (CFA) is a form of Structural Equation Modelling (SEM). CFA predominantly deals with measurement models, that is, to test the relationships between various factors and to test the relationships between the various items and the constructs/factors. CFA is used for four major purposes (Harrington, 2008):

a. Psychometric evaluation
b. Construct Validation
c. Testing method effects, and
d. Testing measurement invariance

CFA is conducted prior to analysing the hypothesised model, as CFA at this stage empowers to improve the model fit to the data by enabling modifications to the measurement model (Brown, 2006). The first step in conducting a CFA is to conduct an EFA that develops and refines the measurement model (based on Willie's (1997) steps/procedures, as mention in the previous section). EFA is more of a data-driven approach whereas; CFA requires stronger empirical and conceptual evidence to guide the specification of the factor model by specifying the number of factors and the pattern of indicator-factor loadings in advance. The primary purpose of evaluating a CFA model in this study was to empirically validate all the better performing items and scales obtained from EFA. In a sense, CFA was conducted to establish the dimensionality, reliability and validity of the constructs in the measurement model (Ping, 2004).

The CFA model assessment provides a range of parameters to test the dimensionality of each factor in the study. In this study, the initial assessment of the unidimensionality of the various factors was tested based on the inter-item and inter-scale correlations using EFA (results are presented in the previous section). But CFA modelling produces a more rigorous and parsimonious analysis (Kelloway, 1998) as EFA technique does not allow for the external consistency (the correlation between items from different scales) and hence the CFA modelling tends to provide different (stricter interpretation) results regarding the dimensionality of the scales used in the study (Anderson and Gerbing, 1988). A few key points need to be noted before actually conducting the CFA analysis. The steps involved in testing a structural and measurement model are described in the following section.

6.2.1 Sample Size

Structural Equation Modelling (SEM) requires a larger sample size to test a model with more stability, in comparison to other statistical techniques (Kelloway, 1998). This is primarily due to the fact that data is input into the statistical tool via a covariance matrix. The observed (from the data) covariance matrix is compared with the estimated covariance matrix. The estimated covariance matrix is derived from the regression analysis results. The regression analysis estimates the correlations between the different constructs in the measurement model. The difference between the correlation matrix and the covariance matrix is defined as the error terms, also known as the residuals. And to analyse the correlation and covariance matrix, a larger sample size is required. Although, the minimum number of sample size required to test a measurement model is still debatable, Kelloway (1998) recommends a minimum of 200 cases. But the complexity of the model also has an impact on the sample size. If there are large numbers of parameters to be estimated, sample size of over 400 may cause concerns (Hair et al., 2006). Therefore, a common recommendation is to ensure to have between five and ten respondents for each parameter in the model (Hair et al., 2006).

6.2.2 Estimation Technique

There are many factor extraction techniques such as Maximum Likelihood (ML), generalised least square, minimum residual analysis, alpha factoring, principal factors, weighted least squares, unweighted least squares and so on (Brown, 2006). The most frequently used technique is the ML estimation. Most SEM software use ML estimation technique as the default method (Diamantopoulos, Siguaw and Siguaw, 2000). A key advantage of the ML estimation technique is that it provides a range of goodness-of-fit indices, which are useful in estimating the stability of the measurement model. In addition, the ML estimation technique provides the most approximate indicators of the relationships between the predicted factors (Brown, 2006). However, the ML estimation technique assumes multivariate normality. That is, if the input data is not normally distributed then important results may be distorted and untrustworthy (Brown, 2006, Brown et al., 2006). Though ML estimation techniques are prone to be too sensitive to data, it is now believed that the robustness of the results is immune to the non-normality of the input data. Therefore, in this study, the ML estimation technique is used to test the measurement and structural model.

6.2.3 Measurement Model Assessment

The primary objective of commissioning a measurement model assessment is to check the overall fit of the model with the data generated. Once the theoretical model is specified, it is time to determine how well the data fits the model. There are two steps to test the model fit (Schumacker and Lomax, 2004). The first is to consider the overall fit of the entire model and the second, is to test the fit of the individual parameters of the model. The first step is to analyse the overall fit of the model. In most of the other statistical tools the key fit index is based on the *F*-test analysis (for example, in ANOVA). Whereas, in SEM there are several number of fit indices and many of these are based on the comparison of the model-implied covariance matrix with the sample covariance matrix. If there is a similarity between the two matrices then the data fits the theoretical model.

The first key criteria used to judge the overall fit of the model is the non-statistical significance of the chi-square (χ^2) test and the root-mean-square error of approximation (RMSEA). The χ^2 test assumes a null hypothesis, in other words, there is no statistical significant difference between the model-implied covariance matrix and the sample covariance matrix. A χ^2 value of zero indicates a perfect fit. However, the χ^2 test is highly sensitive to sample size (Anderson and Gerbing, 1988). In addition, the χ^2 is also highly sensitive to degrees of freedom (*df*) (Bentler and Chou, 1987). Degree of freedom (*df*) of a model is defined as the difference between the number of known parameters (that is, the number of estimated parameters fixed to 1.0) and the number of unknown parameters (that is, the number of parameters that are estimated freely). Since the χ^2 test is highly sensitive to the sample size and the complexity of the model, an alternate measure most widely used is the ratio between chi-square and degrees of freedom, that is, (χ^2/df) (Brown, 2006). The (χ^2/df) test values less than 2 or 3 illustrate a good model fit (Byrne, 2010). Though some researchers argue (for example, Diamantoupulos and Siguaw, 2000) that values less than 5 can be used as a measure of an acceptable fit.

The second key criteria used to measure the overall fit of a model is root-mean-square error of approximation (RMSEA). The formula to calculate the RMSEA value of a given model is as follows:

$$RMSEA = \sqrt{[\chi^2_M - df_M]/[(N-1)df_M]}$$

(Schumacker and Lomax, 2004)

where,

χ^2_M is the chi-square for the model

df_M is the degree of freedom for the model

N is the sample size

The above equation illustrates that RMSEA is a function of sample size, degree of freedom and chi-square value. Bollen and Long (1993) recommend the RMSEA value should be closing towards zero. Browne and Cudeck (1993) as well as Bollen and Long (1993) argue that values less than 0.05 indicates a close approximate fit. In addition, values ranging between 0.05 and 0.08 suggest reasonable error and this indicates a reasonable overall fit. Hu and Bentler (1999) suggest that for models measuring continuous data, a RMSEA value less than 0.06 indicate a good fit. Although, in recent years scholars (for example, Hair et al., 2006) recommend that RMSEA values should be less than 0.5.

There are various other measures of overall model fit that provide further information on the assessment of the measurement model. These include goodness-of-fit index (GFI), comparative-fit index (CFI), non-normed fit index (NNFI), and incremental fit index (IFI). Schreiber et al., (2006) conducted a brief review of articles published in '*The Journal of Educational Research'* and analysed the presentation of the various fit indices used to test the overall fit of the structural model. They found that in general authors preferred CFI, TLI (also known as NNFI), and RMSEA values to test the overall fit of the model. They also argue that there is no one [scientific] way to evaluate the overall fit of the model. They argue that depending on the ratio between the sample size and the degree of freedom, number of analysis conducted on the model, if a comparison model is considered in the study and also the complexity of the model has a huge impact on what indices should be evaluated to measure the fitness of the model. For example, when a one-time analysis of a model is conducted, CFI, TLI and RMSEA values are enough to evaluate the fitness of the model. On the other hand, in case of a model that has been modified (also known as a *'trimmed model'*) than the researcher needs to provide evidence of the χ^2/df test as well. In addition, Schreiber et al., (2006) suggest that if the sample size to the number of parameters measured is small (generally, the rule of thumb is greater than 5) then the researchers need to provide more evidence regarding the overall fit of model. For example, they agree with MacCullum , Browne, and Sugawara (1996, p.144) that *"a sample size of 231 with degree of freedom of 45 would have a power value of 0.8"*. In such a scenario they suggest that researchers/authors need to clearly mention the small sample size to number of parameters measured and provide additional evidence of an overall good model fit. Taking these suggestions, in this study an array of fit indices was used to measure the overall fit of the model. A brief explanation of these fit indices is provided in the following section.

6.2.3.1 Model Fit

In the previous section, a brief explanation of the first key fit measures used to analyse the overall fit of the model was (that is, χ^2/df test and the RMSEA value) provided. The other fit indices used to measure the fit of the model are GFI, CFI, TLI and IFI. GFI (Goodness-of-Fit Index) measures the absolute fit of a model. The calculation of GFI was devised by Tanaka and Huba (1985), and Joreskog and Sorbom (1985) and this measure does not compare the model fit to the data with other models. The formula to calculate the GFI of a given model is as follows:

$$GFI = 1 - \left(\frac{\chi_M^2}{\chi_N^2}\right)$$

where,

χ_M^2 is the chi-square for the model

χ_N^2 is the chi-square for the null model

As stated in the previous section, absolute fit measures compare the difference between the model-implied covariance matrix and the sample covariance matrix; GFI measures the ratio between the model-implied covariance matrix and the sample covariance matrix. GFI does not calculate the fit of the model with a base model to test the overall fit of the model and hence the label *'absolute fit index'*. This equation clearly indicates that as the difference between the covariance between the model-implied and sample-implied grows the value of GFI reduces lesser than 1. Values greater than 0.95 for GFI indicate an overall good fit of the model (Hu and Bentler, 1999). On the other hand, Kelloway (1998) and Diamantopoulos, Siguaw and Siguaw (2000) argue that GFI exceeding greater than 0.90 illustrates that the model fits well. Although, in recent years the relevance of the GFI fit index has been hugely scrutinized (Steiger, 1990; 2000; Marsh, Hau, and Wen, 2004; Marsh, Hau, and Grayson, 2005). For example, Steiger (1989) illustrates how GFI is hugely biased on the ratio of sample size to degree of freedom. He shows that when this ratio is large then the bias is positive and so the fit looks better and if this ratio is small (meaning a large number of degree of freedom) then the bias is negative and the fit looks worse. In addition, Schreiber et al., (2006) state that in the last 15 years authors have reported fit index as low as 0.85. This may be because GFI was the first fit index proposed. Despite the criticism, scholars (for example, Brown et al., 2006; Byrne et al., 2010) argue that when an author states the absolute fit index value of a model, the value of GFI should be accompanied with RMSEA and the χ^2/df test to negate any effect of the sample size to number of degree of freedom ratio bias caused on GFI.

The next array of fit index measures the model fit in comparison to a baseline model (also known as the *'incremental fit index'*). The fit indices discussed so far measure the model fit based on population errors of approximation (also known as the *'absolute fit indices'*). The most quintessential comparative fit index is the normed fit index (NFI) produced by Bentler and Bonett (1980). The formula to calculate the NFI of a given model is as follows:

$$NFI = (\chi^2_N - \chi^2_M)/\chi^2_N$$

where,

χ^2_M is the chi-square for the model

χ^2_N is the chi-square for the null model

Though Normed Fit Index (NFI) is the essential incremental fit index it does not address the chi-square statistics. That is, when models have high values of chi-squares may not provide enough evidence of whether or not the data fits the model well. An index similar to NFI commonly used is the Tucker-Lewis index (TLI) also referred to as NNFI (Non-Normed Fit Index) takes into account the expected value of the chi-square statistics of the model. That is, NNFI measures the overall fit of the model in comparison with a null hypothesis, also known as the *'independence model'* (an independence model is one in which all variables are assumed to be uncorrelated). The formula to calculate the NFI of a given model is as follows:

$$NNFI = \left[\left(\frac{\chi_N^2}{df_N}\right) - \left(\frac{\chi_M^2}{df_M}\right)\right] / [\left(\frac{\chi_N^2}{df_N}\right) - 1]$$

where,

χ_M^2 is the chi-square for the model

χ_N^2 is the chi-square for the null model

df_N is the degree of freedom for the null model

df_M is the degree of freedom for the model

From the above equation it is clear that NNFI provides a better measure (in comparison to NFI) to test [complex] models as it includes the number of degree of freedom. The value of NNFI falls between 0 and 1, and Hu and Bentler (1999) state that value greater than 0.95 indicate a good fit. One of the issues with NNFI is that it highly depends on the average size of the correlation between various variables in the data. That is, if the model is complex and contains many uncorrelated relationships to be tested then the NNFI value will drop considerably and may sink below 0.90. Therefore, Bentler (1992) demonstrate that the threshold value for all incremental fit indices should be 0.90 or larger. This thus indicates that the theoretical model is 90 % better than the independence model.

Comparative Fit Index (CFI) is another important fit index that is often reported to measure the overall fit of the model. Like NFI and NNFI (TLI), CFI is a comparative fit index. CFI was proposed by Bentler and is highly recommended by Kline (2005), Bollen and Long (1993) and Hu and Bentler (1995; 1998). The formula to calculate the NFI of a given model is as follows:

$$CFI = 1 - [\frac{\chi_M^2 - df_M^2}{\chi_N^2 - df_N^2}]$$

CFI is one of the most commonly used indices to measure the overall fit of the model, as CFI does not depend on the sample size (Kline, 2005). In short, CFI measures the error between the theoretical model and the independence model, while adjusting the issues related with complexity of the model (Hair et al., 2006) and the issues related with the sample size (Kline, 2005). The CFI values should ideally range between 0 and 1, with larger values indicating that the data fits the theoretical model well. CFI values greater than 0.95 illustrate a good fit (Kelloway, 1998) but Hu and Bentler (1999) argue that CFI values greater than 0.90 indicate an acceptable fit.

The final incremental fit index that is most commonly reported to illustrate the overall fit of a model is Incremental Fit Index (IFI). As mentioned in the previous section Schreiber et al., (2006) argue that different fit indices are used to measure the overall fit of a model in different scenarios. For example, when the sample size is small, CFI and IFI are commonly presented, as both are not affected by the sample size (Bentler, 1992). On the other hand, when a complex model is evaluated, NNFI/TLI is preferred, as NNFI takes the complexity of the model into consideration. The formula to calculate the NFI of a given model is as follows:

$$IFI = [\frac{\chi_N^2 - \chi_M^2}{df_N^2 - df_M^2}]$$

The IFI values range between 0 and 1, with larger the value representing an overall better fit. IFI values greater than 0.90 represent an acceptable model fit, and values greater than 0.95 illustrate a good fit (Bentler, 1992).

Parsimonious fit indices are relative fit indices and are adjustments to GFI, CFI, and NFI. Most of the fit indices discussed above depend on the sample size and this may result in less rigorous theoretical models (Mulaik et al., 1989). To overcome this problem Mulaik et al., (1989) developed two parsimonious goodness of fit index (that is, PGFI and PNFI). The PGFI calculation is based upon the GFI by adjusting the loss of degree of freedom, and PNFI is calculated by adjusting the loss of degree of freedom in NFI. These fit indices measure the complexity of the model and incorporate a penalty for poor parsimonious; these fit indices are considerably lower than the other goodness of fit indices. Schreiber et al., (2006) state that PNFI is highly sensitive to sample size in comparison to PCFI. Parsimonious comparative fit index (PCFI) values range between 0 and 1, and while there is no threshold level recommended. However, Hair et al., (2006) argue that parsimonious fit indices are most useful when comparing the relative fit of two competing models. In addition, Kelloway (1998) state that it is unlikely to reach a cut-off point of 0.90 for a model that fits well. Mulaik et al., (1989) recommend that it is possible to achieve PCFI values in the range of 0.50 and since it is difficult to interpret this goodness of fit indices, it is best used in tandem with other measures of goodness of fit indices.

As mentioned in section 6.2.3, there are two ways to test the fit of the model. The first is to consider the overall fit of the model by analysing the different goodness of fit indices and checking if these values fall in the recommended range levels illustrating a good overall model fit. The second is to consider the individual parameters of the various variables used in the model. In the next section, the various reliability and validity parameters used to assess individual variables used in the model that leads to achieving an overall satisfactory model fit will be discussed.

6.2.3.2 Model Modification

It is difficult to achieve an overall good model fit (that is, implied model fitting the observed data well) in the first estimation (Kelloway, 1998).Therefore, once the measurement model is evaluated, the next step is to improve the model fit by conducting model modification(s). Statistical software (such as, AMOS, LISREL) provide enough information that can be beneficial in detecting any misspecification (Byrne, 2010). There are two types of information that are relevant in detecting the poorly performing measures. The two are as follows:

a. *Residual Error:* As mentioned in the previous section, SEM in essence tests the fit between the implied model covariance matrix and the sample covariance matrix. Any error in the two covariance matrix is captured by residual covariance matrix. AMOS provides two matrices, that is, standardised and unstandardized residual matrix. Standardised residual matrix provides error scores that are divided by their asymptotically (large sample) standard errors (Jöreskog and Sörbom, 1993). This makes standardised residual matrix easier to interpret (Byrne, 2010). Jöreskog and Sörbom (1993) state that any error terms greater than 2.58 are considered large and this can be set as a cut-off point. On the other hand, Anderson and Gerbing (1988) argue that an absolute score of greater than 2 is considered large. As values greater than 2 represent one standard deviation from the acceptable score, and hence error terms greater than 2 should be noted for deletion to improve the model fit.

b. *Modification Indices:* The other information related to model misspecification provided by AMOS is Modification Indices (MI). The conceptualisation of MI is based on the χ^2 statistics (Jöreskog and Sörbom, 1993). In short, for every fixed parameter specified in the model, AMOS provides a MI value. MI value represents the decrease in the χ^2 value if that fixed parameter were to be deleted. Therefore, the largest MI values indicate that these parameters should be freed. Kelloway (1998) recommend that MI values greater than 5 should be considered for deletion. MI values are not independent of one another and hence the parameters should be freed (deleted) one at a time in an iterative process. As Anderson and Gerbing (1988) argue that at this stage this process becomes more of an exploratory analysis rather than a confirmatory analysis. Hence, scholars (for example, Byrne, 2010; Hair et al., 2006; Kelloway, 1998) argue that any modifications made to improve the model fit need to be meaningful and theoretically justified.

6.2.4 Reliability and Validity Assessment

In CFA model, the principal sources of poor fitting model can be deduced to the following three reasons:

1. The number of factors (too many or too few), that is, poor modelling.
2. The use of poor indicators (checking for factor loadings, inter-item and inter-scale correlation), that is, testing the overall validity and reliability measures of each factor used in the model, and
3. Error in the theory used to justify the model specifications (that is, the use of many uncorrelated factors in a model that leads to high measurement errors).

(Source: Brown, 2006)

The overall goodness of model fit can be improved by identifying and justifying the use of the factors in the model (by conducting an extensive literature review) and testing the reliability and validity of each factor used in the model. Therefore, the next step is to measure how well the factors are represented by their indicators by testing the reliability, validity and unidimensionality of all the factors (Hair et al., 2006).

6.5.4.1 Reliability

The reliability and validity of the scales were measured using EFA (see section 6.3.1) but scholars (for example, Gerbing and Anderson, 1988; Nunnally and Bernstein, 1994) argue that coefficient of alpha reliability assessment is useful but it isn't rigorous as coefficient alpha assessment assumes that scale items are correlated and have no measurement error (Bollen, 1989). In the existing literature, construct (or composite) reliability (CR) is used to measure the internal consistency of the items used in a scale (Fornell and Larcker, 1981). The formula to calculate CR is as follows:

$$CR = \frac{[(\sum\lambda_i)^2 * Var(x)]}{(\sum\lambda_i)^2 * Var(x) + \Sigma Var(e_i)}$$

(Source: DeVellis, 2003)

The above formula can be interpreted as:

$$CR = \frac{Square\ of\ total\ Standardised\ loading}{Square\ of\ total\ standardised\ loading + measurement\ error}$$

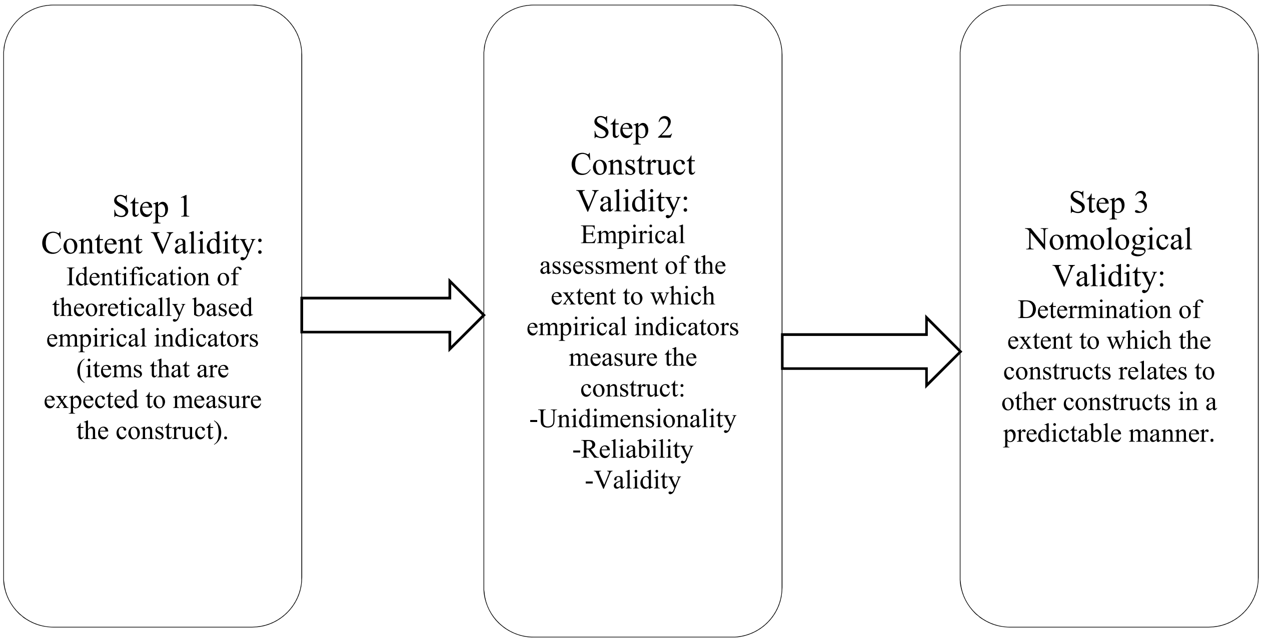
From the above equation, it can be seen that unlike coefficient alpha (α), CR does not consider the measurement error to be zero. Diamantopoulos and Siguaw (2000) argue that CR values should be greater than 0.5. This value indicates that minimum of 50% variance of the factor is explained by its latent variables. On the other hand, Fornell and Larcker (1981) recommend that a minimum threshold value of 0.6 for CR should be established. Hair et al., (2006) argue that ideally the CR values should exceed 0.7 as this indicates that the measurement error is as small as possible. In addition, in the existing literature, scholars (for example, Diamantopoulos and Siguaw, 2000; Fornell and Larcker, 1981; Hair et al., 2006) agree that an adequate CR also indicates a good convergent validity. Convergent validity is defined as how well do the various factors/latent variables converge onto one single factor (DeVellis, 2003).

6.5.4.2 Validity

Another measure used to test the internal consistency of the various factors used in a model is validity. In comparison, reliability is the measure of the degree of consistency of a scale whereas; validity is the measure of the accuracy of a scale in the study (Kerlinger and Lee, 2000). There are different types of validity, such as, content validity, convergent validity, construct validity and nomological validity. The content validity is a non-statistical measure of the scale to test whether the various items (in the scale) measure all aspects of the factor (Nunnally, 1978). For this study, all the constructs (and the scales measuring these constructs) are taken from the existing literature (see Chapter 2) and after conducting an in-depth literature review, the scale measuring all aspects of the factors was chosen (based on the reliability and validity measures provided in the papers in the literature).

Construct validity is a measure of the extent to which the operationalization of the factor does actually measure what the theory says it does, that is, free from any measurement error (O'Leary-Kelly and Vokurka, 1998). Schwab (1980) state that testing construct validity is an important aspect of research and is essential step for assessing the adequacy of the measures. When valid measures of relevant constructs are employed, the research results gains credibility (Churchill, 1979; Peter, 1981; Gerbing and Anderson, 1988). Therefore, unequivocally it is necessary to follow the right procedures to test the validity of the various constructs used in this study. In this study the three step procedure presented by (O'Leary-Kelly and Vokurka, 1998) will be followed to test the constructs for validity. The steps are described in Figure 6.1. Chapters 2 and 3 provide enough evidence to demonstrate logical link between the various measures and these chapters justify the way these constructs are operationalized in this study. Therefore, the content validity of the constructs is justified. The next step is to test the items for unidimensionality. Unidimensionality is defined as an item measuring just one dimension (that is, one factor) in the study (Gerbing and Anderson, 1988).

Figure 6.1 Steps used for testing validity



(Source: O'Leary-Kelly and Vokurka, 1998)

There are several statistical techniques available to analyse the multidimensionality aspect of an item (Rubio, Berg-Weger, and Tebb, 2001). The most commonly used measure to test for multidimensionality items is Cronbach's Alpha (α). Though α is the most commonly used measure to test multidimensionality, it may not be the most rigorous technique (Cortina, 1993). As argued by Gerbing and Anderson (1988) and Nunnally and Bernstein (1994) that adding items may improve the reliability (α) of the scale regardless of the impact of the item on the dimensionality of scale. EFA provides enough evidence by analysing the number of factors the items measure (see Section 5.3). In this study the test for the higher-order EFA provides enough evidence of a unidimensional (also known as a congeneric model) model.

Construct validity of a factor is tested using two validity measures, that is, convergent validity and discriminant validity (Hair et al., 1998; Kerlinger and Lee, 2000). As mentioned in the previous section, an adequate Construct Reliability (CR) is a good measure of convergent validity. In addition, convergent validity is also determined by the Average

Variance Extracted (AVE). The formula used to measure AVE is as follows:

$$AVE = \frac{[(\sum\lambda_i)^2 * Var(X)]}{(\sum\lambda_i)^2 * Var(X) + \Sigma Var(e_i)}$$

(Source: DeVellis, 2003)

The above formula can be interpreted as:

$$AVE = \frac{Sum\ of\ Standardised\ loading\ square}{Sum\ of\ standardised\ loading\ square + measurement\ error}$$

From the above equation it can be seen that AVE is a ratio of the amount of variance extracted from its intended factors/items over the total variance extracted (that is, also adding variance added due to errors) from other constructs as well (Diamantopoulos and Siguaw, 2000). In the existing literature, scholars (for example, Fornell and Larcker, 1981; Hair et al., 2006; Ping, 2004) agree that AVE values greater than 0.5 indicate a good convergent validity measure, that is, more than 50% of the variance extracted is from the intended factors than any other constructs/factors in the model. Netemeyer, Bearden, and Sharma (2003) argue that values near 0.45 are good enough measures for AVE and this should be set as a minimum threshold value for AVE.

Discriminant validity measures the degree to which uncorrelated variables are unrelated (Cozby, 2009; Ping, 2004). Discriminant validity for a construct is measured using the correlation matrix and this was tested using EFA (see Section 5.3.1.2). There are more rigorous AVE tests that provide more accurate evidence regarding the discriminant validity of a construct. The two measures most commonly used to test the discriminant validity of a construct are Average Shared Variance (ASV) and Maximum Shared Variance (MSV). The rule of thumb is, if the ASV and MSV of two factors is less than the square root of AVE (average variance extracted) of the individual factors then, this indicates that there are no discriminant validity issues for the two factors (Ping, 2004).

The third step in O'Leary-Kelly and Vokurka's (1998) procedure to test the validity of a construct is to test for the construct's nomological validity. Nomological validity also termed as 'substantive validity' by Schwab (1980) is defined as *"an observed relationship between measures purported to assess different (but conceptually related) constructs"* (Peter, 1981, p.137). That is, theoretically related constructs are empirically confirmed to be related. In the existing literature there are several procedures available (for example, Bagozzi, Yi, and Phillips, 1991; Bollen, 1989; Tesser and Krauss, 1976). The most commonly used guideline/procedure followed by attitude researchers (that is, researchers who measure attitudes in their analysis, for example in marketing) is to test correlation between the various constructs in the model (Peter, 1981). In this study, drawing from this procedure, the correlation between the various constructs/factors is used as a measure to test for nomological validity. As explained in Section 5.3.1.2, a correlation value of 0.5 shows a strong correlation between the various constructs, but if the correlation value exceeds greater than 0.7 then this may indicate that these constructs measure a common cause (factor). This may be a concern for unidimensionality. From the existing literature it is evident that there is a relationship between the various factors used in the model (See chapters 2 and 3). In addition, correlation matrix analysis was conducted in Section 5.3.1, and there is enough evidence provided to show there is no concern for any nomological validity. To further demonstrate nomological validity, additional statistical analysis is conducted and is presented in the later sections of this chapter and chapter seven.

6.6 Confirmatory Factor Analysis

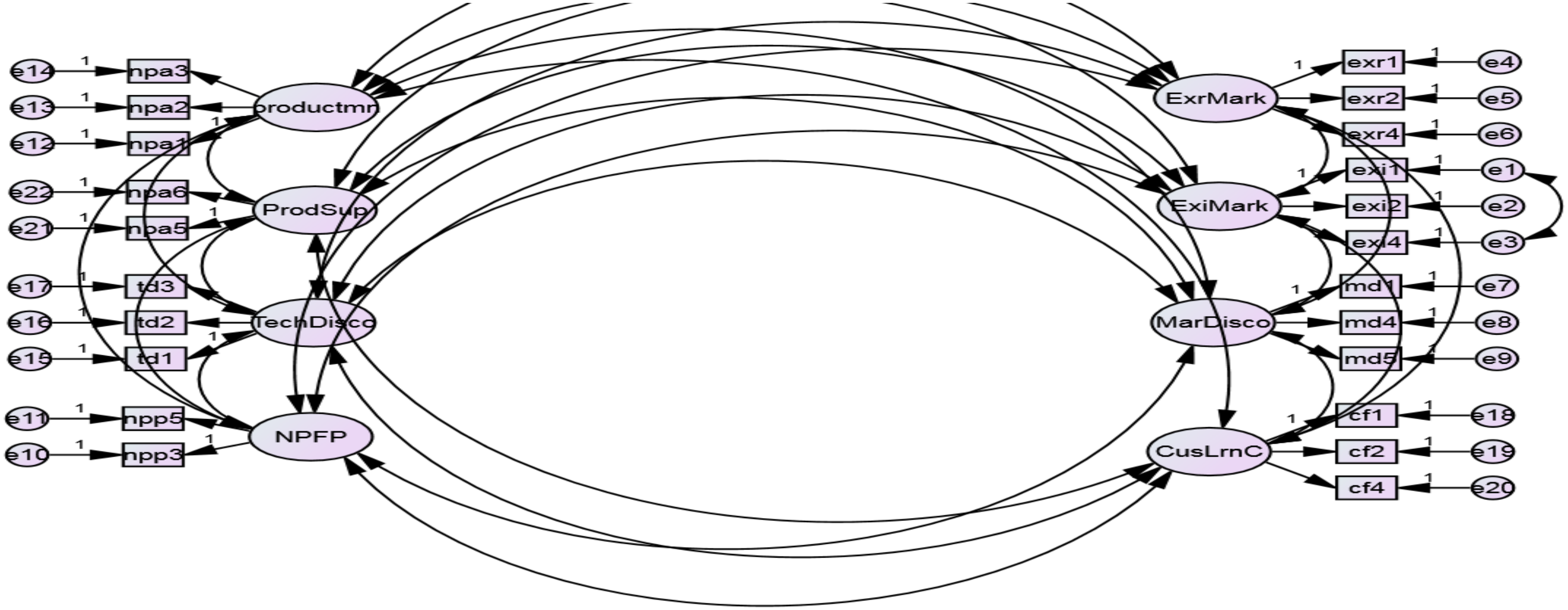
Using AMOS version 22.0, the remaining items that passed from EFA were evaluated using Confirmatory Factor Analysis (CFA). After eliminating the poorly performing items, a total of 21 items measuring 7 factors were included in CFA. Bentler and

Chou (1987) recommend that to conduct a satisfactory structural equation modelling (SEM), a minimum of 15 cases per item measured should be followed. Therefore to conduct a satisfactory SEM in this study, a minimum of 315 cases are required. The available sample size to analyse the model is 178, which is inadequate. But as mentioned in Section 5.3.1.3 a minimum of three items per scale was considered as a threshold, as constructs with two items may have reliability issues. Therefore, this may have an impact on the goodness of fit indices (for example, GFI) as GFI is hugely biased on the ratio of sample size to degree of freedom (see Section 6.2.3.1). Taking these points into consideration, two measurement models were run. The first measurement model comprised of all items measuring the first-order factors. The first-order measurement model analysis was conducted solely to examine the reliability, unidimensionality and validity measures for all the first-order factors. The second measurement model comprised of the two higher-order factors and the remaining three first-order factors.

The first-order measurement model was assessed. The analysis provided a converged solution with an acceptable fit: χ^2=261.36, df = 166 (p<.001), χ^2/df= 1.57. The χ^2/df test was satisfactory as the ratio was below 2. The fit indices were near the recommended levels (GFI, IFI, CFI, NNFI should exceed 0.90). The goodness of fit indices for the first-order measurement model were GFI = 0.88, CFI = 0.96, IFI = 0.96, NNFI = 0.95, PCFI = 0.76, and RMSEA = 0.059 (which illustrates a reasonable fit). It is evident that all fit indices for the first-order measurement model were well above the recommended threshold. The only exception was GFI value, which was relatively low and this might be due to the smaller sample size to items ratio (see Section 6.2.3.1). The parsimonious fit indices (PCFI) have no absolute value. As mentioned in Section 6.2.3.1, parsimonious fit indices are best useful for comparing the goodness of fit of two models. However the modification indices indicated that the model fit can be improved. Following the guidelines provided in Section

6.2.3.2, model was subjected to model modification. The primary concern was the high error correlation between npa4 and npa3. The item 'npa4' measuring 'product superiority' was *"New products or services that are the best of its kind in the market"*. This item may have high correlations with other items and factors, and therefore this item was deleted. The model purification was carried out until no further improvements could be theoretically and/or statistically not justifiable. After this iterative process, the measurement model provided a convergent model with much better acceptable fit. The final first-order measurement model that included 7 factors with 22 items measuring their respective factor was analysed (see Figure 6.2).

Figure 6.2 First-order CFA measurement model



Productmn – Product Meaningfulness
ProdSup – Product Superiority
TechDisco – Technological Discontinuity
NPFP – New Product Financial Performance
ExrMark – Exploratory Market Learning
ExiMark – Exploitative Market Learning
CusLrnC – Customer Discontinuity
MarDisco – Marketing Discontinuity

The resulting first-order measurement model had an overall improvement after dealing with the problematic items. The goodness of fit indices improved to: χ^2= 215.457, df = 180 (p = 0.036), χ^2/df= 1.197, GFI = 0.91, CFI = 0.980, IFI = 0.981, NNFI = 0.98, PCFI = 0.76, and RMSEA = 0.033

In addition to assessing the overall goodness of fit for the first-order measurement model, the reliability and validity of the scales was also assessed. The MSV and ASV calculations were done manually, and the results indicate that AVE is greater than MSV and ASV. As mentioned in Section 6.2.4.2, composite reliability should be above 0.7 and AVE should exceed 0.5 (Hair et al., 2006; Ping, 2004).

Table 6.1: Results of first-order measurement model with the Standardised Factor Loadings (with t-values).

Items	Exploitative Market Learning	Exploratory Market Learning	Technological Discontinuity	Marketing Discontinuity	Product Meaningfulness	Product Superiority	Customer Discontinuity	New Product Financial Performance
Exi1	0.724 (8.567)							
Exi2	0.795 (9.273)							
Exi4	0.655 (fixed)							
Exr1		0.837 (6.690)						
Exr2		0.714 (5.869)						
Exr3		0.694 (fixed)						
Td1			0.809 (fixed)					
Td2			0.941 (11.825)					
Td3			0.694 (9.610)					
Md1				0.678 (fixed)				
Md4				0.791 (5.314)				
Md5				0.803 (6.992)				
Npa1					0.892 (13.461)			
Npa2					0.797 (11.396)			
Npa3					0.827 (fixed)			
Npa5						0.898 (18.44)		
Npa6						0.938 (fixed)		
Cf1							0.846 (fixed)	
Cf2							0.871 (15.285)	
Cf3							0.682 (13.992)	
NPP3								0.819 (Fixed)
NPP5								0.978 (7.39)
AVE	0.526	0.524	0.673	0.545	0.669	0.844	0.759	0.814
CR	0.751	0.794	0.897	0.772	0.858	0.915	0.806	0.897

The AVE for all the constructs in this measurement model exceeds 0.50 and composite reliability (CR) exceeds 0.7. This indicates a good measure for convergent validity. The Average Shared Variance (ASV) and Maximum Shared Variance (MSV) were calculated manually. As explained in Section 6.5.4.2, the two measures most commonly used to test the discriminant validity of a construct are Average Shared Variance (ASV) and Maximum Shared Variance (MSV). Table 6.2 provides the ASV and MSV values calculated for all the constructs.

Table 6.2 Discriminant validity measures

Construct	AVE	MSV	ASV
Exploitative Market Learning	0.526	0.275	0.076
Exploratory Market Learning	0.524	0.275	0.113
Technological Discontinuity	0.673	0.254	0.096
Marketing Discontinuity	0.545	0.304	0.091
Product Meaningfulness	0.669	0.613	0.161
Product Superiority	0.844	0.613	0.145
Customer Discontinuity	0.759	0.016	0.016
New Product Financial Performance	0.814	0.152	0.070

From the above table it is evident that the values of MSV and ASV for each construct are smaller than its AVE. As mentioned in the previous section, if the squared correlation between various variables is less than the individual AVEs then this suggest these constructs have more error-free variance extracted than variance shared with other constructs (Ping, 2004). Therefore, the above results indicate that the variance extracted for all the constructs have more error-free variance than shared variance. In addition, the inter-construct correlations among the constructs were not significantly above 0.70 (Ping, 2004), except for the correlation between Product Meaningfulness and Product Superiority, and Exploratory Market Learning and Exploitative Market Learning. The respective correlations are 0.758 and 0.552. As mentioned in previous section, this high correlation was expected as these are measuring the same underlying construct. In fact, this provides more evidence that exploratory market learning and exploitative market learning are first-order constructs measuring a higher-order construct (that is, Ambidextrous Market Learning), and product meaningfulness and product superiority are first-order constructs measuring a higher-order construct (that is, product advantage).

The standardised residual matrix for the measurement model is provided in Appendix 6A. As it can be seen, the standardised residual covariance for all constructs is less than 2, except for the residual covariance between ‘cf4’ and ‘exr1’, and ‘exr2’ and ‘td3’. The respective standardised residual covariance is 2.58 and 2.6. As mentioned in Section 6.2.3.2, that any error terms greater than 2.58 are considered large and this can be set as a cut-off point. A decision was made to not eliminate these items from the measurement model. The substantive reasoning for this is that the modification indices were not high for these items and the standardised residual covariance was not that higher than 2.58 (as suggested by Jöreskog and Sörbom, 1993).

Thus given the limitation of the number of items (22) to the sample size (178) ratio, the measurement model did return a reliable and robust solution; with all the fit indices meet their recommended cut-off limits, except for GFI (0.88). However, due to the limitation of the number of items to the sample size ratio, this was expected. In addition, all the constructs had no reliability and validity concerns. Consequently, the results indicate that this measurement model is robust, reliable and valid. This indicates that these constructs are valid and reliable for further analysis (that is, higher-order factor analysis).

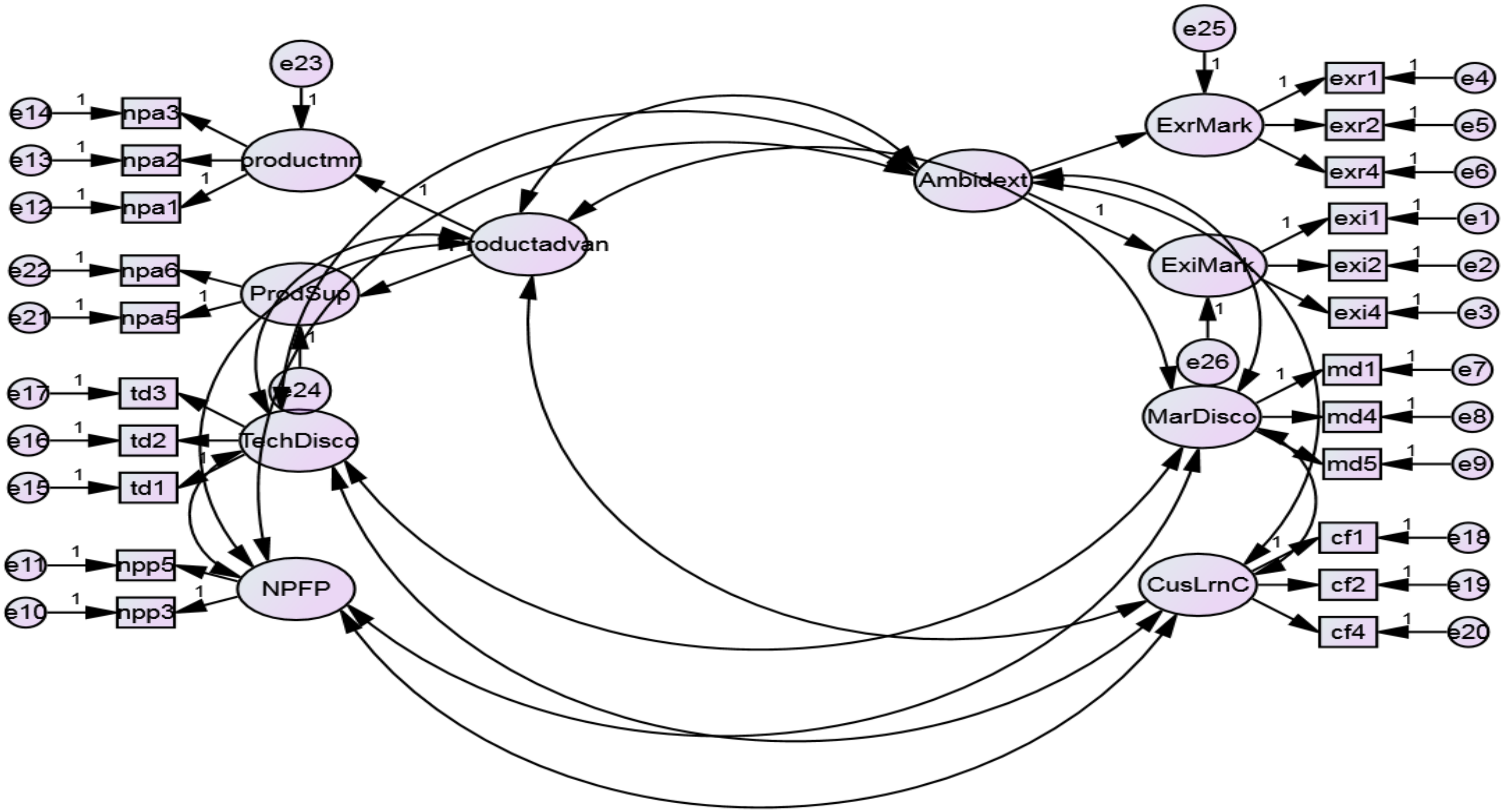
The higher-order measurement model was assessed. The analysis provided a converged solution with an acceptable fit: χ^2=228.572, df = 190 (p = 0.029), χ^2/df= 1.203. The χ^2/df test was satisfactory as the ratio was below 2. The fit indices were near the recommended levels (GFI, IFI, CFI, NNFI should exceed 0.90). The goodness of fit indices for the first-order measurement model were GFI = 0.90, CFI = 0.98, IFI = 0.98, NNFI = 0.97, PCFI = 0.805, and RMSEA = 0.034 (which illustrates a reasonable fit). It is evident that all fit indices for the higher-order measurement model were well above the recommended threshold. The parsimonious fit indices (PCFI) have no absolute value. As mentioned in Section 6.3.3.1, parsimonious fit indices are best useful for comparing the goodness of fit of two models. Table 6.3 provides the fit of the higher-order and first-order measurement model.

Table 6.3 Comparison of fit indices for first-order and higher-order models

	First-order measurement model	**Higher-order measurement model**
χ^2	215.457	228.573
df	180	190
χ^2/df	1.197	1.203
RMSEA	.033	.034
GFI	.91	.91
NNFI (TLI)	.975	.97
CFI	.98	.98
IFI	.98	.98
PCFI	.76	.81

As it can be seen from Table 6.3, the fit of the higher-order and first-order models appear to be almost similar. This comes as a surprise as the fit of the higher-order model was expected to be much better than the fit of the first-order model, as there are more paths specified to capture the covariance in the model (Hair et al., 2006). Except for the parsimonious fit of the higher-order model is expected to be higher than the first-order model. It can be seen from Table 6.3 that the PCFI value

Figure 6.3 Higher-order CFA measurement model



(0.81) for the higher-order model is higher in comparison to the PCFI value (0.76) for the first-order model.

In addition, as it can be seen from Table 6.4, the factor loadings of all items on to their respective factors exceeded the cut-off standardized loading value of 0.5. As stated by Anderson and Gerbing (1988) if the loadings of each indicator are high then this leads to high convergent validity. Therefore, all the higher-order factors in this measurement model pass the convergent validity test. In addition to assessing the overall goodness of fit for the first-order measurement model, the reliability and validity of the scales was also assessed. The AVE for all the constructs in this measurement model exceeds 0.50 and composite reliability (CR) exceeds 0.7. This indicates a good measure for convergent validity. The Average Shared Variance (ASV) and Maximum Shared Variance (MSV) were calculated manually. Table 6.5 provides the ASV and MSV values calculated for all the constructs. From the above table it is evident that the values of MSV and ASV for each construct are smaller than its AVE. This suggests that there is no reliability and validity concerns for the higher-order constructs. Therefore, the overall fit of the higher-order constructs was considered acceptable.

Table 6.4 Discriminant validity measures

Construct	AVE	MSV	ASV
Ambidextrous Market Learning	0.589	0.232	0.102
Technological Discontinuity	0.672	0.299	0.099
Marketing Discontinuity	0.535	0.299	0.295
Customer Discontinuity	0.590	0.082	0.022
Product Advantage	0.786	0.231	0.091
New Product Financial Performance	0.766	0.232	0.112

Table 6.5 Results of higher-order measurement model with the Standardised Factor Loadings (with t-values).

Items	Ambidextrous Market Learning	Technological Discontinuity	Marketing Discontinuity	Customer Discontinuity	Product Advantage	New Product Financial Performance
ExiML **ExrML**	0.950 (4.762) 0.525 (fixed)					
Td1 **Td2** **Td3**		0.804 (fixed) 0.948 (12.723) 0.690 (9.822)				
Md1 **Md4** **Md5**			0.580 (fixed) 0.785 (7.060) 0.810 (6.673)			
Cf1 **Cf2** **Cf3**				0.863 (7.684) 0.854 (6.380) 0.644 (fixed)		
PrMean **PrSup**					0.973 (7.419) 0.765 (fixed)	
Npp3 **Npp5**						0.813 (Fixed) 0.986 (8.029)
AVE	0.589	0.672	0.535	0.590	0.786	0.817
CR	0.726	0.858	0.772	0.806	0.867	0.726

6.6.1 Common Method Variance

In section 6.5.4.2 the importance of validity of the constructs used in the study are discussed in detail. In addition to the content, construct, convergent and nomological validity researchers highlight the possible problem of Common Method Variance (CMV) in behavioural research (for example, Campbell and Fiske, 1959; Fiske, 1982; Podsakoff et al., 2003; Rindfleisch et al., 2008). Common method variance is attributable to the method of measurement, in comparison the other types of validity is more to do with the constructs the measures represent (Podsakoff et al., 2003).

CMV is one of the primary threats to construct validity and this may raise systematic errors (Campbell and Fiske, 1959; Fiske, 1982). This systematic error may cause false internal consistency, and this may lead to a difference between the observed and true relationships (Cote and Buckley, 1988; Fiske, 1982). As mentioned in section 4.3 that cross – sectional studies tend to pose a threat from common method bias (Podsakoff et al., 2003). As discussed in Section 4.4, efforts were made accordingly in designing the questionnaire to address the CMV threat.

To safely reject any suspicions of CMV threats to the study results, further assessments were made. Harman's (1976) single factor test was conducted, based on the concept that if a single factor can explain all the common variance shared by all the observed variables then there is a potential CMV threat present. In order to conduct this test, all the items used to measure the various observed constructs are constrained to load on a single factor. If the data fits the single factor measurement model (also known as the constrained model) significantly better than the multifactor model then the CMV threat is evident.

As it can be seen from the Table 6.6, the results indicate that the data fits the multifactor model significantly better than the constrained model. The result of the Harman's single-factor test was taken to suggest that CMV was not a problem.

Table 6.6 Harman's Single-factor test

	First-order measurement model	Single-factor measurement model
χ^2	215.457	1343.60
df	180	209
χ^2/df	1.197	6.43
RMSEA	.033	.175
GFI	.91	.560
NNFI (TLI)	.975	.388
CFI	.98	.38
IFI	.98	.32
PCFI	.76	.532

6.7 Summary

The purpose of this chapter was to present the results of the confirmatory factor analysis of the higher-order measurement model. Subsequently, following the recommended procedures all items and scales were assessed for reliability and validity. The overall fit of the model was tested and in addition, the internal consistency of all the constructs in the measurement model was tested. Specifically, unidimensionality, convergent validity, discriminate validity, reliability and nomological validity were assessed. The overall measurement model results were suitable for formal structural model testing, which is presented in the next chapter.

Chapter Seven: Hypotheses Testing and Post-Hoc Examination

7.1 Introduction

In the previous chapter, the results of the assessment of the measures used in this study were provided. In the current chapter the conceptual model presented in Chapter 3 is tested. This is followed by an assessment of the five hypotheses in the structural model. To test the conceptual model, Structural Equation Modelling (SEM) technique was chosen. SEM is a preferred statistical technique used by researchers for testing multiple relationships at a time (Hair et al., 2006). SEM is an extension of factor analysis (see Chapters 5 and 6). This chapter is divided in to three sections. First, SEM technique is discussed in detail with a discussion on how to test mediating and moderating hypotheses in SEM is presented. Then second, the results of the five hypotheses are presented and finally, a post-hoc analysis of the structured paths in the structural model will be discussed.

7.2 Structural Equation Modelling (SEM)

SEM is a multivariate technique that combines various aspects of multiple regression and factor analysis to simultaneously measure a series of relationships between observed variables or/and latent constructs (Hair et al., 2006). SEM is the most preferable data analysis technique in marketing and consumer behaviour research (Hair et al., 2006). The primary reason is that in many situations, a web of relationships needs to be tested simultaneously to gain a better insight into the hypothesised relationship and in addition, SEM provides an array of results that are useful in assessing theoretical models (Anderson and Gerbing, 1988). Further, if needed SEM provides enough evidence to determine and modify the theoretical model that fits the data well.

SEM is performed in two steps: measurement model and structural model testing. Testing of the structural model using SEM follows six logical steps and these are:

1. Defining individual constructs
2. Developing and specifying the measurement model
3. Designing a study to produce empirical results
4. Assessing measurement model validity
5. Specifying the structural model
6. Assessing the structural model validity

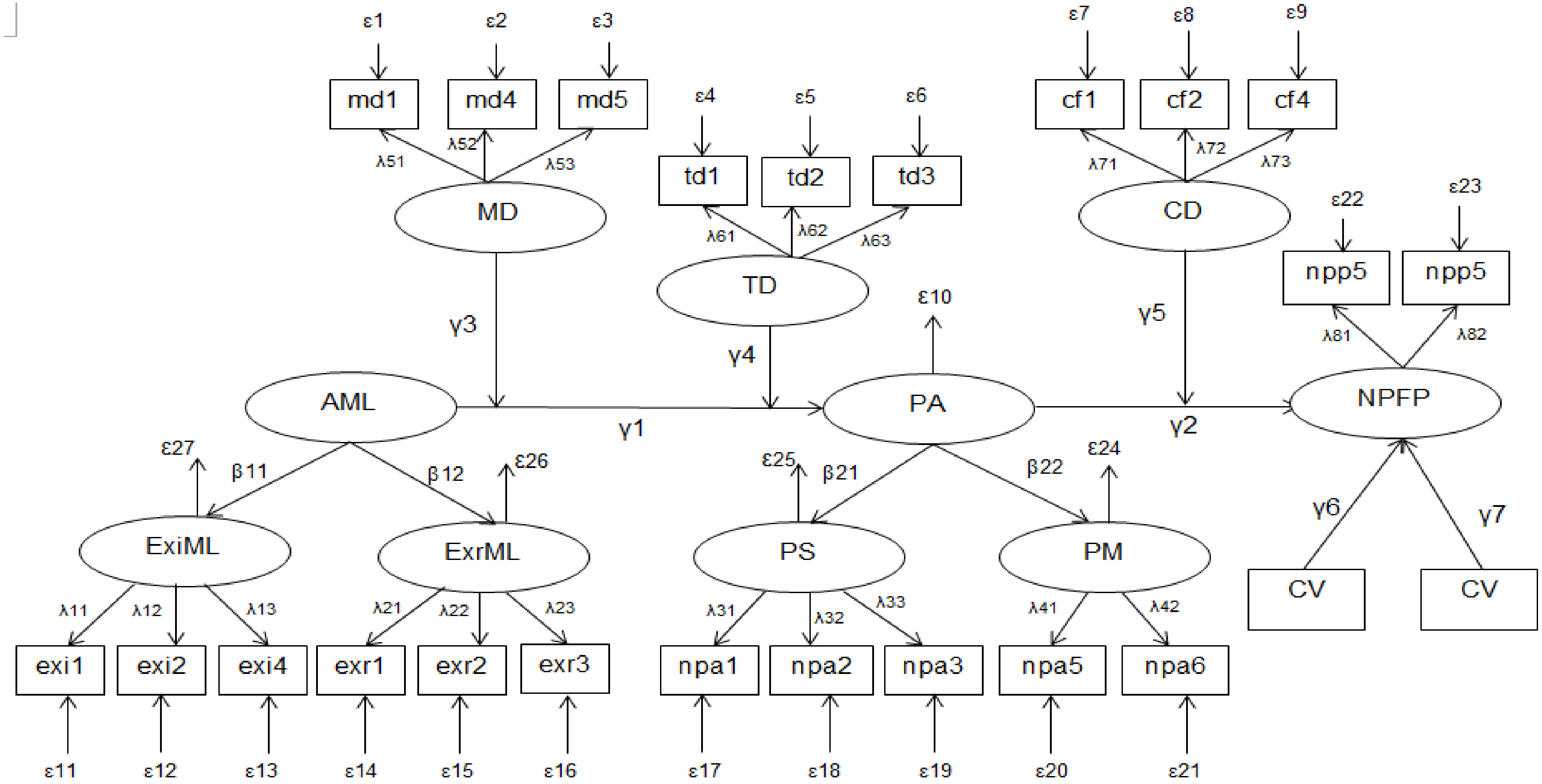
(Source: Hair et al., 2006)

The first four stages of SEM were conducted and the results of these stages are presented in Chapter 6. The fifth stage in SEM is to specify a structural model, and this stage can be further divided into two sub stages. The first is to specify the model and the next stage is to identify the model. Specifying a structural model consists of defining a model based on a relevant theory and a sound theoretical framework (Hoyle, 1995). Testing a structural model using SEM technique is theory based as it is suggested that hypothesis testing using SEM focuses on how well the model fits the data (Hair et al., 2006). In a sense, the focus now shifts from testing the relationship between a construct and its measures/items (testing of measurement model, see Chapter 6) to testing the relationship between different constructs in the model (Anderson and Gerbing, 1982). Hence, as suggested it is necessary to specify the model very carefully (Weston and Gore, 2006). Chapter 2 and 3 provide enough theoretical evidence to justify the testing of the model as one. The model presented in Chapter 3 hypothesises a web of relationships that need to be tested simultaneously. Therefore, following the recommendations from the literature, the model in this study is tested using SEM techniques.

Model identification plays a key role in structural modelling, as this stage is concerned with the information required for obtaining a converged and a unique solution. And to achieve a unique solution, there should be sufficient information to test all the parameters in the structural model. This situation is defined as an "over-identified model" or a "just-identified model" (Diamantopoulos and Siguaw, 2000). The following two factors have an impact on achieving an over-identified model and these are:

1. *To build a proper causal-flow model*: There should be no two way causal relationships between any of the constructs (Diamantopoulos and Siguaw, 2000) and the correlations between exogenous and endogenous variables should be set at zero (Hair et al., 2006).
2. *Sample Size and number of items measuring each construct*: To achieve a unique and converged solution, a minimum number of three items measuring each construct should be used as a rule of thumb though if the sample size is greater than 100 then constructs measured with two items can be used (Anderson and Gerbing, 1984). Though in recent years, Hayduk and Littvay (2012) argue that one or two items are sufficient and three indicators can be helpful at times. They argue that more than three indicators are redundant and do not add any benefit to the research. Therefore, in line with the literature, Figure 7.1 depicts the path diagram for the structural model and as it can be seen, most constructs are measured using three items except product meaningfulness which is measured using two items. Since the sample size used to test this model is 178, there is no potential threat in achieving an over-identified model.

Figure 7.1 Path Diagram



7.3 Developing a structural model using SEM

As mentioned, in comparison to other traditional statistical techniques (such as, Regression analysis, ANOVA, and so on), SEM is more sophisticated and has many advantages in testing complex models. Though, SEM technique is the most preferred multivariate technique in marketing and consumer behaviour research, there are certain major assumptions that underline while testing a structural model. In existing literature, researchers (for example, Anderson and Gerbing, 1988, Hair et al., 2006) state that these assumptions need to be tested for and if valid conclusions are to be drawn from structural model testing, it is necessary that these assumptions need to be satisfied. There are six major assumptions that are associated with SEM and these include, multivariate normality, completely random missing data, large sample size, multicollinearity, independence of observation, and correct model specification (Hair et al., 2006; Kaplan, 2009). This section discusses these underlying assumptions and how steps (tests) were taken (conducted) to satisfy these assumptions to ensure accurate inferences.

1. *Multivariate Normality* – One of the basic assumptions underlying SEM is that the population (data) used to test the measurement and structural model are continuous and are multivariate normally distributed. The primary reason for this assumption is because SEM attains unbiased and efficient results. Substantial statistical research from mid 1980s through the 1990s (for example, Browne, 1982; 1984; Chou and Bentler, 1995; Muthen and Kaplan, 1992; Ping, 1995) illustrate that non – continuous and non-normality data have a negative impact on standard errors (under-estimated), and test of model fit (over-estimated). In addition, this assumption plays a pivotal role when the model is tested using Maximum Likelihood (ML) techniques, as ML estimates are directly derived from normally distributed and continuous population

(Kaplan, 2009). As mentioned in Chapter 5, in this study, ML estimation is used. Therefore, it is important to test for normality and continuous data. Since the data was measured using Likert scale, continuity of the data can be accounted for. There are two kinds of non-normal data: Univariate and Multivariate (Kline, 1988). The key indicators used to measure if the data is univariate normally distributed are: skeweness and kurtosis (Hair et al., 2006). The test to check for univariate normality was conducted in chapter 5 (see Section 5.2.1.2), in addition, to testing for skeweness and kurtosis, Kogomorov-Smirnoff (KS) test was also conducted. These test results concluded that the items used in the current model obeyed the rule of univariate normality. In addition, the distribution curve for all the constructs is presented in Appendix 7A to indicate pictorially that the distribution curves are a bell curve. The tests to check for multivariate normality are: linearity and homoscedasticity (Hair et al., 2006). The test for linearity and homoscedasticity was conducted using bivariate plot analysis. Scatterplots between various variables (see Appendix 7B) reveal that the data is linear and abides by the homoscedasticity rules.

2. *Completely random missing data* **–** The second basic assumption of SEM techniques is that of missing data. Kaplan (2009) argue that randomly missing data may not cause any concerns but on the other hand, if there is a systematic method to missing data then this may be a cause of problem. Missing Value Analysis (MVA) was conducted in Chapter 5 (see Section 5.2.1.1) and the results reveal no cause of concern.
3. *Large sample size* – The size of the sample plays a key role in testing of a structural model using SEM technique. The primary reason is the impact of the sample size on the 'power of statistical inference' (Diamantopoulos and Siguaw, 2000; Hair et al., 2006). This statistical power refers to the probability of rejecting the null hypothesis

when it should be rejected (Hair et al., 2006). *"The probability of failing to reject a null hypothesis when it is actually false"* is due to **Type II error** (Hair et al., 2006; p. 10). One of the three key factors that have an impact on the statistical power is sample size. As sample size increases, the statistical power also increases (Diamantopoulos and Siguaw, 2000). However, in SEM there is a risk of obtaining too much power. Therefore, a sample size of 200 is recommended for achieving good levels of statistical power. Although, when considering the right sample size for testing a particular model, a number of factors (such as, number of parameters, variable loadings and error terms to be estimated) should be taken into consideration as well. Considering the complexity of the structural model that needs to be tested in this study, the sample size of 178 cases for this study is just enough to estimate the structural model.

4. *Multicollinearity* – Multicollinearity is defined as high correlations among the independent (exogenous) constructs (Kline, 1988). Multicollinearity is a major cause for concern as this may result in highly unstable results and difficulty in interpreting the impact of individual exogenous constructs on the endogenous variable(s) (Hair et al., 2006). The issue of multicollinearity is a major concern particularly for marketing researchers (Grewal, Cote, and Baumgartner, 2004). They argue that 31 studies out of 42 published between 1999 and 2000 in marketing journals faced potential multicollinearity problems. Grewal, Cote, and Baumgartner (2004) also argue that Type II errors reach unacceptable levels when multicollinearity is high. In the existing literature, there are several tests put forward to deal with the problem of multicollinearity (for example, Bollen, 1989; Grewal, Cote, and Baumgartner, 2004; Hair et al., 2006; Kaplan, 1994). To test for any multicollinearity issues, in this study, the correlation matrix containing all the bivariate correlations was examined (see

Table 7.6). The rule of thumb when testing for multicollinearity using the correlation matrix is, if the bivariate correlation between any two variables is greater than 0.80 then this model may face issues from multicollinearity (Hair et al., 2006; Grewal, Cote, and Baumgartner, 2004). In addition, Fornell and Larcker (1981) argue that in addition to examining the correlation matrix, testing for Average Variance Extracted (AVE) and discriminant validity may also provide evidence of any issues pertaining to multicollinearity. The results of the AVE test and discriminant validity test presented in Chapter 6 indicate that multicollinearity does not pose any potential problem to the results in the current study. Multicollinearity between moderator variables was tested and the results are presented in the next section.

In addition, to the above mentioned steps taken to satisfy the assumptions of SEM, steps were taken to reduce or remove any potential threats from outliers (see Chapter 4) and Common Method Variance (CMV) (see Chapter 6). These steps and procedures provide enough evidence that the major assumptions that are associated with SEM are dealt with and valid conclusions from the structural model can be drawn.

7.4 Testing of Hypotheses using SEM

In order to test the hypotheses depicted in the conceptual model (Chapter 3) AMOS v.22 statistical package was used. As mentioned in chapters 5 and 6, maximum likelihood (ML) technique was employed. Each path (γ) as shown in Figure 7.1 was assessed using the standardised estimates and the associated t-values/ C.R. (critical ratio). To reject the null hypotheses there are two criteria that should be tested, that is, the path coefficients (standardised estimates) should be statistically significant and should be in the predicted direction (that is, positive or negative) (Hair et al., 2006). As illustrated in the path diagram, all the five hypothesized relationships are one-directional, the critical t-values of 1.645 were used for α = 0.05 (one-tailed t-test). In addition, all the hypotheses are predicted to have a positive relationship except for hypotheses 3 (γ_3) and hypotheses 5 (γ_5). Hypotheses 3a argues that marketing discontinuity negatively moderates the relationship between ambidextrous market learning (AML) and product advantage. Hypotheses 5 argue that customer discontinuity of the product negatively moderates the relationship between product advantage and product performance.

All constructs in the structural model were measured using disaggregation in which all the original items measuring the various constructs were used. The only two constructs with a single item indicator used in the structural model were, R&D expenditure of the firm; and Firm size (Total number of staff) which were used to control the study. In this section the following three topics will be covered: 1) Testing of single item indicators; 2) Testing of mediators in SEM; and 3) Testing of moderators in SEM.

1. *Testing of single item indicators*: As mentioned earlier, traditionally using single item indicators in SEM are frowned upon but in recent years (for example, Hayduk and Littvay, 2012) there is a growing trend of structural models with single item indicators. The primary reasons for not using single item indicators in SEM are: 1) Since single item indicators like other constructs do not have variance and this may lead to some empirical problems as the measurement reliability cannot be measured and even if it was possible, it would be low (for example, Fuchs and Diamantopoulos, 2009); and 2) Aaker and Bagozzi (1979) argue that use of single item indicators in a structural model may lead to biased conclusions. To overcome this problem, Brown (2006) argues that if the error variance of the single item is constrained then there should be no empirical problems. In addition, MacKenzie (2001) argues that by partially constraining the random error, there is a control over the variance extracted from other sources and hence the variance extracted is largely from the underlying

concept itself. The error variance for the single item indicator is calculated using the formula below:

$$\text{Error Variance} = [(1-\alpha) * \delta^2]$$

Where,

α is the composite reliability of each construct

δ is the standard deviation and δ^2 is the variance of the construct

In the case of single item indicators (for example, Firm size), it is not possible to measure its reliability and hence while calculating the error variance of the single item indicator the composite reliability (CR) is assumed to be 0.600.

The only single item indicators used in this model are firm size and the R&D expenditure; and the error variance is tabulated in Table 7.1.

Table 7.1 Single Item constructs

Constructs	**Composite Reliability (α)**	**Standard Deviation (δ)**	**Variance (δ^2)**	**Error Variance (calculated)**
Firm Size (Total staff)	0.600	2.53	6.41	2.56
R&D	0.600	1.62	2.64	1.05

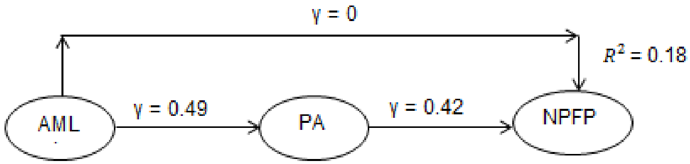
2. *Testing of mediators in SEM*: The use of mediators in the marketing literature is ever growing (Bagozzi, Gopinath, and Nyer, 1999), and the use of mediators in a structural model requires further testing. In a mediational hypothesis, the relationship between the independent and dependent variable is decomposed into two causal paths (Alwin and Hauser, 1975). To test the mediation hypothesis, the direct and indirect relationship was tested and both the hypothesis (that is, the direct and mediation) were significant and this fulfils the criteria for mediation. Testing of mediation in structural

equation modelling is far simpler in comparison to testing the mediation effect in regression analysis (Bollen, Pearl, and Morgan, 2012; Byrne, 2009). To test the mediation effect, SEM allows the ease of interpretation due to the array of model fit information provided by SEM. There are five possible mediation effects as shown in Figure 7.2. Model 1 is called as the *"pure mediation"*, that is there is no direct relationship between the independent and dependent variable. Therefore, in this model the direct relationship is set to 0. Model 2 presents *"partial mediation"* where, the direct and in-direct (that is, mediation hypotheses) are measured. The other three models (Model 3, 4, and 5) represent *"no mediation"* where one of the two hypothesised in-direct relationship or both the hypothesised relation is set to 0. The next step is to test the model fit and measure which of the above model provides the best model fit. From figure 7.2 it is clearly evident that there is a partial mediation between Ambidextrous Market Learning (AML) and New Product Financial Performance (NPFP) which is mediated by Product Advantage (PA) has the best model fit. In addition, r^2 of the dependent variable when comparing the different model is highest in partial mediation (Model 2). Therefore, it is evident that there is partial mediation between ambidextrous market learning and financial performance which is mediated by product advantage. In addition, developing a main effect was useful for testing the use of moderators in SEM (which is covered in the next section).

Testing of moderators in SEM: Testing of moderation hypothesis using any multivariate analysis is an important topic as there are few statistical issues associated with the interaction terms (Little, Bovaird, and Widaman, 2006). When testing for the moderation hypothesis, it is generally modelled using the multiplicative term between the independent variable and the moderator variable (Aiken and West, 1991). The statistical concern with using multiplicative terms is of high multicollinearity and hence this may lead to structural bias (Cohen, 1978; Cronbach, 1987; Little, Bovaird, and Widaman, 2006; Ping, 1995). Therefore to overcome this issue, several researchers (for example, Aiken and West, 1991; Cohen, 1978) argue that using a multiplicative term between mean centred independent variable and moderator variable would eradicate the issue of multicollinearity. Later several scholars (for example, Kromrey and Foster-Johnson, 1998) argued that using a multiplicative term between mean centred independent and moderator variable does not differ and hence the issue of multicollinearity still prevails. To overcome this problem, Ping (1995) and Little, Bovaird, Widaman (2006) recommended the following procedures which were followed to model moderators in this study. The procedure proposed by Ping (1995) involves two steps. The first step of this process is to estimate the main effect model (that is, including only the independent, dependent and mediator variables and the moderators are set to 0). Then construct the full structural model (which includes the moderating variables and the product terms as well). The primary reason for testing the main effect model and the moderator effect model (or the full model) is to test for any significant improvements in χ^2/df test (Ping, 1995). The chi-square of the fully constrained model (that is, the interaction terms were set to zero) was compared with the unconstrained model (that is, the interaction terms were let to freely estimate).

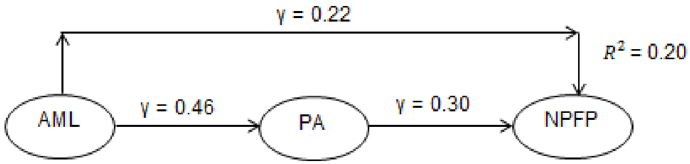
Figure 7.2 Testing of mediator

Pure Mediation (Model 1):



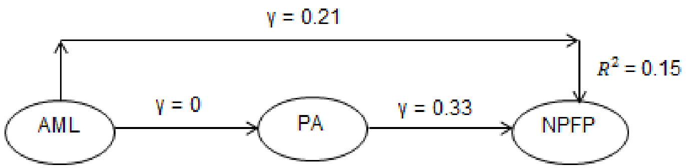
Model Fit: χ^2/df = 1.322, p = .067, GFI = 0.944, CFI = 0.984, IFI = 0.984, TLI = 0.978, NFI = 0.938, PCFI = 0.716, RMSEA = .04

Partial Mediation (Model 2):



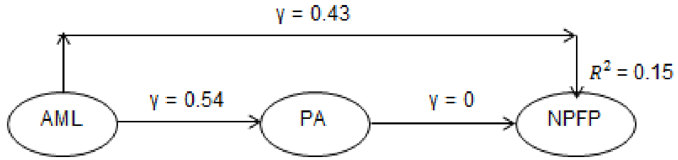
Model Fit: χ^2/df = 1.234, p = .130, GFI = 0.95, CFI = 0.99, IFI = 0.99, TLI = 0.984, NFI = 0.943, PCFI = 0.704, RMSEA = .036

No Mediation (Model 3):



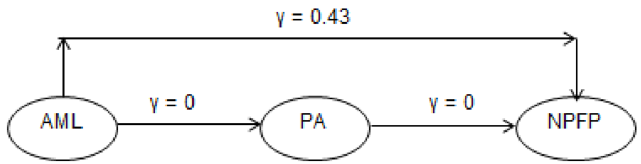
Model Fit: χ^2/df = 1.783, p = .001, GFI = 0.93, CFI = 0.96, IFI = 0.962, TLI = 0.95, NFI = 0.92, PCFI = 0.69, RMSEA = .067

No Mediation (Model 4):



Model Fit: χ^2/df = 1.407, p = .033, GFI = 0.94, CFI = 0.98, IFI = 0.98, TLI = 0.972, NFI = 0.934, PCFI = 0.704, RMSEA = .048

No Mediation (Model 5):



Model Fit: Is not identified

The results of the mediation test (see previous section) indicate that there is a partial mediation between ambidextrous market learning and new product financial performance which is mediated by product advantage. The next step is to measure the effect size of this mediation relationship. The effect size of mediation effect indicates to what extent or to what degree is this relationship (the direct hypothesis, i.e. in this study, the relationship between ambidextrous market learning and new product financial performance) transmitted through the mediated mechanism. In recent years, scholars (for example, MacKinnon, 2008; MacKinnon, Fairchild and Fritz, 2007; Mathieu and Taylor, 2006; Raykov et al., 2008) have discussed many effect sizes with potential application in mediation analysis.

The most popular effect size measure is the Mathieu and Taylor's (2006) measure which indicates whether there is partial, complete or perfect mediation (the results discussed in the previous section). Though this measure provides significant insights into the mediation model, it does not provide a statistical measure that provides more practical importance. In the existing literature, Preacher and Kelley (2011) suggest that researchers should be careful when choosing the most appropriate effect size measure to indicate the strength of the mediation model. They recommend three metric/criteria that one could use in order to choose the most appropriate effect size measure and these are as follows:

1. The most important criterion is whether the effect size measure easily interpretable? Many measures for example, the ratio measures of relative magnitude of the strength of the direct and indirect relationship put forth by Alwin and Hauser (1975) and MacKinnon (1994) can be misleading and may not provide practical insights. This may be because these ratios do not take the variance explained or the covariance between the independent, dependent and mediating variables and only focuses on the path coefficient (γ).

2. The second most important criterion is whether confidence interval can be calculated for the effect size measure? Many measures for example, the indices of explained variance put forth by MacKinnon (2008), and Lindenberger and Potter (1998) can be misleading as argued by Sechrest and Yeaton (1982) that researchers assume that amount of variance to be explained is 100 per cent. Hence, this may lead to false confidence interval levels.
3. The final criterion is whether the effect size measure independent of the sample size? Most of the effect size measures in the existing literature are independent of the sample size.

Therefore, in this study, taking the advantages and limitations into consideration, Preacher and Kelley's (2011) kappa squared (K^2) was chosen to measure the effect size for mediation analysis. K^2 is interpreted as *"the proportion of the maximum possible indirect effect that could have occurred, had the constituent effect been as large as the design and data permitted"* (Preacher and Kelley, 2011, p. 106). This implies if $K^2 = 0$ then there is no mediation and if $K^2 = 1$ then this indicates that the mediating effect is as large as it possibly could have been. The value of K^2 cannot be negative and is between 0 and 1. K^2 depends on the covariance between the mediating, dependent and independent variables, the variance of the three variables and the path coefficients of the mediating effects. K^2 was calculated using the website (http://stats.myresearchsurvey.com/kappasquared/).

The results indicate that the K^2 calculated for the mediation analysis in this study is 0.134 with 95 % confidence interval (-0.068, 0.975). This indicates that the mediation level is at medium as the confidence interval is less than 0.25. This result indicates that there is a medium mediating relationship between AML on PA and NPFP.

To test the interaction term hypothesis, the first step involved calculating the factor loading and the error variance for the interaction terms used in this model (that is, AMLxMD, AMLxTD, and PAxCD). To calculate the factor loading and error variance of the interaction term, it was necessary to create single item measures for all terms involved in the interaction terms (that is, AML, MD, TD, PA, and CD). Then it was important to calculate the error variance for all the single item measures (see Table 7.2).

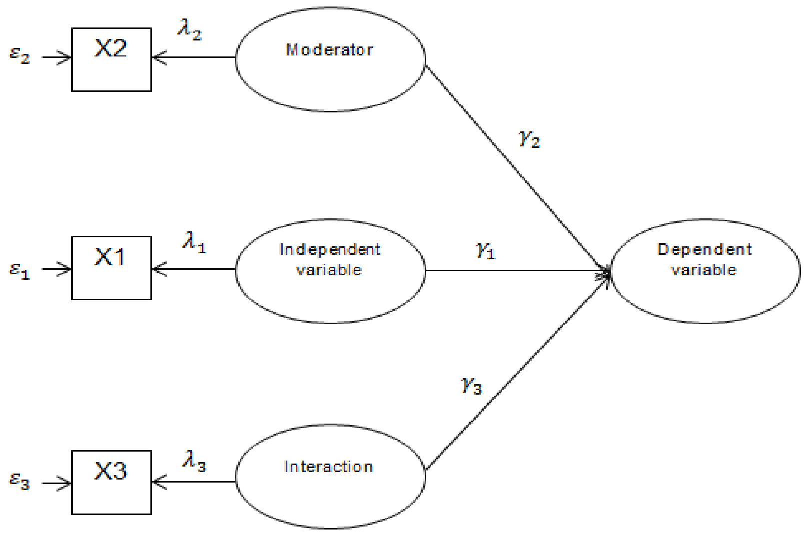
Table 7.2 To calculate the error variance for the single-item constructs

Constructs	**Composite Reliability (α)**	**Standard Deviation (δ)**	**Variance (δ^2)**	**Error Variance (calculated)**
Ambidextrous Market Learning (AML)	0.73	0.97	0.94	0.25
Product Advantage (PA)	0.79	0.99	0.98	0.20
Marketing Discontinuity (MD)	0.77	1.16	1.35	0.32
Technological Discontinuity (TD)	0.85	1.15	1.35	0.21
Customer Discontinuity (CD)	0.787	1.35	1.84	0.39

The next step after calculating the error variance of all the single-item terms used in the interaction term, it was necessary to calculate the factor loading and error variance of the interaction term. The interaction term used in the model was a single-item measure, which was calculated by multiplying the aggregate independent variable and aggregate moderator variable. Then this interaction term was residual-centred (Ping, 1995). To calculate the error variance and the factor loading of the interaction terms, Figure 7.3

illustrates the interaction model. As seen from the figure, the objective is to calculate λ_3 andθ_3, that is the error variance of the interaction term.

Figure 7.3 Calculating the error variance and factor loading of the interaction term



(Adapted from Ping, 1995)

The formula used to calculate the factor loading of the interaction term was:

Factor Loading = (Summated factor loading of independent variable) x (Summated factor loading of dependent variable)

$\lambda_3 = \lambda_1 * \lambda_2$

(Source: Ping, 1995)

, and the formula to calculate the error variance of the interaction term is as follows:

$\theta_3 = \lambda_1^2 * \theta_2 + \lambda_2^2 * \theta_1 + \theta_1 * \theta_2$

Error variance of the interaction term = [$(independent\ variable\ loading)^2$ * moderator error variance] + [$(moderator\ loading)^2$*(independent variable error variance)] + [(moderator error variance) * (independent variable error variance)]

The error variance and the factor loading of the three interaction terms were calculated using the above equations and are presented in Table 7.3.

Table 7.3 Factor loading and error variance of the interaction terms

Interaction Term	Factor Loading	Error variance
AMLxMD	0.68	0.401
AMLxTD	0.69	0.357
PAxCD	0.77	0.411

The next step involved in testing the moderating effect is to test the moderation effect by comparing the chi-square values of the fully constrained v/s the unconstrained model. To test the moderation effect, first the complete structural model was estimated with the interaction terms fixed at 0 and all other effects were let to estimate freely. In the second step, the structural model was estimated with all parameters tested freely. To test the moderation effect, the reduction in chi-square value from the fully constrained to the unconstrained model was checked. If the model did not fit the data well in the case of the unconstrained model then this clearly indicates that the use of the moderator terms in the model is inappropriate. The values of the model fit are presented in Table 7.4.

Table 7.4 Model fit comparison between fully constrained and unconstrained

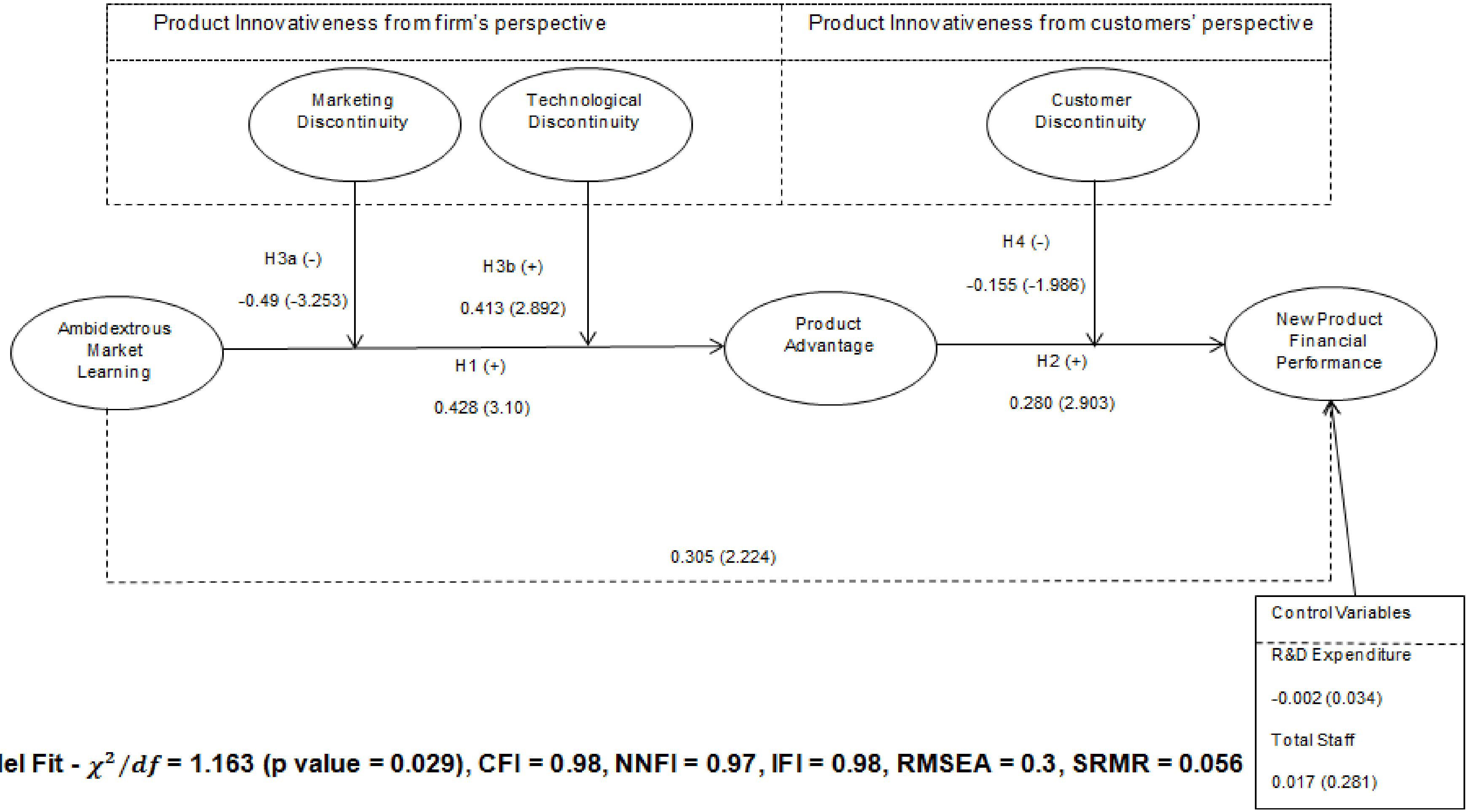
Model	χ^2/df	P	CFI	TLI	NNFI	RMSEA
Fully constrained	1.424	0	0.94	0.93	0.94	0.049
Unconstrained	1.162	0.033	0.98	0.97	0.98	0.030

The above table clearly indicates that the model fits the data better when the model is unconstrained and this unconstrained model is taken further to test the hypotheses. The resulting model fit showed above average fit indices. Though the p-value was close to the minimum value of 0.05 but was not greater than 0.05. The other fit indices illustrate an overall good model fit (all values greater than 0.95). In addition, the composite reliability, average variance extracted (AVE) and discriminant validity of all the constructs in the structural model were tested again. The AVE was greater than 0.50 and the composite reliability was greater than 0.70 for the all constructs. The structural model is also presented in Figure 7.4. In the next section, the results of the hypotheses testing are presented.

7.5 Results of Hypotheses testing

The path coefficients and the t-values for all the hypotheses (including the control variable relationships) are presented in Table 7.5. All the hypothesised relationships are statistically significant. The results of testing hypothesis H1 and H2 are supported. That is Ambidextrous Market Learning (AML) is positively related with Product Advantage (PA) and PA is positively related with new product financial performance (NPFP). The result of H1 adds to the ambidexterity - product performance debate. As mentioned in Chapter 3, by focusing on the bi-polar view of AML, exploitation market learning, that is, focusing on the current product-market experience and analysing the current needs and wants of the customer leads to developing products which are perceived by customers as useful and non-risky (that is, product meaningfulness). And on the other hand, exploration market learning, that is, focusing on the emerging technologies and market trends would lead to developing products which are unique in comparison to its competing products. In this section the results of all the hypotheses will be discussed in-detail.

Figure 7.4 Structural model results



Model Fit - χ^2/df = 1.163 (p value = 0.029), CFI = 0.98, NNFI = 0.97, IFI = 0.98, RMSEA = 0.3, SRMR = 0.056

Table 7.5 Hypothesised Relationships

Hypothesis	**Relationships**	**Standardised Coefficients**	**t-values**
H1	Ambidextrous Market Learning ➡ Product Advantage	0.428	3.171
H1a	Ambidextrous Market Learning ➡ New Product Financial Performance	0.305	2.224
H2	Product Advantage ➡ New Product Financial Performance	0.280	2.903
H3a	Marketing Discontinuity x Ambidextrous Market Learning ➡ Product Advantage	-0.490	-3.253
H3b	Technological Discontinuity x Ambidextrous Market Learning ➡ Product Advantage	0.413	2.892
H4	Customer Discontinuity x Product Advantage ➡ New Product Financial Performance	-0.155	-1.986
Control Variable	R&D Expenditure ➡ New Product financial Performance	-0.002	-0.021
Control Variable	Firm Size (Number of employees) ➡ New Product Financial Performance	0.017	0.173

χ^2/df = 1.162 (p = 0.033), CFI = 0.98, IFI = 0.98, NNFI/TLI = 0.97, RMSEA = 0.030, GFI = 0.89, SRMR = 0.056
One-tailed t-test values were taken due to one-directional hypothesised relationship hence, critical t-value is 1.645 and 2.325 for p<0.05 and p<0.01 respectively

Table 7.6 Correlation Matrix

	AML	MD	TD	MDxAML	TDxAML	CD	CDxPA	RND	FS
AML	**1**								
MD	0.287	1							
TD	0.190	0.538	1						
MDxAML	-0.058	0.005	-0.108	1					
TDxAML	-0.025	-0.092	0.012	0.657	1				
CD	0.096	0.069	0.284	0.009	0.135	1			
CDxPA	-0.007	0.071	0.148	0.035	0.120	0.003	1		
RND	0.320	0.183	0.130	0.144	0.075	0.420	-0.035	1	
FS	0.200	-0.080	0.041	-0.024	-0.049	-0.146	0.060	-0.188	1

AML – Ambidextrous Market Learning
MD – Marketing Discontinuity
TD – Technological Discontinuity
CD – Customer Discontinuity
RND – Research and Development Percentage
FS – Firm Size (total number of employees)

7.5.1 Hypotheses 1 and 2

The results support hypotheses H1 and H2. The path coefficient of H1 is 0.428 at t-value of 3.171. This result supports the ambidexterity literature debate. That is, ambidextrous market learning is positively related to product advantage. As mentioned, in Chapter 2, researchers (for example, Kyriakopoulos and Moorman, 2004; Miller and Friesen, 1986; Yannopoulos, Auh, and Menguc, 2012) argue that by focusing on two different activities firms tend to find it detrimental to their growth and in addition, a small group of researchers find ambidexterity to have a negative impact on radical innovations. This positive result clearly indicates that ambidextrous market learning firms tend to develop products which are simultaneously superior to its competing products and meaningful to its customers. Therefore, in line with the existing literature (for example, Hughes, Martin, Morgan, and Robson, 2010; Jansen, Tempelaar, van den Bosch, and Volberda, 2009; Wang and Rafiq, 2014) this result adds to the debate that ambidextrous (market learning) firms develop products with advantage in high-tech industries.

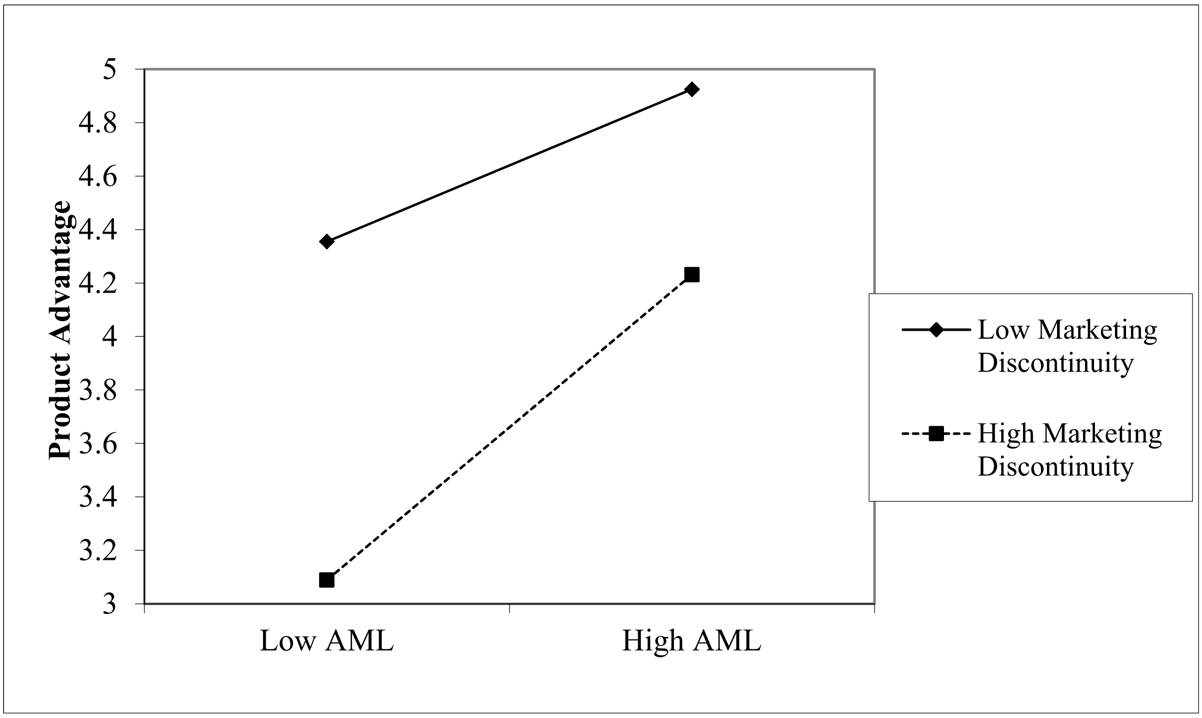
In addition, as mentioned in chapter 2, Junni et al., (2013) illustrate that their meta-analysis on the ambidexterity literature resulted in a non-significant relationship between ambidexterity and performance. The results of H1 and H2 clearly indicate that ambidextrous market learning has a positive and a significant impact on new product financial performance (direct and in-direct). The path coefficient of H2 is 0.280 at a t-value of 2.903. This positive result clearly indicates that product advantage is positively related to new product financial performance. This result answers one of the questions raised in the ambidexterity literature of 'whether there is any benefit of implementing ambidextrous culture/design/behaviour?' The result of H1 and H3 provides insight into how ambidextrous market learning has an impact on product advantage and hence new product financial performance, which in the existing literature is not yet discussed. In addition, in the existing literature the primary focus has been to measure the impact of ambidexterity on firm performance (for example, Clercq, Thongpapanl, and Dimov, 2013; Chang and Hughes, 2012; Lin et al., 2012) though there are some studies focusing the impact of ambidexterity on product performance (for example, He and Wong, 2004; Hughes et al., 2010; Wang and Rafiq, 2014; Li and Huang, 2012).

The structural model used to test the hypotheses was controlled using two key indicators, firm size; and R&D expenditure as a percentage of turnover. Control variables are added in the model to test the model in different contexts, that is, if the relationship between the control variable and the endogenous variable is significant then the inclusion of the control variable in the main model is justified (Becker, 2005). R&D expenditure plays a pivotal role in product development strategy. For example, Cyert and March (1963) argue that firms with high levels of R&D expenditure may focus more on exploration activities. He and Wong (2004) argue that firms with high amounts of slack resources may be more effective at developing an ambidextrous strategy. In addition, a high level of R&D expenditure also indicates that firms may focus more on developing more innovative products. Though the use of R&D expenditure is not that common in the existing literature on ambidexterity, there are few studies (for example, Wang and Rafiq, 2014) focusing on controlling the model with R&D expenditure, as this may potentially have an impact on the results. The relationship between R&D expenditure and new product financial performance was non-significant (t-value of -0.021) with a path coefficient of -0.002. The other control variable used in this model is firm size in terms of number of employees. Firm size in terms of number of employees is the most commonly used control variable in the ambidexterity literature (for example, Chang and Hughes, 2012; Clercq, Thongpapanl, and Dimov, 2013; Chang and Hughes, 2012; Lin et al., 2012; Fernhaber and Patel, 2012). Firm size was included as a control variable in this study primarily because firm size can potentially influence product performance by affecting the number of products developed and the human resources available to develop products. The relationship between firm size and new product financial performance was non-significant (t-value of 0.173) with a path coefficient of 0.017. Considering the strength of these relationships in comparison to the strength of the hypotheses, and the (non)significance of these relationships clearly indicates that there is no bias exerted from the control variables on the relationship between other variables.

7.5.2 Results of the moderator variables

The hypothesis H3a states that the positive relationship between ambidextrous market learning and product advantage is lower, the higher the marketing discontinuity. This hypothesis is significant (t-value of -3.253) with a path coefficient of -0.490. This result indicates that the relationship between ambidextrous market learning and product advantage reduces as the firm develops products that are aimed at new customers/markets or the firm develops new product line and/or a new product category. Figure 7.5 represents this relationship in a graphical format. In line with the existing literature, (for example, Tatikonda and Rosenthal, 2000; Song and Parry, 1999) the result indicates that uncertainty involved in developing innovative products for new customers is much higher and hence more challenging to clearly understand what are the needs and wants of the customer. In addition, as a firm operating in a high-tech industry faces challenges from new competitors in new markets, the uncertainty involved in developing superior products in comparison to the competitors is much higher.

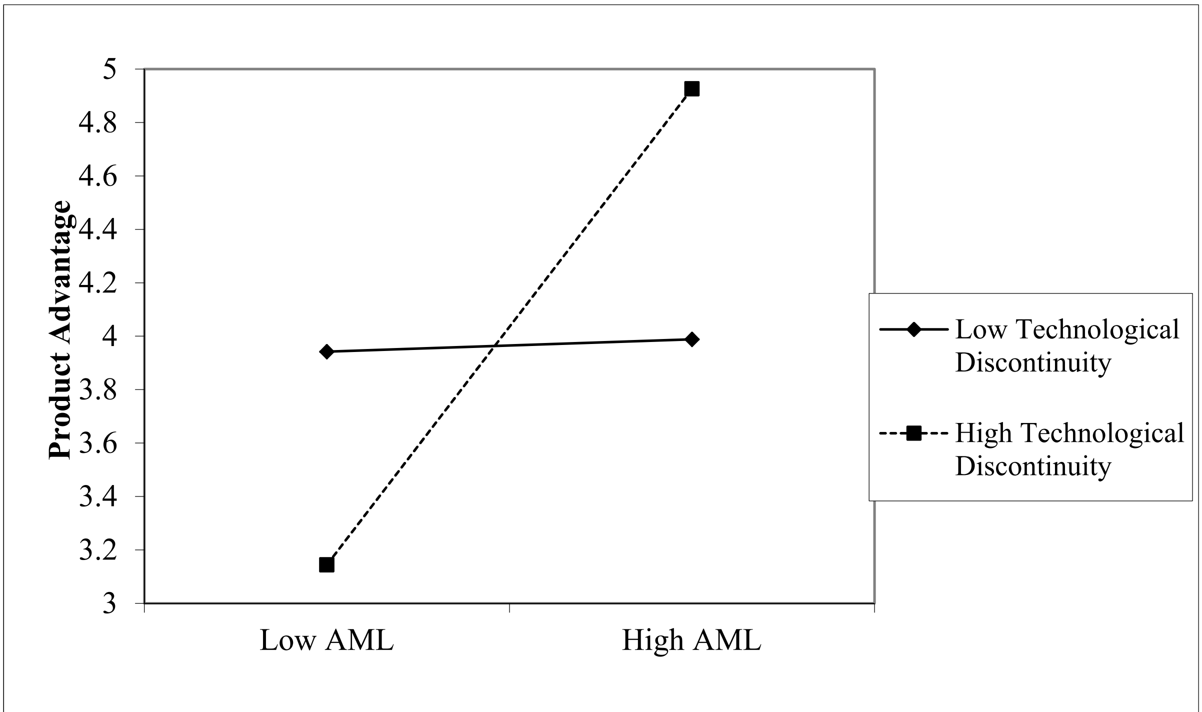
Figure 7.5 Graphical representation of MD x AML on Product Advantage



From Figure 7.5 it is clear that ambidextrous market learning firms operating in high-tech industries should focus on developing products for their current market. This negative relationship could be explained due the fact that in high-tech industries, firms face competitive challenge and high market turbulence because of which firms need to focus on their current product line and focus on developing products for their current customers. In this competitive market firms need to defend their own turf. The other interesting finding from this graph is that at low levels of ambidextrous market learning, firms develop products with more advantage when firms are catering to the needs and wants of new customers. This could be because firms developing new product line or product category for new customers should primarily focus on exploratory market learning and not focus on being ambidextrous. The other key finding here is that product advantage is highest when firms indulge in high levels of ambidextrous market learning.

The hypothesis H3b states that the positive relationship between ambidextrous market learning and product advantage is higher, higher the technological discontinuity. This hypothesis is significant (t-value of 2.892) with a path coefficient of 0.413. This result indicates that the relationship between ambidextrous market learning and product advantage increases as the firm develops new products with the use of new technology or a new engineering process was employed. Figure 7.6 represents this relationship in a graphical format.

Figure 7.6 Graphical representation of TD x AML on Product Advantage

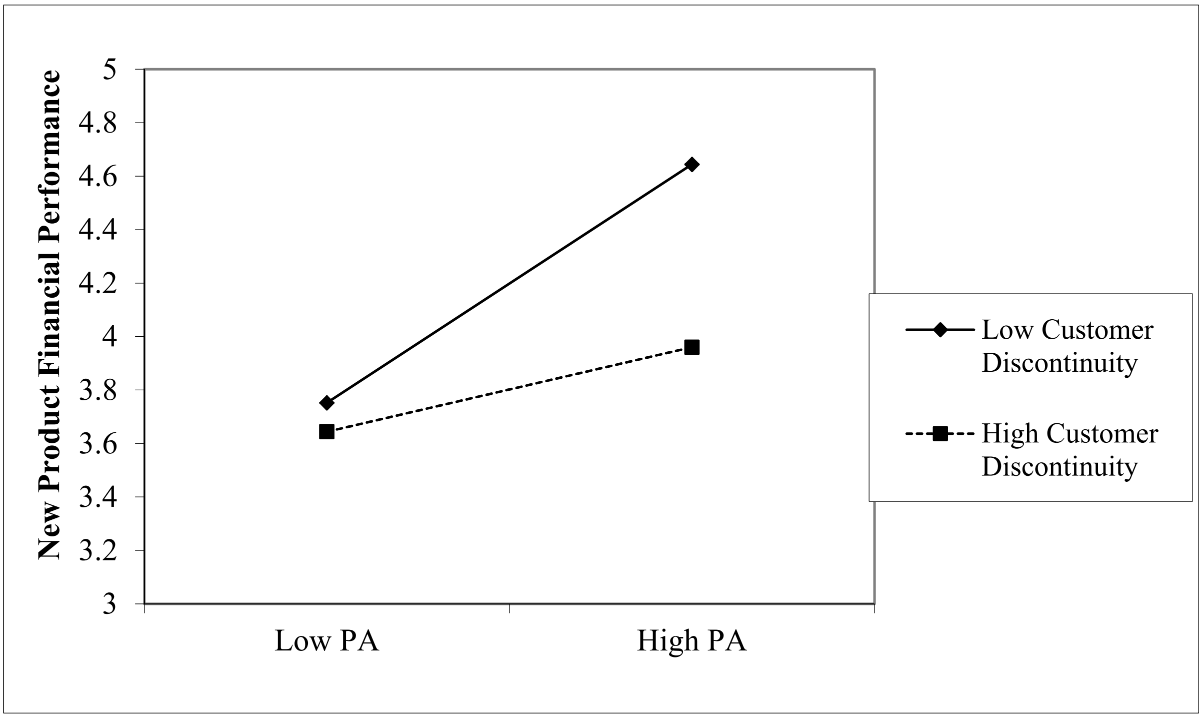


In line with the existing literature, (Day, 1994; 2002; Levinthal and March, 1993) the above graph indicates that when firms tend to be ambidextrous, they learn about how the competitors develop new products, what processes or new technology can be applied to make the product more superior and in addition, firms learning about their current process and technology more in-depth to understand whether they can develop new products that are both superior and meet the needs and wants of the customer. Therefore, firms operating in high-tech industries need to keep one eye on their process and one eye on the changing market trends. A non-significant direct relationship could also be explained due to the fact that as firms develop new technology or new production technique without understanding the needs and wants of the customers firms develop products with no benefits and these products tend to not be meaningful to the customers and hence not superior. From Figure 7.6 it is clearly evident that firms develop products with more advantage when firms employ a high level of ambidextrous market learning strategy and develop these products with high levels of technological advancements.

From both the above figures it is clear that at low levels of technological discontinuity and high levels of marketing discontinuity there is hardly any difference between when the firm employs high or low levels of ambidextrous market learning. In the post hoc analysis, the combined effect of the product innovativeness from the firm's perspective will be discussed in detail.

The hypothesis H4 states that the positive relationship between product advantage and new product financial performance is lower, the higher the customer discontinuity. This hypothesis is significant (t-value of -1.986) with a path coefficient of -0.155. This result indicates that the relationship between product advantage and new product financial performance reduces as the firm develops new products which require a major learning effort and a behavioural change to use the new product. Figure 7.7 represents this relationship in a graphical format.

Figure 7.7 Graphical representation of CD x PA on New product financial performance



From Figure 7.7 it is clearly evident that new product financial performance is the highest when product advantage is high and low customer discontinuity. In line with the existing literature (Calantone, Chan, and Cui, 2006; McNally, Cavusgil and Calantone, 2010) that customers unaware of the products due to its innovativeness makes it even more difficult for the customers to trust the product and it takes longer to fully understand the potential advantages of the product. Though in the existing literature, the relationship between customer discontinuity and product performance is extensively covered but the relationship between product innovativeness from the customer's perspective and product performance is inconsistent and unclear, this result sheds new light on the relationship between product advantage, customer discontinuity and new product financial performance.

The result indicates that firms operating in high-tech industries that develop new products that have high product advantage but does not require major learning effort from the customers tend to be financially more successful. For example, an automobile part manufacturing firm develops a new part that may increase the fuel efficiency of the car but would require the automobile manufacturing firm to redesign the entire car would find it difficult to be financially successful. In the next section, a post-hoc analysis of the relationship between ambidextrous market learning and product advantage is discussed in detail.

7.6 Post-Hoc Analysis I

The individual moderating effects of marketing discontinuity and technological discontinuity were discussed in the previous section. In this section, how ambidextrous market learning has an impact on product advantage when the effects of both the moderating variables are taken together is discussed. The structural equation used to assess the overall effect is as shown below:

$$PA = 0.428*AML + 0.143*MD + 0.054*TD + 0.413*AML*TD - 0.490*AML*MD$$

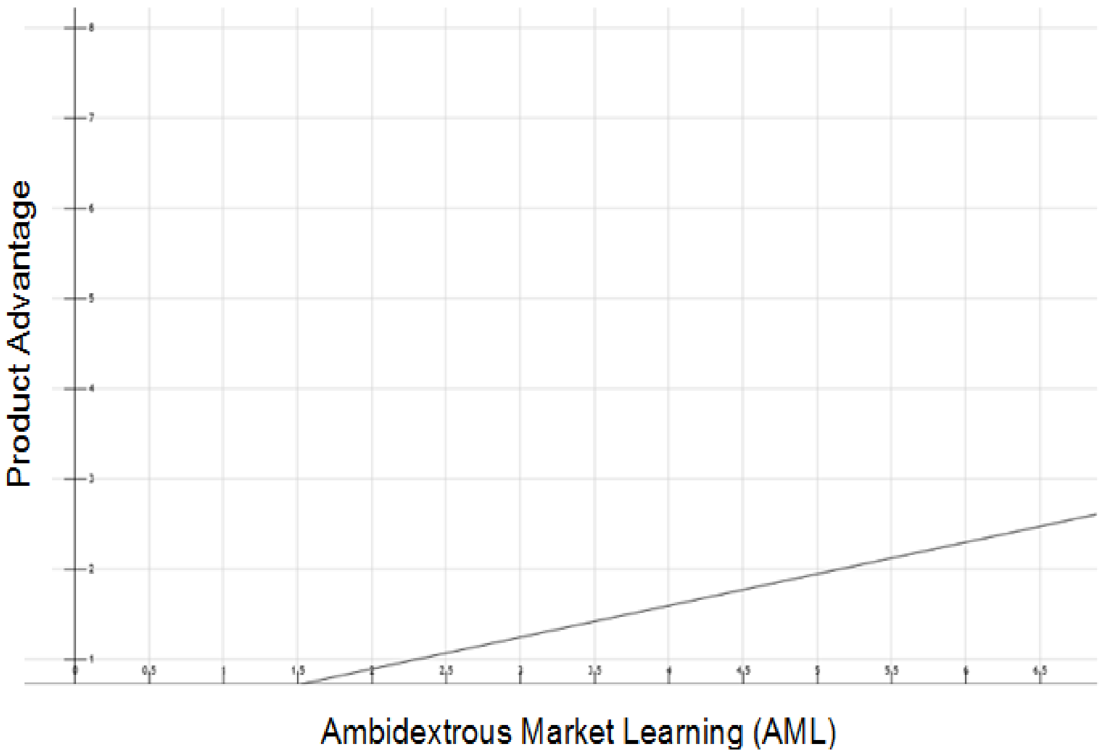
The above equation represents how ambidextrous market learning interacts with marketing and technological discontinuity (that is, product innovativeness from the firm's perspective) and act as antecedents to product advantage. This explanation provides evidence to when it is useful to implement an ambidextrous market learning strategy. In the above equation, the variables range between 1 and 7, based on the questionnaire and the coefficients range from -1 to 1. Based on this equation there are four scenarios that rise.

1. When MD = 1 and TD = 1;
2. When MD = 7 and TD = 1;
3. When TD = 7 and MD = 1; and
4. When MD = TD = 7

The first two scenarios explain how ambidextrous market learning firms operating in the High-tech industries develop new products with advantage when firms do not implement a new technological process or a new manufacturing process or develop a new production process to develop new products for the same market (i.e. scenario 1) and for different markets (i.e. scenario 2). On the other hand, the last two scenarios explain how ambidextrous market learning firms operating in high-tech industries develop new products with advantage when firms implement a new technological process or a new manufacturing process or develop a new production process to develop new products for the same market (i.e. scenario 3) and for different markets (i.e. scenario 4). The four scenarios are explained, using graphs presented in Figure 7.8, 7.9, 7.10 and 7.11.

Scenario 1 (MD = TD = 1): Is there any advantage in implementing ambidextrous market learning culture or behaviour when firms are not investing in new technology to develop new products (TD = 1) and when firms are not searching for new markets/customers for their existing products? To formulate this scenario, in the above mentioned equation, the strength of marketing discontinuity (MD) and technological discontinuity (TD) was considered as 1.

Figure 7.8 Graphical representation of the integrated effect on PA (MD and TD = 1)

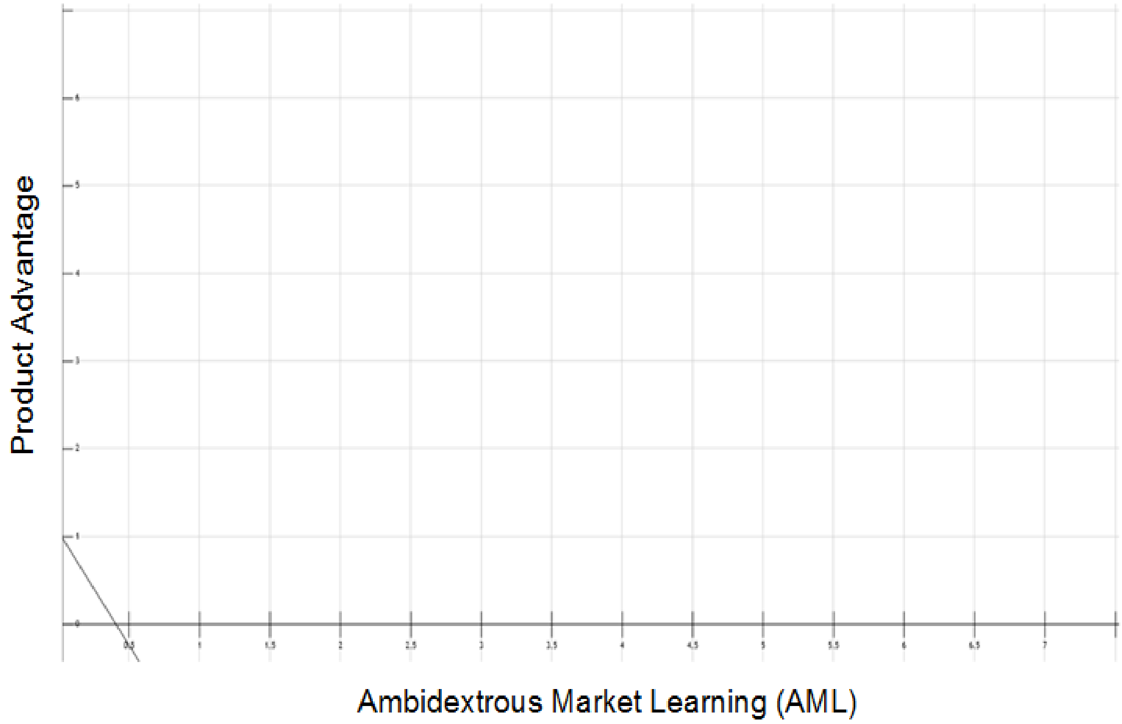


From the above graph it can be seen that AML has a positive impact on product advantage (i.e. products that are simultaneously superior to its competing products and is meaningful to its customers). Though it can be seen that there is lag, i.e. at low levels of AML there is no impact on product advantage and even when firms have high levels of ambidextrous market learning (that is, simultaneously focusing on high levels (nearing 7 on the Likert scale) of exploratory and exploitative market learning leads to developing products with low levels of product advantage (as it can be seen from the above Figure). This is in line with the existing literature, for example, Day (1994) argues that in order to achieve sustainable competitive advantage, knowledge on improving current learning process comes from practices outside the industry. Therefore, at low levels of ambidextrous market learning, firms tend to develop products with no product advantage when MD and TD are low. It is an implementation cost that firms incur without receiving any additional benefits by not creating competitive advantage.

In addition, firms operating in high-tech industries are constantly faced with a high marketing and technological turbulence. Therefore, firms need to create an atmosphere that enables market information on the existing product/market through analysing the prior projects and simultaneously enable market information through studying of emerging competitors and technologies. Therefore, firms need to implement high levels of AML strategy to develop products with high advantage.

Scenario 2 (MD = 7, TD = 1): Is there any advantage to implement ambidextrous culture when firms are investing to search for new markets for their existing products (that is, TD is low)? To formulate this scenario, in the above mentioned equation, the strength of marketing discontinuity (MD) was taken as 7 and technological discontinuity (TD) was considered as 1.

Figure 7.9 Graphical representation of the integrated effect on PA (MD = 7 and TD = 1)



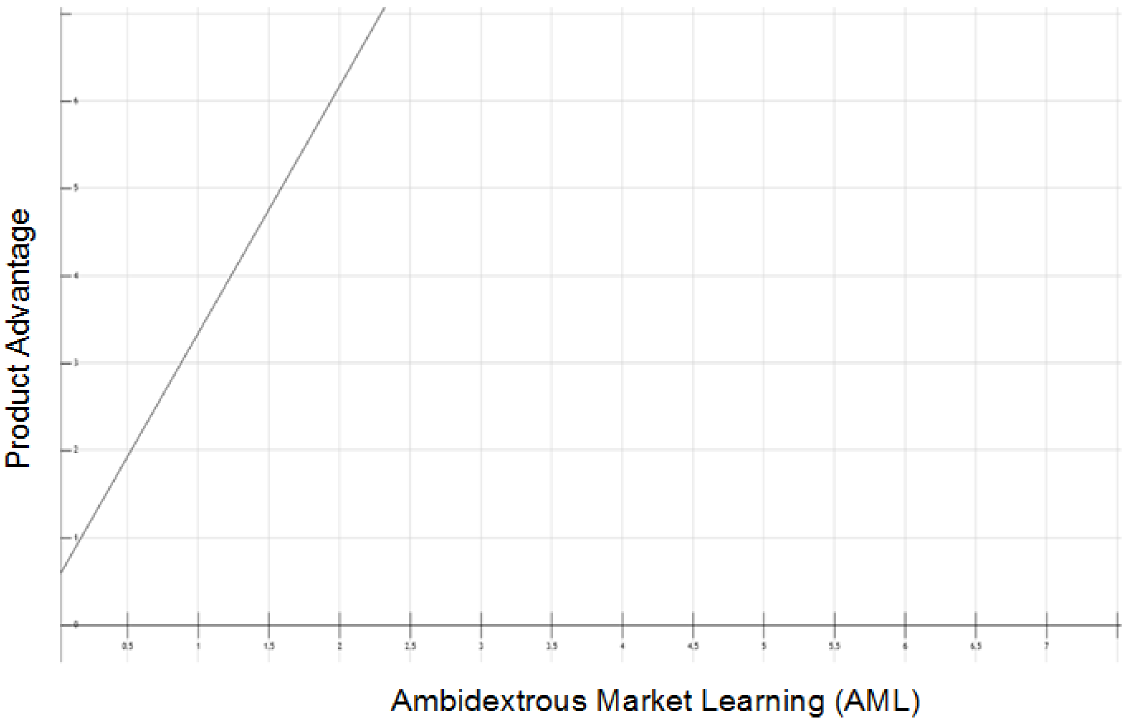
In such a scenario, firms are looking for new markets but not investing in new technologies to develop new products for new markets or customers. In such a case there is no impact of ambidextrous market learning on product advantage. This result is in line with the characterisation of firms operating in high-tech industries by Pavitt (1990). He argues that high-tech firms are highly differentiated. *"Specific technological skills in one field (e.g., developing pharmaceutical products) may be applicable in closely related fields (e.g., developing pesticides), but they are not much use in any many others (e.g., designing and building automobiles)"*. (p. 19).

In addition, Adams, Day and Dougherty (1998) argue that when firms develop new products in tangent with the customers, tend to be more successful. They argue that firms should not make the mistake of assuming that technology constitutes the product design. They state that *"when firms went out to see these customers, listened to them, and then used their extensive technology knowledge to see both the real needs of customers and how they* *might meet those needs. They leveraged their technology knowledge by talking to possible co-producers to develop a new manufacturing facility, by co-designing the chemicals with users by giving them R&D samples and then working with them on formulations for various uses”* (p. 412) tend to develop successful products.

Therefore, when AML firms tend to develop new products without the input of the customers and developing new products without implementing a new production process or a new manufacturing process or a new production process, tend to develop products with no product advantage. Hence, when firms enter new markets (geographically new or new product line) customers tend to prefer the competing products which are already available in the market or products which are technologically advanced.

Scenario 3 (TD = 7, MD = 1): Is there any advantage in implementing ambidextrous market learning culture or behaviour when firms are investing in new technology to develop products for the existing market? To formulate this scenario, in the above mentioned equation, the strength of marketing discontinuity (TD) was taken as 7 and technological discontinuity (MD) was considered as 1.

Figure 7.10 Graphical representation of the integrated effect on PA (TD = 7 and MD=1)



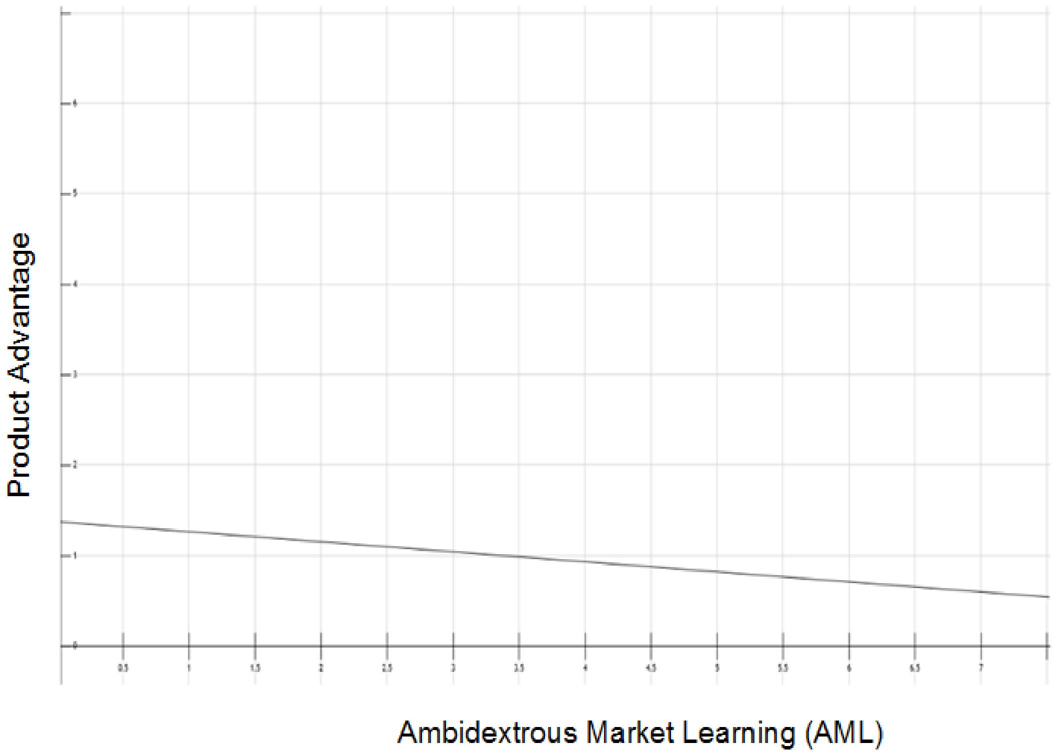
In such a scenario, AML firms tend to develop products with high levels of product advantage. This is primarily because; firms understand the needs and wants of the existing customers and develop technologically innovative products that are meaningful to their customers and simultaneously superior to competing products. This result is in line with the existing literature, for example, Prahalad and Ramaswamy (2004) argue that *"companies can no longer act autonomously, designing products, developing production processes, crafting marketing messages and controlling sales channel with little or no interference from customers"* (p. 5).

Therefore, even at low levels of AML firms tend to develop new products by implementing new production process or technology process for their current or existing customers, these firms tend to develop new products with high product advantage.

In addition, Adams, Day and Dougherty (1998) and Day and Moorman (2010) argue that when firms develop product from the inside out (i.e. the inner technological strengths and capabilities drive the new product development process), face significant problems in locating and defining the "right" potential users. Hence, by focusing on the current customers and by solving the problems of existing customers, firms can find the "right" and potential use of their new product.

Scenario 4 (TD = 7. MD = 7): Is there any advantage to implement ambidextrous market learning when firms are investing in new technology to develop products for new markets? To formulate this scenario, in the above mentioned equation, the strength of marketing discontinuity (TD) and technological discontinuity (MD) was considered as 7.

Figure 7.11 Graphical representation of the integrated effect on PA (TD = 7 and MD=7)



Firms operating in high-tech industries mostly try to cater to the needs and wants of new customers and at the same time want to develop technologically advanced products. This helps firms develop new products that are superior and high-tech firms get an opportunity to cater to the needs and wants of a large audience. The above result is in line with the existing literature, for example, Porter (1998) argues that when a firm engages in a generic strategy tend to fail and are defined as "stuck in the middle". He states that *"becoming stuck in the* *middle is often the manifestation of the firm's unwillingness to make choices about how to compete"* (p.17). When firms are undecided between inside-out (i.e. the inner technological strengths and capabilities drive the new product development process) and outside-in (i.e. focusing on providing value to the customers while working on providing a good customer experience) strategy, they are stuck in the middle. In this scenario, firms are undecided whether to focus on entering new markets or to focus on new technological process to develop new products.

Therefore, as seen from the above graph, the linear effect of AML on product advantage is almost a horizontal line. That is, at low and high levels of AML, firms do not develop products with high advantage, since the uncertainty linked in terms of marketing and technology is high. In fact, at high levels of AML (as seen from the above graph), firms tend to develop products with low advantage in comparison at low levels of AML; firms tend to develop products with higher advantage. This result is in line with the existing literature, for example, Adams, Day and Dougherty (1998) and Day and Moorman (2010) argue that *"concentrating on the technology is a comfortable way to avoid ambiguity of the market data, since solving technology problems and designing product features, no matter how complicated, are still less ambiguous than trying to determine user needs"* (p. 411). Therefore, when firms operating in high-tech industries implement high levels of AML, firms tend to be more ambiguous about the market data and hence this results in developing products that are not simultaneously superior and meaningful to the customers.

The above discussion of the results of the hypotheses testing also raises few questions. Firstly, the operationalization of ambidextrous market learning and product advantage as higher-order constructs raises few questions. That is, in this model, is ambidextrous market learning in fact measuring the shared variance between exploratory and exploitative market learning or is it measuring something completely different which is just labelled as ambidextrous market learning. In addition, Junni et al. (2013) argue that future studies should also report the results of models in which ambidexterity is measured as a multiplicative, difference and an addition term to give an overall perspective of how ambidexterity construct has an impact on performance. The results of the other three models are discussed later in the next section and the results are presented in Appendix 7C and 7D.

7.7Post-Hoc Analysis II

To measure ambidextrous market learning as simultaneous integration of exploratory and exploitative market learning activities within a business unit, in this study, it was operationalised as a higher-order construct. To validate the results, ambidextrous market learning was operationalised as a multiplicative term, an addition term, and a difference term to compare and check the results (Junni et al., 2013). When ambidextrous market learning is operationalised as an addition term of exploratory market learning and exploitative market learning provides similar results. The results of the model completely changes when ambidextrous market learning is measured as a difference term. The ambidextrous market learning and product advantage relationship is non-significant and has a negative relationship. The interaction terms between market discontinuity and ambidextrous market learning; technological discontinuity and ambidextrous market learning have a non-significant impact on product advantage. This is in line with He and Wong's (2004) work. They found that ambidexterity has a positive impact on sales growth when ambidexterity is operationalised as a multiplicative term but found the same result as non-significant. This result in line with the literature that states that firms applying an ambidextrous strategy should try to achieve high levels of exploration and exploitation activities and not try to balance between the two activities. In the final case, when ambidexterity is measured as a multiplicative term, the strength of all relations are weaker but the most interesting result here is that, though the interaction term between market discontinuity and ambidextrous market learning; and the interaction term between technological discontinuity and ambidextrous market learning are non-significant but the sign/direction of the results has reversed (see Table 7.7)

Table 7.7 Comparison of results

Ambidextrous market learning as a higher-order construct	**Ambidextrous market learning as a multiplicative term**
AMLxMD → PA -0.490 (-3.253) AMLxTD → PA 0.413(2.892) AML → PA 0.428(3.171)	AMLxMD → PA 0.176(1.547) AMLxTD → PA -0.071 (-0.656) AML → PA 0.131(1.650)

The results in the above table illustrates that when ambidextrous market learning is operationalised as a multiplicative term, as an ambidextrous market learning firm goes further away from its product-market domain, the relationship between ambidextrous market learning and product advantage is higher. Though, in the literature it is argued that innovative products tend to be more successful in familiar markets (Song and Parry, 1999; Kanter, 1983). This comparison provides interesting insight into the ambidexterity literature because, as mentioned most studies measuring ambidexterity have operationalised ambidexterity as a multiplicative term (for example, Brion, Mothe, and Sabatier, 2010; Morgan and Berthon 2008; Hughes at al., 2010; Gibson and Birkinshaw, 2004).

In addition, two additional models were developed to test the validity of product advantage as a higher-order construct in the main model. The results indicate that when product meaningfulness and product superiority are measured using two models, the results of the hypotheses testing indicate similar results. Table 7.8 provides a comparison of the results of the hypotheses testing.

Table 7.8 Comparison of hypotheses testing

Product Advantage in the main model (1)	**Product superiority as a single-order (2)**	**Product meaningfulness as a single-order (3)**
AML → PA 0.428 (3.171)	AML → PS 0.319 (2.539)	AML → PM 0.406 (2.973)
MD → PA 0.143 (1.244)	MD → PS 0.212 (1.687)	MD → PM 0.161 (1.334)
TD →PA 0.054 (0.510)	TD → PS -0.015 (-0.136)	TD →PM 0.037 (0.332)
AMLxMD→ PA -0.490 (-3.253)	AMLxMD→ PS -0.542 (-2.773)	AMLxMD→PM -0.497 (-2.630)
AMLxTD →PA 0.413(2.892)	AMLxTD →PS 0.435(2.333)	AMLxTD →PM 0.440 (2.521)
PA → NPFP 0.28 (2.903)	PS → NPFP 0.243 (2.879)	PM → NPFP 0.263 (2.90)
CD→ NPFP -0.179 (-2.10)	CD→ NPFP -0.205 (-2.575)	CD→ NPFP -0.160 (-2.085)
CDxPA→ NPFP -0.155 (-1.986)	CDxPS→ NPFP -0.074 (-0.948)	CDxPM→ NPFP -0.061 (-1.158)

The above comparison sheds new light on the main model tested in the previous chapter (first column of in Table 7.8), in the second column, the results of the model measuring product superiority are presented. In comparison to the main model (column 1), the impact of ambidextrous market learning; and the moderated relationship of marketing discontinuity and technological discontinuity on product superiority are similar (varying in strength of the relationship). This indicates that the higher-order construct measures a certain part of product superiority. When firms develop new products using new technology or engineering or technological processes then firms need to be highly ambidextrous market learning, that is, when firms tend to use new technology to develop new superior products it tends to fail instead firms should develop new superior products using new technology that is in line (synchronised) with the superiority of the product.

In addition, this comparison of the results also indicate that when product advantage is moderated by customer discontinuity then the direct negative impact of customer discontinuity is stronger than when customer discontinuity moderates the product advantage and new product financial performance hypothesis. In comparison, when firms develop superior or meaningful products (not both characteristics together) then the interaction term, which is the moderated effect is nullified or non-significant. This indicates that when firms tend to develop new products that have this shared characteristics or the commonalities (between product meaningfulness and product superiority) then the product has a smaller negative effect of customer discontinuity on new product financial performance. This in line with one of the key findings of the main model is one of the key contributions to the NPD literature.

7.8 Chapter Summary

In this chapter, first why Structural Equation Modelling (SEM) was chosen and the underlying assumptions of SEM were discussed. Then the steps taken to check for these assumptions were presented. After this, a brief discussion of how hypotheses are tested (that is, mediators and moderators) using SEM. Following that, the results of the final structural model was discussed and the results of the hypotheses was discussed in detail. The results clearly indicate that ambidextrous market learning has a positive impact on product advantage but this is not the case in all the scenarios. In addition, due to high product advantage the negative impact of customer discontinuity (that is, product innovativeness from the customer's perspective) is reduced. Therefore, this result provides evidence that firms operating in high-tech industries should focus on developing new products which are technologically advanced and should implement an ambidextrous market learning strategy to create competitive advantage.

Chapter Eight: Discussion and Conclusions

8.1 Introduction

In this chapter the final concluding remarks, the discussion of the main findings are summarised, and the implications of the research findings on theory and practice are presented. And finally, the limitations of this study are discussed and how future research can tackle these limitations is also proposed. To achieve the above mentioned objectives, this chapter is divided into four sub-sections. First, the key results are discussed and how these results have a theoretical contribution is presented. Second, how the key findings of this study have a practical application is discussed. Third, the limitations of the study are presented and based on the limitations, a plan is proposed for future research. And, finally concluding remarks of this study are drawn.

8.2 Discussion of the key results and theoretical implications

New Product Development (NPD) is essential for firms operating in high-tech industries to create a competitive advantage. Though, in recent years, there is a widening gap between the capacity of the marketing teams and the accelerated complexities of the market (Day, 2011). In addition, in high-tech industry, the needs and wants of the customers are constantly altering, and require greater integration between R&D and marketing capabilities. As new product success is more likely to result from implementing a market-driven strategy (for example, Kohli and Jaworski, 1990; Slater and Narver, 1994a; Quinn, 1986).

Hence, Slater and Narver (1995) argue that firms that tend to learn faster about the markets than their competitors tend to be more successful. In recent years, researchers have taken insights from organisational learning and marketing; and argued that market learning plays a crucial role in developing successful products and services. Over the years scholars have argued that there are two types of organisational learning, for example, March (1991) in his unprecedented work differentiates between exploration learning and exploitation learning. Based on March's (1991) definition, Levinthal and March (1993) state that there are two types of market learning, that is, exploratory market learning and exploitative market learning and both market learning strategies are equally important for firm success.

Initially, learning theorists demonstrate that exploitation learning tends to limit the amount of exploratory learning and vice versa (for example, March, 1991). Despite the early criticisms, in the recent years, scholars argue that firms must engage in both market learning strategies to be competitive (for example, Kim and Atuahene-Gima, 2010; Kyriakopoulos and Moorman, 2004). Following these recommendations, recent research has shifted the focus from *"whether"* to *"how"* firms can achieve implementing both market learning strategies. Despite the number of studies illustrating the importance of implementing both market learning strategies has grown exponentially, the existing literature is silent on whether there is an advantage to implementing these two strategies simultaneously. In addition, the existing literature does not focus on when is it beneficial to implement both market learning strategies simultaneously.

The aim of this research was to address the above-mentioned gaps and provide insights on the benefits of implementing a strategy that enables both exploratory and exploitative market learning simultaneously and focus on when to implement such a strategy. Therefore, taking insights from two existing literature, ambidexterity and market learning literature, in this study, Ambidextrous Market Learning (AML) is defined. The current study of AML in high-tech industry makes several important contributions to the theory. Most importantly, this is a first research on whether AML firms tend to develop products with high advantage.

This study draws on the Day and Wensley's (1988) S-P-P framework and underpins the AML construct on the organisational learning theory. To the best knowledge of the researcher, this is the first study that empirically examines how firm's capability to simultaneously learn about the market in an exploratory and exploitative manner act as a key source of positional advantage. Specifically, insights were gained regarding the positional advantage that high-tech firms can achieve from implementing an ambidextrous market learning strategy.

In addition, this study also adds to the NPD literature within the marketing strategy literature (for example, Kim and Atuahene-Gima, 2010; Yannopoulos, Auh, and Menguc, 2010) by examining the moderating effects of product innovativeness from the firm's and customers' perspective in the same model (for example, Danneels and Kleinschmidt, 2001; Cooper and Kleinschmidt, 1991). This study also sheds light on the situation when AML strategy may become more valuable for the managers and when the implementation may be harmful for new product financial performance.

8.2.1 Ambidextrous marketing learning and Product advantage

The role of market learning is recognised as a potential source of advantage within the broader management literature and more specifically in the NPD literature (for example, Slater and Narver, 1995; Day, 1994; 2011; Kim and Atuahene-Gima, 2010; Quinn, 1986; Yannopoulos, Auh, and Menguc, 2010). Focusing on the narrow field of NPD research, a few studies empirically examine the individual effects of exploratory and exploitative market learning on product advantage and new product financial performance (for example, Kyriakopoulos and Moorman, 2004; Kim and Atuahene-Gima, 2010; Yannopoulos, Auh, and Menguc, 2010). However, the existing literature is yet silent on how simultaneously focusing on exploratory and exploitative market learning may affect product advantage. Given the number of theoretical papers suggesting that by integrating the two types of market learning firms tend to bridge the gap between the market complexities and the marketing capabilities of the firm (for example, Day, 1994; 2011; Levinthal and March, 1993), this research is set to test the impact of AML on product advantage.

This study draws in line with Day's (1994) theoretical implication that by having an open minded inquiry AML firms can anticipate emerging needs and forecast market responses and convert this into positional advantage. The results of this study indicate that by implementing an AML strategy firms tend to create an atmosphere that encourages sense-and-response approach to meeting customer goals than having a reactive approach to the market conditions (Day, 2011).

The results of this study also provide valuable insights into the ambidexterity literature. In organisational theory, the ambidexterity construct is viewed as an emerging paradigm (Raisch and Birkinshaw, 2008). Focusing on the NPD literature, the ambidexterity construct has been applied extensively (for example, He and Wong, 2004; Atuahene-Gima, 2005; Ebben and Johnson, 2005; Hughes et al., 2010; Venkataram, Lee and Iyer, 2007; Brion, Mothe, and Sabatier, 2010). Despite the exponential growth of studies focusing on ambidexterity, the literature portrays the ambidexterity phenomenon as 1 and 0s. In the current study, based on the results from recent studies (for example, Cao, Gedajlovic, Zhang, 2009; Lewin and Volberda, 1999; Yalancinkaya et al., 2007), it is argued that ambidextrous market learning can be viewed as a degree of the simultaneous integration of exploratory and exploitative market learning activities. Focusing on how to measure ambidextrous market learning, a few studies (for example, Wang and Rafiq, 2014; Lubatkin, Simsek, and Ling, 2006; Kortmann, 2014) have measured "ambidexterity", i.e. the simultaneous pursuit of exploration and exploitation activities as a higher-order construct. Given that by definition AML is firm's simultaneous integration of exploratory and exploitative market learning activities within a business unit. In line with the above-mentioned few studies, in this study ambidextrous market learning is operationalized as a higher-order construct.

8.2.1.1 Operationalization of Product advantage

In addition, the results of this study also provide valuable insights into the NPD literature. Product advantage is defined as the unique benefits that the product offers and the extent to which it is superior to competing products (Atuahene-Gima, 1995; Calantone and Di Benedetto, 1988; Li and Calantone, 1998). Product meaningfulness can be provided by offering new (unique) attributes and functionalities which indicate a strong market orientation dimension (Cooper, 1979). And, product superiority refers to the degree to which a product outperforms competing products along existing attributes and functionalities which indicates a strong technical/production orientation dimension (Cooper, 1979).

The existing literature has frequently operationalized product advantage as an aggregate construct consisting of product meaningfulness and product superiority (Rijsdijk et al., 2011). Rijsdijk, et al. (2011), however, argue that these are two distinct components of product advantage. In line with Cooper (1979) in this study it is argued, that both dimensions are important characteristics of new products and having both dimensions simultaneously tend to facilitate new product success (p. 98). Taking insights from the existing literature, in this study, product advantage is defined as the extent to which a new product offers unique benefits that are meaningful to the customers and simultaneously the extent to which it is superior to competing products. Therefore the product advantage construct is operationalised as a higher-order construct consisting of product meaningfulness and product superiority. Therefore, this research in line with Hernard and Szymanski (2001) contributes to the NPD literature by illustrating that product advantage is a higher-order construct. To the best knowledge of the researcher, this is the first study that examines product advantage as a higher-order construct.

The results of the Schmid-Leiman Solution (SLS) test indicate that the first-order constructs of product advantage, i.e. product meaningfulness and product superiority are two different constructs (see section 5.5 in chapter 5) and not a single construct. Additional test results clearly indicate that product advantage should be measured as a higher-order construct (for example, the factor loadings of the EFA in section 5.5, the discriminant validity and reliability measures of the higher-order constructs in CFA in section 6.6). This research contributes to the NPD literature by showing that the product advantage construct is a higher-order construct.

8.2.2 Moderating effect of Product Innovativeness

This study sheds light on the relationship between product innovativeness and product advantage. In the existing NPD literature, scholars have found conflicting results for the relationship between product innovativeness and product advantage. The confounding results are partly attributed to two key reasons, first, the plethora of measures used to assess product innovativeness (Calantone et al., 2006; Danneels and Kleinschmidt, 2001) with conceptualizations either not adequately distinguishing between firm (Danneels and Kleinschmidt, 2001; Garcia and Calantone, 2002) and customer perspective of innovativeness (Atuahene-Gima, 1995; Souder and Song, 1997), or being too broad (Danneels and Kleinschmidt, 2001). Second, scholars have addressed the concept of product advantage construct as product innovativeness (e.g., Atuahene-Gima, 1995; Li and Calantone, 1998).

In the recent years scholars have started to address this problem and advised future researchers to clearly distinguish between the two variables (for example, Calantone, Chan, and Cui, 2006; McNally, Cavusgil, and Calantone, 2010; Rijisdijk, Langerak, and Hultink, 2010). In addition, a very limited number of research studies explore the relationship between product advantage and product innovativeness. For example, McNally, Cavusgil and Calantone (2010) found that product advantage positively impacts customer discontinuity (product innovativeness) and on the other hand, Calantone, Chan and Cui (2006) found that product innovativeness positively impacts product advantage. And, Song and Parry (1999) illustrate that product innovativeness (a single-order construct measuring both, marketing and technological discontinuity) acts as a moderating variable between marketing and technical proficiency on product advantage.

In this study, in line with Danneels and Kleinschmidt (2001) and McNally, Cavusgil and Calantone (2010), product innovativeness from the firm's and customers' perspective is empirically tested. In the current research, product innovativeness from the firm's perspective is defined on two dimensions, i.e. marketing discontinuity and technological discontinuity and from the customers' perspective product innovativeness is defined as customer discontinuity. Taking insights from information processing theory and the higher levels of learning required in uncertain situations, the moderating relationship between marketing and technological discontinuity is examined individually.

8.2.2.1 Moderating effect of Marketing Discontinuity and Technological Discontinuity

This study is the first attempt to explore the moderating effect of marketing and technological discontinuity on product advantage. Taking insights from Kohli and Jaworski (1990) study, that knowledge about the market and market synergy has been considered as an important factor. Consequently, it was hypothesised that as high-tech firms go further away from the current product-market domain, it is more challenging to gauge the needs and wants of the new customers. Findings from this study confirmed this hypothesis. In particular, marketing discontinuity negatively moderates the relationship between AML and product advantage. The implication here is that in the existing literature the direct association between product innovativeness and product advantage might be overly simplistic.

This study has also sought to explore the moderating influence of technological discontinuity on product advantage. On the other hand, a summary of the NPD literature on the importance of the technological development in the process of making new products has been considered as a key factor (for example, Kline, 2013; Porter, 1985; Bianchi et al., 2014). Consequently, this study extends knowledge on how technological advance can improve the superiority of the product. For example, based on the results of analysing a case study on a chemical based firm, Adams et al., (1998) find that *"they (the chemical firm) leveraged their technology knowledge by talking to possible co-producers to develop a new manufacturing facility, by co-designing the chemical with users and by giving them R&D samples"* (p. 412) tend to develop products that meet the needs and wants of the customers and are superior. They argue that firms that tend to listen to their customers and can apply new technical skills effectively develop new products that are simultaneously meaningful and superior. In line with Adams et al., (1998), the results of this study implicate that as firms implement new technological process or a production process or a new manufacturing process based on the customer feedback tend to develop products that have high product advantage.

Given the importance of managing new product development process in high-tech industries, this result contributes to the NPD literature by providing a more in-depth knowledge on the product innovativeness and product advantage paradox and shed new light on this relationship.

8.2.2.2 Moderating effect of Customer Discontinuity

There is an abundance of research done on how customers perceive product as innovative. Lawton and Parasuraman (1980) take insights from psychology and human behaviour literature and define product innovativeness from the customers' perspective as *"the degree of behavioural change or learning effort required by potential customers to adopt the new product*" (p. 20). Scholars and researchers have labelled product innovativeness from the customer's perspective differently; for example, 'degree of product newness to customers' by Atuahene-Gima (1995), 'customer discontinuity' by McNally, Cavusgil, and Calantone (2010), 'customer familiarity' by Calantone, Chan, and Cui (2006), 'customer switching cost by Eliashberg and Robertson (1988) and for this study it is labelled as 'customer discontinuity', but essentially they all measure product newness from the customer's perspective by adapting the Lawton and Parasuraman (1980) definition of product innovativeness from the customers' perspective.

Empirical evidence has consistently identified product advantage as conducive to new product financial performance (Calantone et al., 2006; Henard and Szymanski, 2001; Li and Calantone, 1998; Montoya-Weiss and Calantone, 1994; Song and Parry, 1997; Szymanski et al., 2007; McNally et al., 2010). The effects of product innovativeness on new product financial performance, on the other hand, are mixed. Atuahene-Gima (1995) argues that product innovativeness from the customer's perspective has a moderating relationship between market orientation and product performance but the results were not supported. Similarly, Calantone et al. (2006) identify a negative relationship between customer familiarity (or degree of newness to the customer) and product performance. In contrast, McNally et al. (2010) establish a non-significant relationship between customer discontinuity and product performance.

This study is the first attempt to explore the moderating effects of product innovativeness from the firm's and customers' perspective in one model. To the best knowledge of the researcher, this is the first study that measures the moderating effect of customer discontinuity on the product advantage and new product financial performance linkage. The rationale for this moderator relationship is that when new technology is deployed to develop new products with high advantages, such products is likely to be fairly unique and therefore likely to involve high learning effort for customers (McNally et al., 2010). In addition, when firms enter new markets or product line, a behavioural change is required from the customers' perspective.

Learning effort represents the costs incurred by the customers in learning about new products and the amount of changeover costs in using the new products (especially in technology-intensive business-to-business markets). Consequently, it was hypothesised that a high a low level of customer discontinuity would make the product more appealing and from the customers' perspective easier to learn the advantages of the product. Findings from this study confirmed this hypothesis. Thus, by modelling customer discontinuity as a moderator of the link between product advantage and new product financial performance, this study sheds new light on product innovativeness and its relationship with new product financial performance.

8.2.2.3 Combined moderating effect of Marketing and Technological Discontinuity

The individual moderating effects of marketing discontinuity and technological discontinuity were discussed in the previous section. In this section, how ambidextrous market learning has an impact on product advantage when the effects of both the moderating variables are taken together is discussed. Consequently, this study extends knowledge on when it is beneficial to implement both market learning strategies simultaneously. In this way, this study addresses a central caveat in March's (1991) work, that the *"learning processes do not necessarily lead to increase in both average performance and variation"* (p. 83). This study is a renewed effort to examine the AML effect in the context of product innovativeness from the firm's perspective in high-tech industries.

As the results of this study show, implementing an ambidextrous market learning strategy is not always beneficial. Implementing an AML culture helps firms develop products with high product advantage when firms focus on developing new products with new technological advancements. This result is in line with the characterisation of firms operating in high-tech industries by Pavitt (1990). He argues that high-tech firms are highly differentiated and by entering new markets or developing new product lines tend to challenging for the firms. Despite having an open-minded market research, firms face new challenges that is, difficult to convert the market knowledge into product advantage. However, when the firm develops new products for new markets, which is in tangent with the customers, tend to be more successful. Therefore, firms operating in high-tech industries need to focus on having a *"market-driven"* strategy to overcome the potential disadvantages of entering a new market.

In sum, it can be concluded that the AML – product advantage relationship is more complex than the normative theory suggests. The results of this study could also be taken to suggest that the overall benefits of AML on product advantage are greater than on the variation of product advantage. That is, when firms operating in high-tech industries implement an ambidextrous market learning strategy is more valuable than when they pay attention to either focusing on exploratory or exploitative market learning. But in certain situations and scenarios, it may be more beneficial to implement either one of the strategies to develop products that have high advantage.

8.3 Methodological Implications

In addition to the theoretical implications, methodologically this study has introduced a novel approach to the study of product advantage and ambidextrous market learning. Unlike prior NPD literature, product advantage construct has been measured as an aggregate score of both dimensions, i.e. product meaningfulness and product superiority. The methodological implications that can be drawn from the results of this study indicate that product advantage is a higher-order construct and operationalizing it as a single-order factor may hinder the growth of the existing knowledge.

Another methodological implication that can be drawn from this study relates to the reliability and validity test of the higher-order constructs, i.e. ambidextrous market learning. In the existing literature, studies (for example, Wang and Rafiq, 2014; Lubatkin, Simsek, and

Ling, 2006; Kortmann, 2014) that have measure ambidexterity as a higher-order have not assessed the higher-order constructs using rigorous methods, such as SLS techniques (Schmid and Leiman, 1957). For example, Wang and Rafiq (2014) and Lubatkin, Simsek, and Ling, 2006 do not report the validity and reliability measures of the higher-order constructs. Given the above validity and reliability issues in ambidexterity literature, it can be argued that the strength of the relationships could be overestimated. On the basis of this methodological lapse, the current study is novel because all the psychometric measures were adequately estimated.

8.4 Practical Contributions

The key findings of the main model indicate that firms that gather market information by focusing on simultaneously gathering market information that is generated via experiments/exploring and via improving the current product-market domain by exploiting develop an open-minded culture that enables the firms to gather market information that can be implemented in developing products which are superior and simultaneously meaningful to the customers. Though it is beneficial to indulge in ambidextrous market learning when firms are focused on developing products using new technology. If the firm is developing a product based on the current technology (which can be defined as incremental innovation) or developing a product for its current market then low levels of ambidextrous market learning has no impact on product advantage. Even in the case of high ambidextrous market learning, the positive impact of ambidextrous market learning on product advantage is very small and this may raise the next key question that is, does it outweigh the implementation cost.

The main implication of this study for managers is that firms need to develop an ambidextrous market learning behaviour when firms are implementing a technologically advanced process to develop new products. When firms develop new technology or new engineering process to develop new products then firms need to learn about the technology applied and whether this technology would in fact enhance product benefits. The results indicate that firms have to keep one eye on the current customers and the current competitors they face and in the meantime also keep one eye on the changing demands of the customers and learn about what their competitors are working on. Gathering information regarding what technology the firm's key competitors are working on provides useful information regarding the technological trends and this helps in predicting the future of the industry.

In the highly competitive and technologically turbulent environments firms may lose their current position in trying to enter new product-market domains. Having said this, if firms operating in high-tech industries tend to develop technologically advanced products and market this to new customers or the new product takes the firm up against new competitors then this would tend to be successful. But on the other hand, if the firm operating in high-tech industry enter new markets or meet the needs and wants of new customers via their old products then this would lead in a failure to develop products which meet the needs and wants of the customer. The other key findings that has a practical contribution is that when firms focus on entering new markets or cater to new customer needs then the firm should focus on gathering exploratory market learning rather than focusing on exploratory and exploitative market learning.

In addition, the negative effect of customer discontinuity provides evidence that firms need to develop innovative products which require less learning effort from the customers. When firms develop new products that require a high learning effort or requires the customers to change their behaviour to adapt to the new product, it becomes more challenging for the customers to completely understand the advantages of the product. This has been the challenge that managers face and that is how to develop innovative products that requires no or small learning efforts from their customers (or firms need to find ways of reducing the learning effort required by customers).

8.5 Limitations and future research design

The limitations of this study can be divided primarily into the applications of the model used in the study and the methodological limitations. These limitations are a source for potential future research and these are as follows:

8.5.1 Applications of the conceptual model

This study sheds new light and provides useful insights in the ambidexterity, market learning and NPD literature; however this research is not free from limitations. This study measures the ambidextrous market learning impact of product advantage. The consequence of ambidextrous market learning were chosen based on previous research (Henard and Szymanski, 2001; Calantone, Chan, and Cui, 2006; Evanschitzky, Eisend, Calantone, and Jiang, 2012). This led to neglecting the effect of ambidextrous market learning on other product characteristics, such as speed to market (for example, Fang, 2008; Lynn, Skov, and Abel, 1999; Smith, 1999; McNally, Akdeniz, and Calantone, 2011), product cost (for example, Kim and Atuahene-Gim, 2010; Dodds, Monroe, and Grewal, 1991; Rao and Monroe, 1989), product design (for example, Ulrich, 2003; Sanchez and Mahoney, 1996; Green, Carroll, and Goldberg, 1981), brand name (Rao and Monroe, 1989; Maheswaran, Mackie, and Chaiken, 1992; Keller, Heckler, and Houston, 1998). The inclusion of these constructs may have influenced the findings of this study and this could have shed new light in the NPD literature. This could provide further explanation on how market and technological discontinuity may have an impact on product cost or speed to market product characteristics. Therefore, future research can investigate these relationships and develop more complex models with a larger data set to provide greater insight into the impact of ambidextrous market learning in high-tech industries.

In addition, the conceptual model measures the impact of ambidextrous market learning on new product financial performance. This result offers new insights by focusing on the financial product performance measures as the key dependent variable, but future research is needed to explore different performance objectives set by firms. In high-tech industries firms may have different objectives while developing new products, for example, Leiblein, Reuer, and Dalsace (2002) argue that firms develop new technologically advanced products to gain the first mover advantage and then wait for other firms to catch up and then develop products that have larger market share and financial performance (Porter, 1985). This could also shed new light on how customer discontinuity may impact technological performance of the product. Furthermore, the other key performance objectives used in the NPD literature are market performance (Griffin and Page, 1996) and this may provide fruitful insights into whether firms operating in high-tech industries focus on market performance or technological performance. The other limitation in the conceptual model is not including various aspects of innovativeness. In the current model the focus is primarily on product innovativeness, that is, both from the firm's perspective and customer's perspective, but other type of innovativeness from the existing literature that may have an impact on the product performance is: brand innovativeness (for example, O'Cass, Boisvert, and Ashill, 2011; Klink and Athaide, 2010; Blythe, 1999). This could act as a consequence of customer discontinuity which may have an alternate positive impact on product performance.

In the ambidexterity literature there is a clear consensus in regards to the importance of environmental factors (Burn and Stalker, 1961; Junni et al., 2013). In this conceptual model, none of the environmental factors were taken into consideration, primarily because the focus is to measure how firm's internal resources that is, knowledge regarding product innovativeness process and ambidextrous market learning has an impact on product advantage and product performance. In addition, since the study focuses on high-tech industries, the environmental factors that is, market turbulence; technological turbulence and competitive intensity are considered to be high. Considering the contingency theory future research may, therefore, investigate how ambidextrous market learning may have an impact on product advantage in different market and technological turbulence.

In the current model, R&D intensity that is, the percentage of R&D expenditure over turnover and firm size acts as a control variable but yet in the ambidexterity literature one of the key debate is regarding the resources available in the firm. Due to the complexity of the current model and using key controls variables, the impact of slack resources (for example, Atuahene-Gima, 2005; Voss et al., 2008) plays a crucial role on how quickly and effectively implement an ambidextrous culture in the business unit. This could shed new light on the results of the current model and may explain how firms can successfully enter new product-market domain and not simultaneously have a negative impact on product advantage.

8.3.2 Research methodological limitations

The ambidexterity hypothesis has been extensively measured in the high-tech industries yet the current model provides useful insights into how ambidextrous market learning firms can develop new innovative products. To the best of knowledge of the researcher, in the existing literature there are no studies that measure the impact of ambidextrous market learning on product performance. However, to generalise the findings of this study, this conceptual model must be replicated in different settings. The current study was conducted in the firms operating in the high-tech industries in the United Kingdom, which is an advanced western economy. Therefore, it is important to replicate the conceptual model in other advanced economies (for example, other European countries or North America).

In addition, in this model there are constructs that measure product innovativeness from the firm and customers' perspective, therefore it is essential that the ambidextrous market learning hypothesis can be compared between business-to-business (B2B) and business-to-consumer (B2C) context. In comparison to the customers in the B2C, the customers in the B2B market may not be that concerned about the learning effort entailed with innovative products and may be happy to utilise new products that are highly innovative. Therefore, it is important to replicate the conceptual model in different industries.

One of the primary concerns of this model is the use of cross-sectional data (for example, Rindfleisch et al., 2008; Bagozzi and Yi, 1991; Bagozzi, 1984). This is because several studies in the literature argue that the benefits of implementing an ambidextrous culture may have a long term effect (for example, March, 1991; Duncan, 1976; Levinthal and March, 1993). Therefore, future research is called to consider using longitudinal designs to analyse the long term effects or ambidextrous market learning. In addition, the results of a longitudinal research may vary in regards to the moderating effecting of marketing discontinuity on AML and product advantage. The current study focused on the products that were developed in the firm/business unit in the last three years. Given the long-term benefit of entering a new market or developing a new product line could be negated due to the cross-sectional design of the current study.

The other major methodological limitation that may be a cause of concern is using single source of information (for example, Ernst and Teichert, 1998; Campbell, 1995; Canell, Oksenberg and Converse, 1977; Kumar, and Dillon, 1990). Ernst and Teichert (1998) illustrate how using single informant bias can affect the results in NPD research. They illustrate when the performance of the product was asked to measure by informants in different departments there were large deviations in their answers. This can be incorporated in future research to reduce the impact of common method variance (CMV) by either looking for responses from multiple informants in the firm or secondary information can be used to minimise CMV.

8.4 Conclusion

To conclude, this study provides useful insights and expands current knowledge of ambidexterity and NPD. This research also makes key contribution to practice and unpacks the concepts of product innovativeness and product advantage and examines their effects on new product performance, taking into account both the firm and the customer's perspectives. The empirical evidence broadens our understanding regarding how ambidextrous firms tend to develop innovative products and whether the implementation cost of ambidexterity is beneficial. The results also shed light on the importance of differentiating between the various attributes of product advantage and these attributes have a lot of shared characteristics. The results also indicate that firms operating in high-tech industries may have to focus on implementing new technology or innovative engineering process to develop new products. In addition, there is empirical evidence that ambidextrous market learning firms tend to develop products with high product advantage when the firms want to be innovative. If the firms do not focus on entering new markets or develop new products using new technology, then there no relationship between product advantage and low levels of ambidextrous market learning.

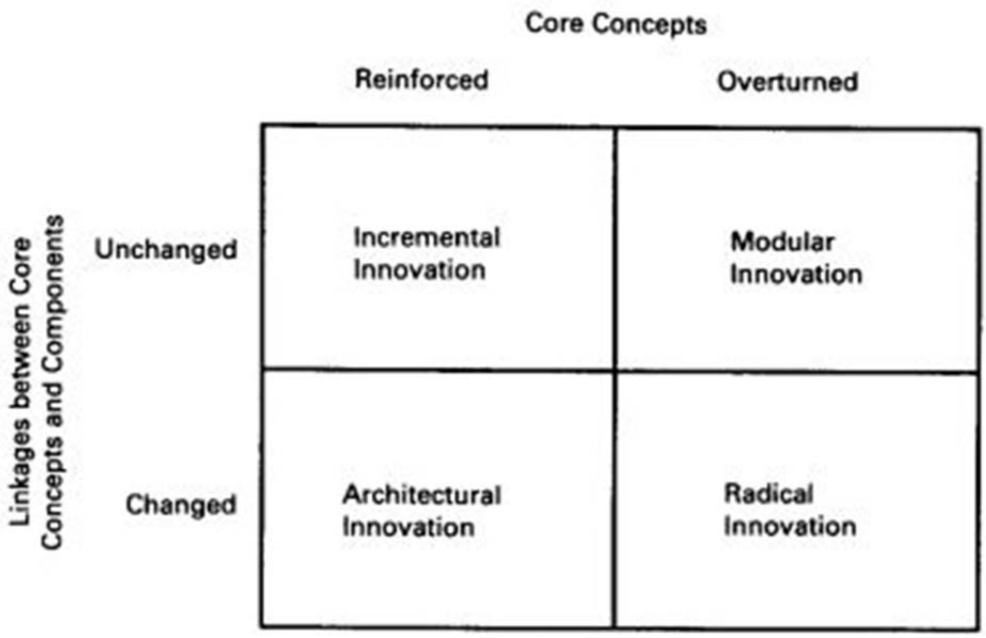
Finally, this study acknowledges its limitations and provides guidance for future research. The impact of ambidextrous market learning on product performance has opened a new can of worms and hopefully the results of this study will guide and encourage future researchers to explore this relationship in different research settings.

Appendices

Appendix 2A: Product innovativeness typologies

In the NPD literature there are two key typologies of new products used and these are: the Booz, Allen, and Hamilton (1982) typology and the other is, Henderson and Clark (1990) typology. These two typologies use different and distinct features of new products to differentiate between the various categories of innovation. These two typologies have an imminent role in defining the different types of innovation.

The Henderson and Clark (1990) typology uses *"the distinction between component and system knowledge to differentiate four categories or types of innovation"* (Smith, 2010, p. 32). They primarily focus on the technological aspect of product innovativeness. They state products are actually systems, and these systems are integrated with different components and the different configurations of these components. They point out that to make a product customarily require two distinct types of knowledge. First, the component knowledge, which is the knowledge regarding the various components used within the overall system, which forms a part of the *"core design concepts"* (Henderson and Clark, 1990). And the second type of knowledge is the system knowledge, which constitutes the knowledge regarding the way the components are integrated and linked together. They use a two-dimensional matrix and differentiate between the four types of product innovation (see Figure 2.2).



Typology of innovations (Source: Henderson and Clark, 1990; p. 12)

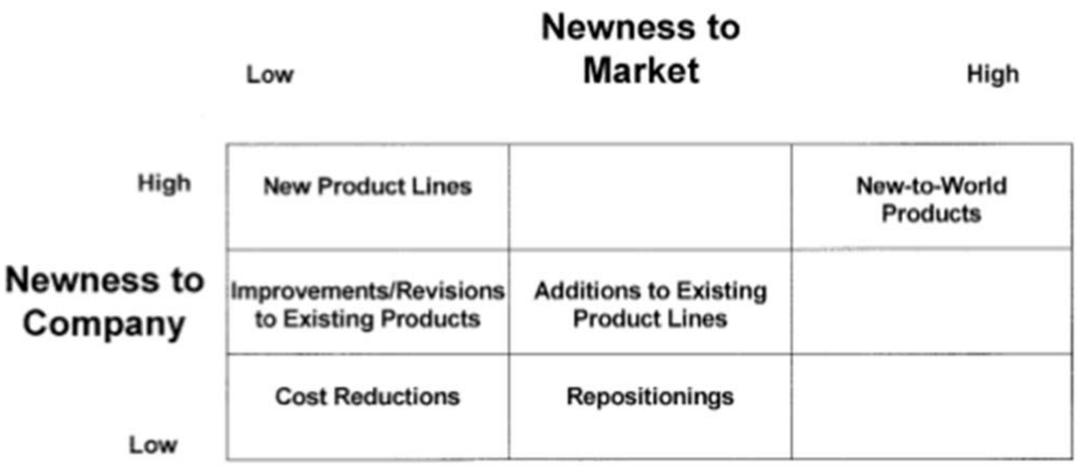
The typology categories new products along reinforced and overturned core concepts (on the x-axis) and changed and unchanged linkages between the core concepts and components (on the y-axis). In the existing literature, radical and incremental innovation are polarised as being at the opposite extremes. This typology introduces two intermediate (between the two extreme types) distinct types of innovation, which are modular innovation and architectural innovation. These four types of innovation can be well explained using Figure 2.3.

Innovation	Components	System	Example
Incremental	Improved	No change	New models of iPhone
Modular	New	No change	Clockwork radio
Architectural	Improved	New configuration/architecture	Sony Walkman
Radical	New	New configuration/architecture	Jet engine

Changes associated with types of innovation (Source: Smith, 2010, p. 32)

As it can be seen from the above figure, radical innovation addresses new design, and a new set of core concepts embodied in the components. This is the principal form of innovation and on the other hand, incremental innovation is moderate changes to the existing products. These two types of innovation (that is, radical and incremental) are commonly used in the ambidexterity literature. Fundamentally, this is because to develop radically innovative products a firm must focus on exploration activities and to develop incremental products a firm must endeavour on exploitation activities.

The other typology of new products that is commonly used in the NPD literature is the Booz, Allen, and Hamilton (1982) typology. Compared to the Henderson and Clark (1990) typology, in this typology, products are classified along two dimensions of newness. On the x-axis, products are classified based on the newness to the market, and on the y-axis products are classified based on the newness to the company. Booz, Allen, and Hamilton state that new products can be classified primarily on the newness to the firm and newness to the customers. Products that are new to the firm may not necessarily be new to the customers (because the firm may be developing new product line); on the other hand, products can be new to the market but not necessarily new to the firm (firms may reposition their products to a new market). Therefore it is important to classify products based on the newness to the firm and newness to the markets (see Figure 2.4). From the figure below, it can be seen on one end of the spectrum is new-to-world products are new to the customer and new to the firm, and on the other end is cost reduction products. These products are primarily introduced in the market to improve the position of the firm in the market (to gain competitive advantage). Between these two ends of the spectrum, there are improvement/revision to the existing products. These products are somewhat new the firm but not new to the market. The customers may have used the product earlier and may be unsatisfied with certain features or design aspect of the product. Listening to the feedback from the market, firms tend to develop products with incremental changes in the product dimensions. Additions to the product lines products are the other classification of product innovation, which are somewhat new to the customer and new to the firm. Compared to improvement/revision to the existing products, these products are more innovative and have substantial element of newness to the existing product.



Booz, Allen, and Hamilton typology (Source: Danneels and Kleinschmidt, 2001, p. 360)

Appendix 2B: Summary of the empirical results of studies linking ambidexterity and NPD literature

Author(s)	Theory	Ambidexterity construct conceptualisation	Ambidexterity construct operationalization	Sample Data	Product characteristics studied	Key Findings
He and Wong (2004)	RBV Theory	Resource allocated for exploration and exploitation in the product-market perspective	Interaction and Balance	206 Manufacturing firms (Mixed)	Product innovation intensity and process innovation intensity	Interaction term has positive impact on Sales growth rate and balance term has negative impact
Brion, Mothe, and Sabatier (2010)	Organisation theory	Adapted from He and Wong (2004)	Interaction	108 firms (Mixed)	No	Exploration and exploitation competence moderated long-term and short-term on innovation ambidexterity
Chang and Hughes (2012)	Top management	Existing knowledge required for exploitation innovation and departing from existing knowledge for exploration innovation (Adapted from, Jansen et al., 2006; He and Wong, 2004; Birkinshaw, Hood and Jonsson, 1998	Balance	243 firms (mixed)	No	Structural, Leadership and Social characteristics have a positive impact on innovation ambidexterity
Fernhaber and Patel (2012)	Not explicitly mentioned	Adapted from Lubatkin et al., (2006)	Latent congruence modelling	215 High-Tech firms	Product Portfolio Complexity (PPC)	Ambidexterity and absorptive capacity (moderators) enhance the PPC and growth hypothesis.
Lubatkin et al., (2006)	Behavioural (role of Top management)	Develop scales to measure Exploratory and exploitation orientation	Interaction, balance, Higher-order and addition	139 SME (mixed)	No	Ambidextrous orientation has positive impact on firm performance. Additive term model is superior
Cao, Gedajlovic and Zhang (2009)	Not explicitly mentioned	Adapted from He and Wong (2004)	Interaction and difference	122 firms (Mixed)	No	Difference term is more beneficial to resource-constrained firms.
Hoang and Rothaermel (2010)	Organisational learning and Network	Internal/external exploitation and Internal/external exploration	Internal exploitation x external exploration, internal exploration x external exploitation	412 R&D in pharmaceutical firms	No	Internal exploitation x External exploration has a negative effect on project performance.

Author(s)	Theory	Ambidexterity construct conceptualisation	Ambidexterity construct operationalization	Sample Data	Product characteristics studied	Key Findings
Hughes et al., (2010)	RBV	Adapted from He and Wong (2004)	Additive term	260 International New Ventures	Cost leadership and marketing differentiation advantage	Marketing differentiation strategy has a strong positive impact on innovation ambidexterity, whereas, cost leadership strategy has no impact. Innovation ambidexterity has a positive impact on cost leadership and marketing differentiation advantage
Li and Huang (2012)	Not explicitly mentioned	Adapted from Jansen et al., (2006; 2009)	Interaction	253 Taiwanese firms (mixed)	No	Ambidexterity mediates the hypothesis between product development proficiency (that is, marketing and technical proficiency) and new product performance.
Lin et al., (2012)	RBV	Adapted from Atuahene-Gima (2005)	Interaction	214 Taiwanese SBU (mixed)	No	Innovation ambidexterity mediates the hypothesis between learning capability and business performance
Jansen et al., (2009)	Behavioural (Top management)	Adapted from Jansen et al., (2006) – exploration and exploitation innovation – that is, improving existing product-market and seeking new opportunity	Interaction	230 firms (Mixed)	No	Focusing on structural mechanism the aim to focus on how firms may pursue ambidexterity
De Visser et al., (2009)	Organisational learning	Incremental and Radical NPD processes	Interaction	155 firms (Mixed)	No	Different structure (processes) are required for ambidexterity culture
Wang and Rafiq (2014)	Organisational learning	Adapted from Atuahene-Gima (2005)	Higher-order	150 UK and 242 Chinese High-tech firms	Radical, Incremental innovation and speed to market	Contextual ambidexterity mediates the hypothesis between ambidextrous organisational culture and product innovation outcomes (radical, incremental and

speed to market).

Author(s)	Theory	Ambidexterity construct conceptualisation	Ambidexterity construct operationalization	Sample Data	Product characteristics studied	Key Findings
Blindenbach and den Ende (2014)	Organisational learning	New to the world products and process improvements	Interaction	2865 manufacturing and service firms	No	Having separate units for exploration and exploitation has a positive impact on ambidexterity
Rothaermel and Alexandre (2009)	RBV	Single item scales to measure technical knowledge applied	Ratio	143 Manufacturing firms	No	Ambidexterity enhance firm performance in a curvilinear manner, which is positively moderated by absorptive capacity
Blome, Schoenherr, and Kaesser (2013)	Complementarity, transaction cost and relational exchange theory	Adapted from He and Wong (2004)	Additive	238 Manufacturing firms	Cost and Innovation (that is, design and quality)	Ambidextrous governances has a positive impact on cost and innovation, which is positively moderated by Organisational ambidexterity
Grover, Purvis and Segars (2007)	Chaos and complexity	Develop two models measuring antecedents for incremental and radical innovation.	Separate models	154 Telecommunication firms	No	Firms are using a balance approach to innovativeness by using paradoxical and dual structures
Ho, Fang and Lin (2011)	RBV	Technology and design capabilities	Interaction and difference	109 Telecommunication Taiwanese firms	No	A balance between the allocation of management attention and resources between the two capabilities.
Kortmann (2014)	Behavioural (Top management)	'Innovative ambidexterity' Adapted from Jansen et al., (2009)	Higher-order	83 firms from USA and 78 firms in India	Innovation and cost orientation	Innovation and cost orientation mediates the hypothesis between ambidexterity oriented (that is, adaptability and alignment) and innovative ambidexterity
Kouropalatis, Hughes and Morgan (2012)	Organisation theory and contingency theory	High levels of strategic flexibility and high levels of commitment to product-market strategy as being highly ambidextrous	Based on cluster-analysis to divide	141 High-tech firms in UK	No	High levels of ambidexterity exhibit greater levels of resources, decentralisation product-market strategy effectiveness, and

						implementation effectiveness in comparison to low levels of ambidextrous strategy
Author(s)	**Theory**	**Ambidexterity construct conceptualisation**	**Ambidexterity construct operationalization**	**Sample Data**	**Product characteristics studied**	**Key Findings**
Chang, Hughes and Hothe (2011)	Organisation and contingency theory	Adapted from He and Wong (2004)	Difference	265 firms (Mixed)	No	In a dynamic environment, Innovation ambidexterity partially mediates the relationship between firm factors (i.e., centralisation and connectedness) and firm performance.
Lin and McDonough (2011)	Strategic leadership theory and Organisational learning	Adapted from Atuahene-Gima (2005) and Cooper and Kleinschmidt (2000)	Additive	125 Taiwanese firms (Mixed)	No	Knowledge sharing culture mediates the relationship between strategic leadership and innovation ambidexterity and this relationship is moderated by organisational culture
Lin and McDonough (2014)	Cognitive theory	Innovation ambidexterity – adapted from Atuahene-Gima (2005) and Cooper and Kleinschmidt (2000)	Interaction	190 Taiwanese firms (Mixed)	No	Reflection and Independent cognitive style impacts intra-SBU learning and inter-SBU learning which has an impact on innovation ambidexterity
Patel, Messersmith, and Lepak (2013)	Not explicitly mentioned	Adapted from Lubatkin et al., (2006)	Latent congruence modelling	215 High-tech SME (Mixed)	No	High performance work system (i.e., participation, mobility, training, staffing, job description, appraisal, job security and incentive rewards) is necessary for organisational ambidexterity.
Salvador, Chandrasakeran and Sohail (2014)	Not explicitly mentioned	Product configuration ambidexterity, that is, effectiveness and intelligence	Interaction	108 manufacturing firms	No	Response to changing needs of customer positively mediates the relationship between product configuration ambidexterity and product performance.
Author(s)	**Theory**	**Ambidexterity construct**	**Ambidexterity**	**Sample Data**	**Product**	**Key Findings**

		conceptualisation	**construct operationalization**		**characteristics studied**	
Wei, Yi and Guo (2013)	RBV and organisational learning theory	Adapted from Atuahene-Gima and Murrary (2007) measuring organisational learning	Interactive	213 Chinese firms (Mixed)	Time to market, development cycle, market potential	Resource and coordination flexibility positively moderate the relationship between ambidexterity and new product development performance.
Wong, Wong, and Boon-itt (2013)	Information processing and relational view theory	Internal and external integration (from the perspective of supply chain management) form the two activities that define ambidexterity.	Interactive and difference	151 Automotive firms in Thailand	Product innovation	In addition to internal and external integration having a positive impact on product innovation (adding new features to products), interactive and difference terms of ambidexterity are positively related to product innovation.
Yang, Fang, Fang, Chou (2014)	Organisational learning theory	Knowledge exchange and knowledge protection between alliance form ambidexterity	Interactive	127 High-tech Taiwanese firms	No	Interactive learning between alliance partners and reciprocal commitment learning have a positive impact on knowledge exchange and protection respectively that forms ambidexterity and this has a positive impact on performance of cooperation.
Li (2014)	Upper echelons and inter-group	Based on Jansen et al., (2006) innovation ambidexterity is measured	Additive	196 Chinese firms (Mixed)	No	Team diversity positively impacts ambidexterity mediated via strategic planning and intra-group conflicts have a negative impact.
Derbyshire (2014)	Not explicitly mentioned	Exploitation and exploration innovation tendencies adopted by the firms	Additive	45113 enterprise from 15 countries (Mixed)	No	Innovation ambidexterity has a strong impact on sales-growth
Author(s)	**Theory**	**Ambidexterity construct conceptualisation**	**Ambidexterity construct**	**Sample Data**	**Product characteristics**	**Key Findings**

			operationalization		**studied**	
Nosella (2014)	Organisational learning	Adapted from Atuahane-Gima (2005) to measure innovation ambidexterity competence	Interactive	88 High-tech firms	Innovation performance	Ambidexterity acts as mediator between searching for distant and local knowledge having a positive impact on innovation and economic performance.
Voss and Voss (2013)	Organisational learning	Measure product and market - exploration and exploitation	Interactive	162 Theatre firms	No	Product ambidexterity (that is new projects taken by the theatre company and offering same show to their strengths. There interactive terms have positive and negative impact on ticket sales.
Sanal et al., (2013)	Not explicitly mentioned	Adapted from Atuahene-Gima (2005) to measure innovation ambidexterity	Interactive	558 Turkish firms (mixed)	No	Organisational ambidexterity mediates the hypothesis between responsive and proactive market orientation and incremental and radical innovation performance
Russo and Vurro (2010)	Organisational learning and contingency theory	Measure external exploration and exploitation is inter-firm technology learning and internal exploration and exploitation is intra-firm activities	Interactive	664 FC-based formal alliance	Innovation performance.	Internal exploitation is necessary to enhance external agreements.

Appendix 4A: Main study questionnaire

Thank you for agreeing to participate in our research project on "New product development in high technology industry". By completing the survey you are providing invaluable insights that are critical for the accuracy and success of this research project.

Even if you are not sure what the answer to a question is, please try to answer all questions. An approximate indication that reflects your opinion is more valuable to us than an incomplete questionnaire.

Any information you provide will be treated in ABSOLUTE CONFIDENCE; at no time will a company/business unit or any participating individual be identified in the results.

GUIDELINES FOR COMPLETING THE QUESTIONNAIRE

- This questionnaire should be answered by an individual who has a good overview of the new product development within the company/business unit. If you feel you are not the right person to respond to the questionnaire, we would be grateful if you could pass it to the colleague you consider might be more appropriate to answer the questions.

- The purpose of this study is to collect information on how companies develop new products. To stress again, all of your answers will remain CONFIDENTIAL.

- At some points in the questionnaire you might feel that we are asking you similar ques
due to methodological issues and we would kindly ask you to fill them in even if they se

- All the questions refer to the business unit/company that you work, unless stated o

THANK YOU VERY MUCH FOR YOUR HELP

Hitesh Kalro
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What is your job title?

What is your position in the company?

CEO/Director/Owner

Senior manager

Middle manager

Junior manager

Other, please specify.

What is the length of your experience in working in new product development? (in years)

0 - 1 year	1 - 3 years	3 - 5 years	5 - 8 years	8 - 10 years	10 + years
○	○	○	○	○	○

How long have you been with the company/business unit? (in years)

0-1 year	1-3 years	3-5 years	5-8 years	8-10 years	10 + years
○	○	○	○	○	○

And how long within the current role? (in years)

0-1 year	1-3 years	3-5 years	5-8 years	8-10 years	10+ years
○	○	○	○	○	○

How many new product development projects have you worked on, so far?

1 - 5	6 - 10	11 - 15	16 - 20	21 - 25	26 - 30	30 +
○	○	○	○	○	○	○

In answering the question please click the option that best reflects your opinion:

In this company/business unit....

	Not at all (1)	(2)	(3)	(4)	(5)	(6)	To a very great extent (7)
Strong emphasis on the development of new and innovative products or services.	○	○	○	○	○	○	○
Strong emphasis on R&D, technological leadership, and innovation.	○	○	○	○	○	○	○
Develop many new lines of products or services.	○	○	○	○	○	○	○
Initiate actions to which competitors then respond.	○	○	○	○	○	○	○
First to introduce new products or services, techniques, and technologies.	○	○	○	○	○	○	○

In answering the question please click the option that best reflects your opinion:

In this company/business unit....

	Not at all (1)	(2)	(3)	(4)	(5)	(6)	To a very great extent (7)
Adopt a very competitive, "undo-the-competitors" posture	○	○	○	○	○	○	○
Strong proclivity for high - risk projects (with chances of very high returns)	○	○	○	○	○	○	○
Bold, wide - ranging acts are necessary to achieve the firm's objective.	○	○	○	○	○	○	○
Adopt a bold, aggressive posture to maximize the probability of exploiting opportunities.	○	○	○	○	○	○	○

Thinking about the information your firm/business unit gathers, how far do the following scenarios hold true?

In our firm/business unit,

	Not at all (1)	(2)	(3)	(4)	(5)	(6)	To a very great extent (7)
We constantly monitor our level of commitment and orientation to serving customer needs	○	○	○	○	○	○	○
We measure customer satisfaction systematically and frequently.	○	○	○	○	○	○	○
We help customers anticipate developments in the markets.		○					

We continuously try to discover additional needs of our customers of which they are unaware.	○	○	○	○	○	○	○
We work closely with lead users who try to recognize customer needs, months or even years before the majority of the market recognizes them.	○	○	○	○	○	○	○
We extrapolate key technological, business and customer lifestyle trends to gain insight into what customers in our current market would need in the future.	○	○	○	○	○	○	○

Please click the option that best describes the situation in your company...

	Not at all (1)	(2)	(3)	(4)	(5)	(6)	To a very great extent (7)
Our strategy for competitive advantage is based on our understanding of customer's needs.	○	○	○	○	○	○	○
We innovate even at the risk of rendering our own products obsolete.	○	○	○	○	○	○	○
We believe this business exists primarily to serve customers.	○	○	○	○	○	○	○
We incorporate solutions to inarticulate customer needs in our new products and services.	○	○	○	○	○	○	○
We search for opportunities in areas where customers have a difficulty expressing their needs.	○	○	○	○	○	○	○
We are more customer-focused than our competitors.	○	○	○	○	○	○	○

Thinking about the information your firm/business unit gathers, how far do the following scenarios hold true?

	Not at all (1)	(2)	(3)	(4)	(5)	(6)	To a very great extent (7)
We freely communicate information about our successful and unsuccessful customer experiences across all business units.	○	○	○	○	○	○	○
We brainstorm on how customers use our products or services to discover new customer needs.	○	○	○	○	○	○	○
Data on customer satisfaction are disseminated at all levels in this business unit/firm on regular bases.	○	○	○	○	○	○	○

If you were to take into consideration the resources at the disposal of the new product development team in your company/business unit for new product/service development, in your opinion, how would you rate the following situations?

	Strongly Disagree (1)	(2)	(3)	(4)	(5)	(6)	Strongly Agree (7)
This business unit/firm has uncommitted resources that can be quickly used to fund new strategic initiatives.	○	○	○	○	○	○	○
This business unit/firm has few resources available in the short run to fund its initiatives.	○	○	○	○	○	○	○
We are able to obtain resources at short notice to support new strategic initiatives.	○	○	○	○	○	○	○

The section that follows, contains questions regarding approaches that the company/business unit use to understand why an undesirable marketing outcome may have occurred. How far do you agree/disagree with the following....

	Strongly Disagree (1)	(2)	(3)	(4)	(5)	(6)	Strongly agree (7)
Managers search for a solution to slow sales under the assumption that they need to understand their customer needs/wants better.	○	○	○	○	○	○	○

Managers search for solutions to new product development under the assumption that there is a scope for improving our current product line.							
Managers search for a solution to poor advertising performance under the assumption that brand credibility can best be established through the use of well-known spokesperson.							
Managers search for a solution to slow sales under the assumption that it is time to search for new ideas, unique/creative solutions.							
Managers search for a solution to new product development under the assumption that it is time to search new technology, which complements our current product line.							
Managers search for a solution to poor advertising performance under the assumption that a spokesperson endorsement may not be the best way to build brand credibility.							

How far do the following statements describe the situation in this business unit/company...
We....

	Not at all (1)	(2)	(3)	(4)	(5)	(6)	To a very great extent (7)
Use new ideas that are consistent with our current product - market experiences by analysing current customers' needs and competitor products.							
Undertake activities that help to utilize or integrate the firm's current market experience.							
Use market information and ideas that may contribute to the firm's existing product - market through analysis of experience with prior projects, current competitors and technologies.							
Emphasises using proven ideas for solutions to marketing problems by surveying current customers.							

How far do you agree/disagree with the following statement...
We.......

	Strongly Disagree (1)	(2)	(3)	(4)	(5)	(6)	Strongly Agree (7)
Use market information that takes the company/business unit beyond its current product market experience through market experiments.							
Use novel products or services that may not necessarily be successful in the current market through contact with non-customers, studying of emerging competitors and technologies.							
Aim to collect new information that enables us to learn new things in our market.							
Use market information and generate new ideas involving experimentation and high risk.							

How far do the following statements describe the products/services introduced by your company/business unit in the last three years.
Relative to our key market competitors, the products/services we offer in our market(s) are:

	Much less than our key competitors (1)	(2)	(3)	(4)	(5)	(6)	Much more than our key competitors (7)
New products or services that provide many benefits to the customer.							
New products or services that offer much value to the customer.							
New product or services that offer many advantages.							
New products or services that are superior to the							

competing products	
New products or services that are the best of its kind in the market.	
New products or services that are superior to competing products.	

How far do you agree/disagree with the following statements that describe the products/services introduced by your company/business unit in the last three years.

	Strongly Disagree (1)	(2)	(3)	(4)	(5)	(6)	Strongly Agree (7)
Our products or services required a major learning effort by the customer.							
It took a long time before customer could understand the products' or services' full advantages.							
Product or service concept was difficult for customer to evaluate or understand.							
Products or services were more complex than what we have introduced before in the same market.							
Our products or services involved high changeover costs for the customer.							
Our products or services required considerable advance planning by the customer before use.							

How far does the following statement describe the products/services introduced by your company/business unit in the last three years.

To what extent was the product or service category an existing one to the company/business unit - you had sold products in this category before now?

	Not at all (1)	(2)	(3)	(4)	(5)	(6)	To a very great extent (7)
To what extent were the products or services category an existing one to the company/business unit - you had sold products or services in this category before now?							
To what extent were the competitors that these products or services took you up against familiar ones - ones you had faced before?							
To what extent was the distribution channel system that you used for the products or services familiar or an existing one?							
To what extent was the type of products or services a familiar one for you?							
To what extent was the technology used in the development of the products or services familiar or in-house technology to you?							
To what extent could the products or services be introduced using existing company/business unit plant and/or equipments.							

This section contains questions regarding the performance of the products/services introduced by your company/business unit in the *last three years*. We are interested in your opinion regarding the questions that follow. Any information you provide will be treated in ABSOLUTE CONFIDENCE.

How satisfied/dissatisfied are you with the products/services introduced, in achieving the goals set by your business unit/company:

	Very Dissatisfied (1)	(2)	(3)	(4)	(5)	(6)	Very Satisfied (7)
The market share goals							
The sales - volume goals							
The revenue goals							
The overall goals							
The profitability goals							

The return on investment goals

The section that follows contains questions regarding the environment your company/business unit operates under.

How much do the following statements describe the environment that your business unit/company operates under...

	Not at all (1)	(2)	(3)	(4)	(5)	(6)	To an extreme extent (7)
In our kind of business, customers' product or service preference changes quite a bit over time.							
Our customers tend to look for new products or services all the time.							
Our customers are very price sensitive but on other occasions, price is relatively unimportant.							
We are witnessing demand for our products or services from customers who never bought them before.							
New customers tend to have product or service related needs that are different from those of our existing customers.							
We cater to too many of the same customers that we need in the past.							

The section that follows contains questions regarding the environment your company/business unit operates under.

How far do you agree/disagree with the following statements that describe the environment that your business unit/company operates under...

	Strongly Disagree (1)	(2)	(3)	(4)	(5)	(6)	Strongly Agree (7)
The technology in our industry is changing rapidly							
Technological changes provide big opportunities in our industry							
It is very difficult to forecast where the technology in our industry will be in the next two to three years.							
A large number of new product ideas have been made							
possible through technological breakthroughs in our industry.							
Technological developments in our industry are rather minor.							

The section that follows contains questions regarding the environment your company/business unit operates under.

How far do you agree/disagree with the following statements that describe the environment that your business unit/company operates under...

	Strongly Disagree (1)	(2)	(3)	(4)	(5)	(6)	Strongly Agree (7)
Competition in our industry is cutthroat.							There
are many "promotion wars" in our industry.							
Anything that one competitor can offer, other can match it readily.							
Price competition is a hallmark of our industry.							
One hears of a new competitive move almost every day.							
Our competitors are relatively weak.							

This final section is about your company. All the information you provide will be kept in strict confidence; at no time will the company or any participating individual be identified in the results.

Which industry does your firm operate in?

Automobile

IT

Computers (hardware and software)

Chemicals

Electrical and Electronics

Biotechnology

Pharmaceuticals

Mechanical

Others, please specify.

In the last three years, how many new products were introduced by your company/business unit in the UK?

1 - 5	6 - 10	11 - 15	16 - 20	21 - 25	26 - 30	>30

How many full - time/ full - time equivalent staff are employed by your company/business unit in the UK?

1 - 25	26 - 50	51 - 100	101 - 250	251 - 500	501 - 1000	>1000

Of these, how many work in the new product development department?

1 - 10	11 - 20	21 - 50	51 - 75	76 - 125	126 - 250	>250

What year was your company/business unit founded?

Approximately, what was your average ANNUAL TURNOVER last year? Amounts are in million £

0 - 10 M	11 - 20 M	21 - 50 M	51 - 75 M	76 - 125 M	126 - 250 M	251 - 500 M	501 - 1000 M	>1000 M

On average, what percentage of your firm's/business unit's turnover invested in R&D, over the last 3 years?

0% to <2%	2% to <4%	4% to <6%	6% to <8%	8% to <10%	10% to <12%	12% to <16%	16% to <20%	>20%

Regarding the answers you have provided....

	Strongly Disagree (1)	(2)	(3)	(4)	(5)	(6)	Strongly Agree (7)
I have a good overview of the new product development department in our company							
I am competent to answer the above questions.							
I have a good overview of the company's situation (e.g. performance, environment, product/service)							
My job role qualifies me to answer questions about the new product development in my company.							

Please use this space to add any additional information. We would like to get any feedback from you, to improve our research project. Your feedback is important to us. Thank you.

Contact me: H.Kalro@lboro.ac.uk

Appendix 4B: First email and the reminder email

Dear Mr. ………..,

My name is Hitesh Kalro and I am a PhD student in the School of Business and Economics at the Loughborough University conducting research under the supervision of Dr Mohammed Rafiq. We are researching new product development and performance in High-Tech firms. We are conducting a survey on 1500 highly innovative firms in the UK. Through your participation, we hope to understand how companies can best satisfy the needs of their customers and what the best new product development process is. The results of the study will help companies like yours develop successful new products.

As you are the …………. at …………..., and an expert in this area, you can provide us with useful insight by completing the online questionnaire. All the information that you provide through your participation in this study will be kept confidential. Further, you will not be identified in the thesis or in any report or publication based on this research. At the end of the study a detailed industry report will be provided to all who have been instrumental in this study.

Completion of the questionnaire would take approximately 20-25 minutes of your time. I would like to assure you that this study has been reviewed and received ethical clearance through the Office of Research Ethics at the Loughborough University. However, the final decision about participation is yours.

Please follow the link to the online survey:https://lborobusiness.eu.qualtrics.com/SE/?SID=SV_3UkjiqvOCje9W1D

Username: npd7806
Password: lboro8047
Thank you in advance for your co-operation in this research.

Yours sincerely,
Hitesh Kalro
Doctoral Student
School of Business and Economics
Loughborough University
E-mail: h.kalro@lboro.ac.uk
Office Telephone: 01509 228842

Dr. Mohammed Rafiq
Reader in Retailing and Marketing
School of Business and Economics
Loughborough University
http://www.lboro.ac.uk/departments/sbe/staff/academic-research/msmr.html

Reminder email:

Dear Mr. …………,

I hope that you have received the link to my online questionnaire on "New product development in High – Tech firms in the UK" a week ago.
If you have not yet had a chance to complete the questionnaire, I would like to take this opportunity to emphasize that I am still very keen to obtain your response, since your participation could really make a difference between the success and the failure of this project and of my PhD as well.
Let me remind you and re-assure you that all replies are kept in strict confidence according to the University data protection guidelines. If you have any problem accessing the questionnaire, or have any questions regarding the study, please do not hesitate to contact me.
I look forward to your response.

Please follow the link to the online survey: https://lborobusiness.eu.qualtrics.com/SE/?SID=SV_3UkjiqvOCje9W1D
Username: npd2331
Password: lboro8002

Thank you in advance for your co-operation in this research.

Yours sincerely,

Hitesh Kalro
Doctoral Student
School of Business and Economics
Loughborough University
E-mail: h.kalro@lboro.ac.uk
Office Telephone: 01509 228842

Dr. Mohammed Rafiq
Reader in Retailing and Marketing
School of Business and Economics
Loughborough University
http://www.lboro.ac.uk/departments/sbe/staff/academic-research/msmr.html

Appendix 5A: Reliability (Cronbach's coefficient value) assessment results for all scales

Construct	**Reliability**
Exploratory market learning	**0.790**
Exploitative market learning	**0.804**
Marketing discontinuity	**0.788**
Technological discontinuity	**0.846**
Customer Discontinuity	**0.875**
Product meaningfulness	**0.875**
Product Superiority	**0.930**
New Product financial performance	**0.925**

Appendix 5B: Exploratory Factor Analysis for Subset 1:

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	5.470	39.074	39.074	5.470	39.074	39.074	3.861
2	2.671	19.076	58.151	2.671	19.076	58.151	3.165
3	1.315	9.392	67.543	1.315	9.392	67.543	3.574
4	.752	5.373	72.916	.752	5.373	72.916	3.858
5	.696	4.969	77.885				
6	.629	4.494	82.379				
7	.495	3.533	85.912				
8	.429	3.063	88.974				
9	.398	2.844	91.818				
10	.347	2.480	94.298				
11	.276	1.973	96.271				
12	.229	1.636	97.907				
13	.154	1.101	99.007				
14	.139	.993	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Pattern Matrix[a]

	Component			
	1	2	3	4
exi1			-.828	
exi2			-.823	
exi3			-.803	
exi4			-.647	
exr1		.822		
exr2		.844		
exr3		.578		
exr4	.200	.811		
npa1				-.825
npa2				-.914
npa3	.361			-.620
npa4	.790			
npa5	.894			
npa6	.902			

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 9 iterations.

Appendix 5C: Exploratory factor analysis for Subset 2

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	4.256	25.034	25.034	4.256	25.034	25.034	3.918
2	3.735	21.969	47.004	3.735	21.969	47.004	3.143
3	2.278	13.402	60.406	2.278	13.402	60.406	2.803
4	1.334	7.846	68.251	1.334	7.846	68.251	3.067
5	.898	5.282	73.533				
6	.741	4.356	77.890				
7	.653	3.842	81.732				
8	.617	3.631	85.363				
9	.544	3.203	88.566				
10	.411	2.419	90.984				
11	.353	2.076	93.060				
12	.259	1.526	94.586				
13	.251	1.479	96.065				
14	.228	1.341	97.405				
15	.182	1.069	98.474				
16	.152	.893	99.367				
17	.108	.633	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Pattern Matrix[a]

	Component			
	1	2	3	4
cf1	.834			
cf2	.815			
cf3	.825			
cf4	.633			
cf5	.813			.311
cf6	.766	.321		
md1		.759		
md2		.686		
md3		.759		
md4		.731		
md5		.643		-.254
td1				-.887
td2				-.887
td3				-.761
npp3			.912	
npp4			.939	
npp5			.934	

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Appendix 5D: Schmid-Leiman Solution for 2 level higher order Factor analysis

```
.
Matrix.
* Enter first-order pattern matrix.
compute F1 = {0.049, 0.87;
             -0.07, 0.857;
             0.287, 0.591;
             0.835, 0.091;
             0.889, 0.01;
             0.943, -0.02}.
*enter first-order variable names.
compute varname = {"npa1"; "npa2"; "npa3"; "npa4"; "npa5"; "npa6"}.
*enter first-order factor names.
compute f1name = {"ProdSup", "ProdMean"}.
*enter second-order factor loadings.
compute F2 = {0.496; 0.498}.
*enter second-order factor name.
compute f2name = {"ProdAdv"}.
* END OF INPUT.
print F1/Format"f5.3" /rnames=varname /cnames=f1name.
compute C1=ncol(F1).
print F2/format"f5.3" /rnames=f1name /cnames=f2name.
compute C2=ncol(F2).
Compute zw1=1-rssq(f2).
Compute Unique=Mdiag (zw1).
compute zw1=sqrt(unique).
compute B={F2,zw1}.
Compute SLP=F1*B.
compute hrtot=rssq(SLP).
compute C1end=C1+C2.
compute C1start=C2+1.
compute zw2=slp(:,C1start:C1end).
compute HR1st=rssq(zw2).
compute zw3=SLP(:,1:C2).
compute HR2nd=rssq(zw3).
compute HCtot=cssq(SLP).
compute Htot=mssq(SLP).
compute Htot100=HCtot &/ Htot.
compute Htotsum=msum(HCtot) / Htot.
compute zw4=Htot100(1:C2).
compute zw5=Htot100(C1start:C1end).
compute EXG=rsum(zw4).
compute EXF=rsum(zw5).
compute results1={SLP, HRtot, HR2nd, HR1st}.
compute slpname={f2name, f1name, "H² total", "H² G", "H² 1st"}.
print results1/ format "f5.3" /title="factor loadings of Schmid-Leiman Solution and h²"
/rnames = varname /cnames=slpname.
```

```
compute results2={HCtot, Htot;
        Htot100, Htotsum}.
compute fixedn2={f2name,f1name,"total"}.
print results2 /format"f5.3"/ title="sum of squared loadings"
/rlabels="H²" "%" /cnames=fixedn2.
print EXG /format"f5.3"/ title="percentage of exracted variance explained by general factors
(%)".
print EXF /format"f5.3"/ title="percentage of extracted variance explained by first order
factors (%)".
    End Matrix.
```

```
* Schmid-Leiman Solution for 2 level higher order Factor analysis.
Matrix.
* Enter first-order pattern matrix.
compute F1 = {0.680, 0.031;
          0.835, -0.078;
          0.737, 0.121;
          0.069, 0.766;
          -0.093, 0.743;
          0.145, 0.575}.
*enter first-order variable names.
compute varname = {"exi1"; "exi2"; "exi4"; "exr1"; "exr2"; "exr4"}.
*enter first-order factor names.
compute f1name = {"ExiML", "ExrML"}.
*enter second-order factor loadings.
compute F2 = {0.524; 0.536}.
*enter second-order factor name.
compute f2name = {"AML"}.
* END OF INPUT.
print F1/Format"f5.3" /rnames=varname /cnames=f1name.
compute C1=ncol(F1).
print F2/format"f5.3" /rnames=f1name /cnames=f2name.
compute C2=ncol(F2).
Compute zw1=1-rssq(f2).
Compute Unique=Mdiag (zw1).
compute zw1=sqrt(unique).
compute B={F2,zw1}.
Compute SLP=F1*B.
compute hrtot=rssq(SLP).
compute C1end=C1+C2.
compute C1start=C2+1.
compute zw2=slp(:,C1start:C1end).
compute HR1st=rssq(zw2).
compute zw3=SLP(:,1:C2).
compute HR2nd=rssq(zw3).
```

```
compute HCtot=cssq(SLP).
compute Htot=mssq(SLP).
compute Htot100=HCtot &/ Htot.
compute Htotsum=msum(HCtot) / Htot.
compute zw4=Htot100(1:C2).
compute zw5=Htot100(C1start:C1end).
compute EXG=rsum(zw4).
compute EXF=rsum(zw5).
compute results1={SLP, HRtot, HR2nd, HR1st}.
compute slpname={f2name, f1name, "H² total", "H² G", "H² 1st"}.
print results1/ format "f5.3" /title="factor loadings of Schmid-Leiman Solution and h²"
/rnames = varname /cnames=slpname.
compute results2={HCtot, Htot;
          Htot100, Htotsum}.
compute fixedn2={f2name,f1name,"total"}.
print results2 /format"f5.3"/ title="sum of squared loadings"
/rlabels="H²" "%" /cnames=fixedn2.
print EXG /format"f5.3"/ title="percentage of exracted variance explained by general factors
(%)".
print EXF /format"f5.3"/ title="percentage of extracted variance explained by first order
factors (%)".
    End Matrix.
```

Appendix 6A: Standardised residual covariance matrix for first-order CFA

Standardized Residual Covariances (Group number 1 - Default model)

	npa6	npa5	cf4	cf2	cf1	td3	td2	td1	npa3	npa2	npa1	npp5	npp3	md5	md4	md1	exr4	exr2	exr1	exi4	exi2	exi1
npa6	.000																					
npa5	.000	.000																				
cf4	.154	.591	.000																			
cf2	-.574	-.500	-.325	.000																		
cf1	.541	.648	.163	.044	.000																	
td3	1.276	.769	1.039	-.151	-.680	.000																
td2	-.042	-.137	2.122	.219	-.605	-.037	.000															
td1	-.266	-.493	.971	-.130	-.450	-.167	.045	.000														
npa3	.741	.505	1.033	.041	1.116	.832	-.042	-.201	.000													
npa2	-.710	-.160	.338	-.842	.930	.891	-.055	-.295	-.159	.000												
npa1	-.149	-.115	-.339	-.987	.435	1.371	-.125	-.429	-.118	.236	.000											
npp5	-.081	.037	-.416	-.134	.227	1.626	-.446	.227	-.278	-.260	.266	.000										
npp3	.283	.441	-.426	.144	.307	2.401	.496	.631	-.184	-.071	.365	.000	.000									
md5	.713	-.395	.961	.372	.463	.790	.288	.372	.364	.846	.706	-.442	-.042	.000								
md4	.238	-.791	.208	-.439	-.515	1.050	-.515	-.411	-1.389	-1.354	-.079	.440	.609	.025	.000							
md1	-.062	-1.078	-.243	-.370	-.099	-.335	-.129	-.156	-.781	.747	.417	-.131	.562	-.220	.167	.000						
exr4	1.374	1.156	1.787	2.458	1.414	1.483	.149	-.261	1.054	.560	.397	-.372	.506	-.875	-1.071	-.105	.000					
exr2	.177	.287	.863	1.206	.209	2.095	.457	.557	.642	.429	-.034	-.076	.519	.710	.214	1.520	-.133	.000				
exr1	-.572	-.998	-.563	-1.053	-1.874	.633	-.538	-.739	-.931	.674	-.686	.019	1.281	.030	-.366	1.179	-.023	.082	.000			
exi4	-.737	-.871	.026	-1.423	-.308	-.107	-.218	-1.162	-.829	-.356	-.062	.760	.601	-1.750	-.296	1.201	.403	.465	.991	.000		
exi2	.888	-.066	.304	-.779	.113	.217	.229	-1.014	.496	.566	-.049	-.493	-.816	.646	.176	2.208	-.324	-.568	.169	-.188	.000	
exi1	.047	-.417	1.501	.299	1.541	.740	.429	-.509	-.041	.559	-.401	.168	-.054	-.482	-.822	.759	.255	-1.212	-.108	.000	.122	.000

Appendix 6B: Standardised residual covariance matrix for higher-order CFA

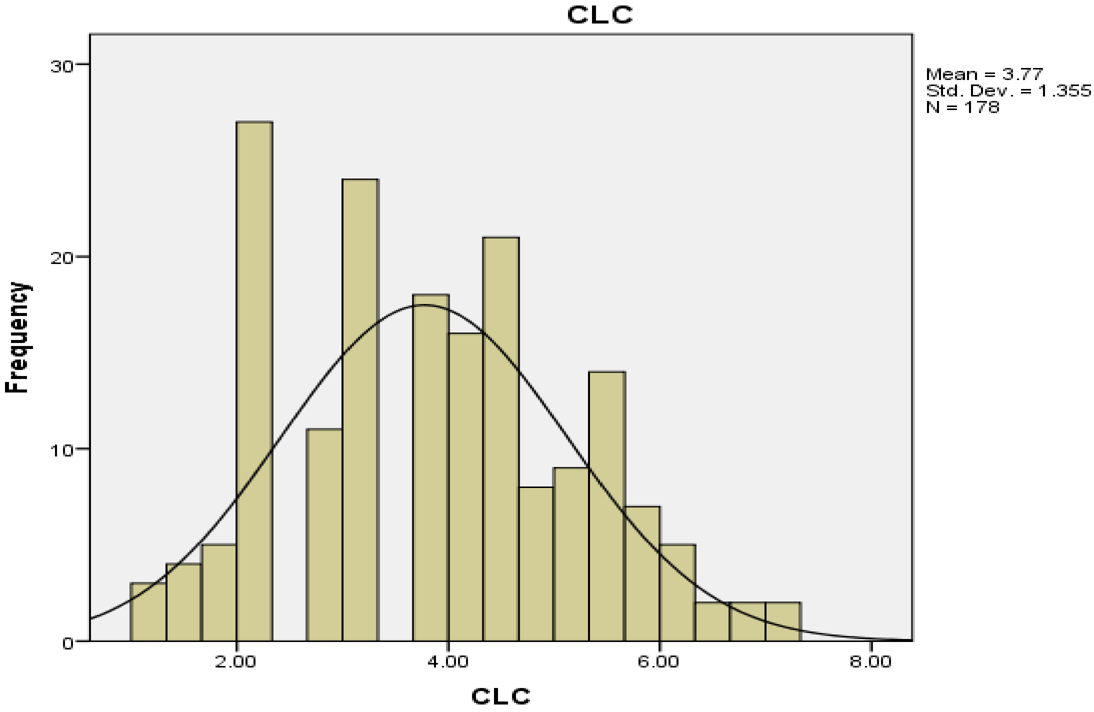
Standardized Residual Covariances (Group number 1 - Default model)

	npa6	npa5	cf4	cf2	cf1	td3	td2	td1	npa3	npa2	npa1	npp5	npp3	md5	md4	md1	exr4	exr2	exr1	exi4	exi2	exi1
npa6	.000																					
npa5	.000	.000																				
cf4	.546	.966	.000																			
cf2	.070	.116	-.239	.000																		
cf1	1.143	1.225	.027	.042	.000																	
td3	1.318	.808	1.065	-.057	-.675	.000																
td2	-.018	-.116	2.134	.310	-.634	-.032	.000															
td1	-.224	-.453	.997	-.027	-.451	-.101	.031	.000														
npa3	.742	.502	.778	-.350	.707	.848	-.053	-.188	.000													
npa2	-.704	-.157	.093	-1.218	.537	.908	-.063	-.281	-.155	.000												
npa1	-.151	-.120	-.614	-1.409	-.006	1.388	-.138	-.416	-.122	.238	.000											
npp5	.011	.124	-.422	-.175	.240	1.671	-.384	.280	-.315	-.293	.225	.000										
npp3	.417	.569	-.442	.091	.299	2.438	.547	.674	-.160	-.045	.390	.000	.000									
md5	.978	-.145	.947	.363	.433	.803	.243	.376	.203	.692	.531	-.425	-.009	.000								
md4	.527	-.518	.199	-.440	-.537	1.118	-.488	-.346	-1.515	-1.474	-.218	.476	.657	.041	.000							
md1	.132	-.895	-.252	-.375	-.120	-.318	-.153	-.146	-.893	.639	.295	-.116	.588	-.272	.194	.000						
exr4	.897	.699	2.504	2.627	2.532	2.436	1.420	.833	.969	.479	.304	-.475	.443	-.493	-.680	.175	.000					
exr2	-.314	-.184	1.598	2.401	1.352	2.079	1.766	1.688	.549	.342	-.134	-.187	.450	1.105	.618	1.808	.080	.000				
exr1	-1.230	-1.627	.285	.314	-.567	1.743	.937	.535	-1.128	.482	-.899	-.205	1.122	.431	.047	1.473	-.060	.025	.000			
exi4	-.715	-.851	-.068	-1.562	-.462	-.195	-.351	-1.267	-.513	-.047	.282	1.144	.960	-1.828	-.351	1.147	.725	.789	1.244	.000		
exi2	.456	-.475	.125	-1.049	-.177	-.065	-.174	-1.343	.452	.526	-.098	-.471	-.745	.238	-.189	1.913	-.351	-.605	-.060	.041	.000	
exi1	-.050	-.511	1.372	.106	1.331	.588	.205	-.688	.217	.813	-.127	.495	.267	-.657	-.966	.634	.518	-.956	.037	-.545	.125	.000

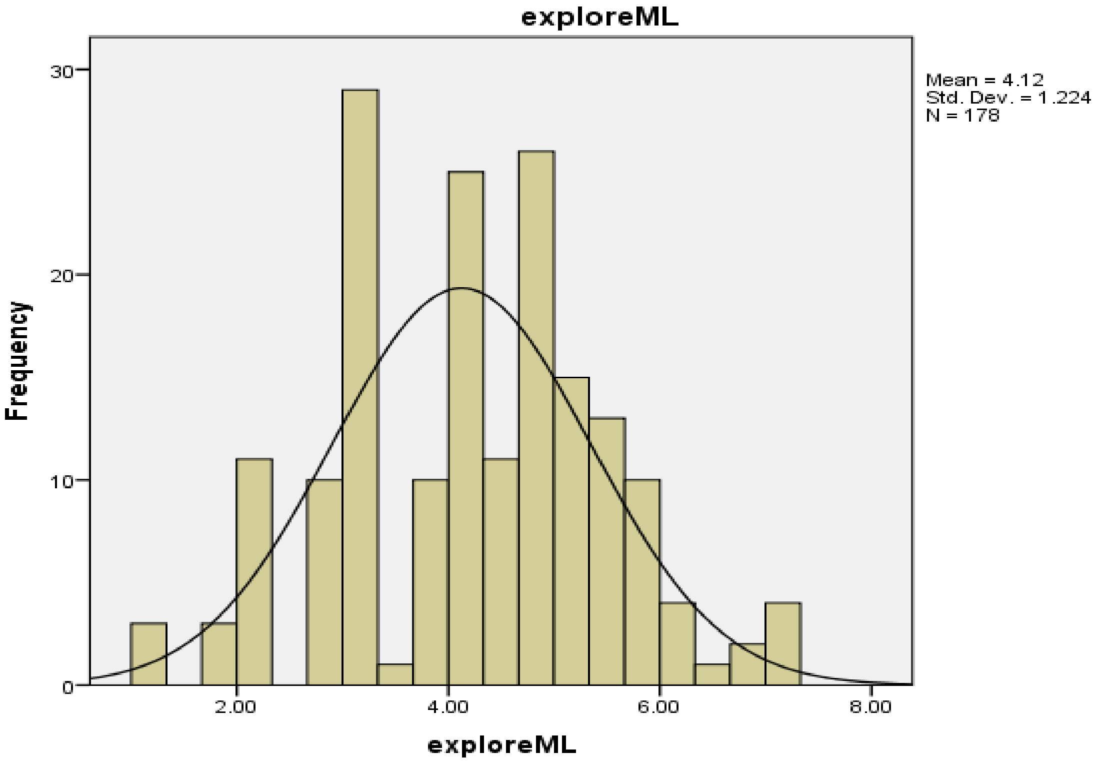
Appendix 7A: Test for Normal distribution

Appendix 7A: Test for Normal distribution

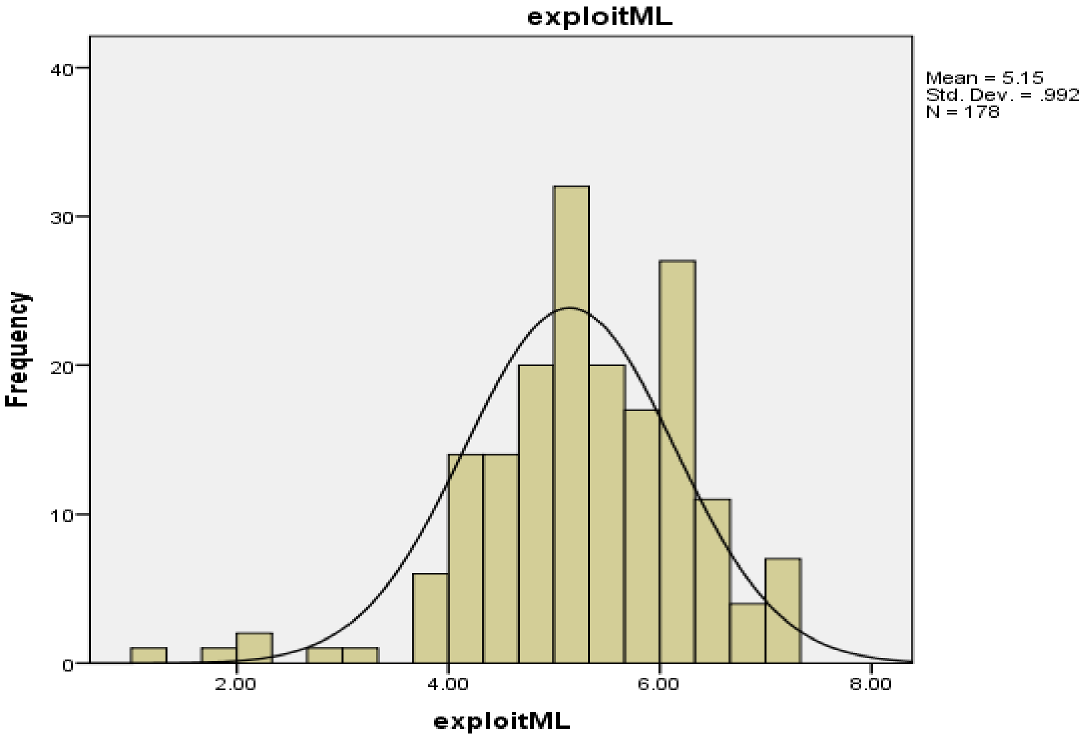
Customer Discontinuity



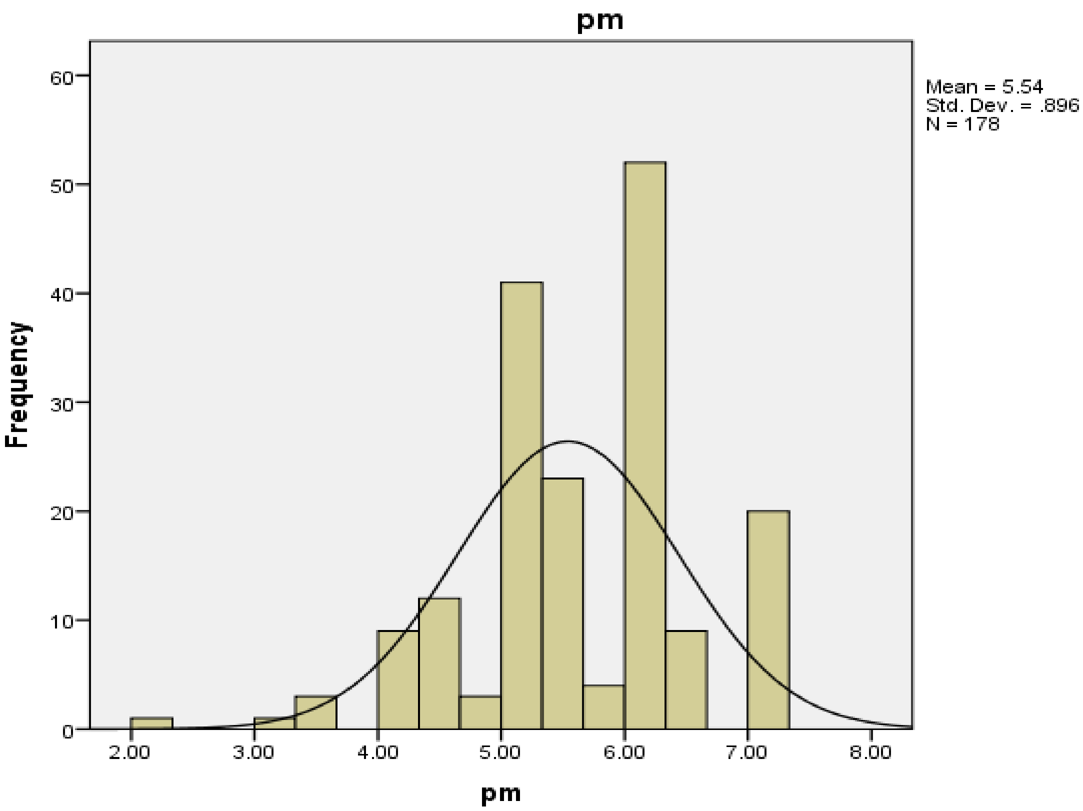
Exploratory Market Learning



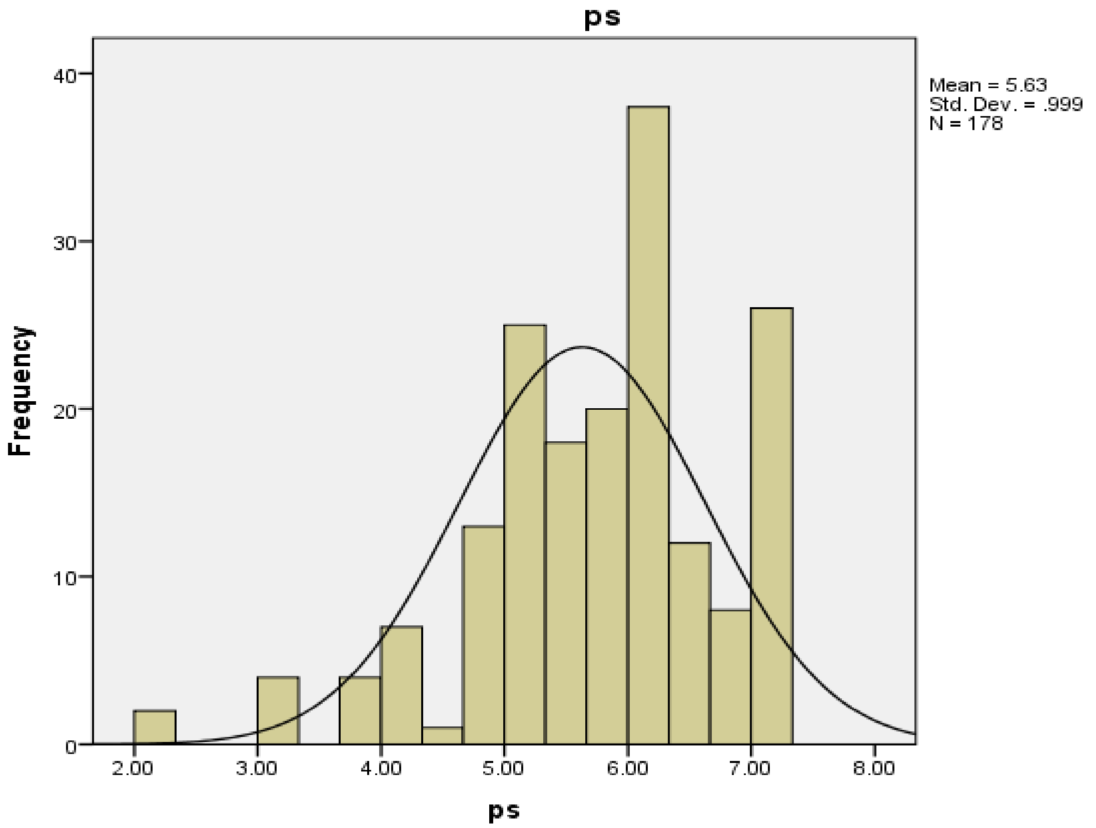
Exploitative Market Learning



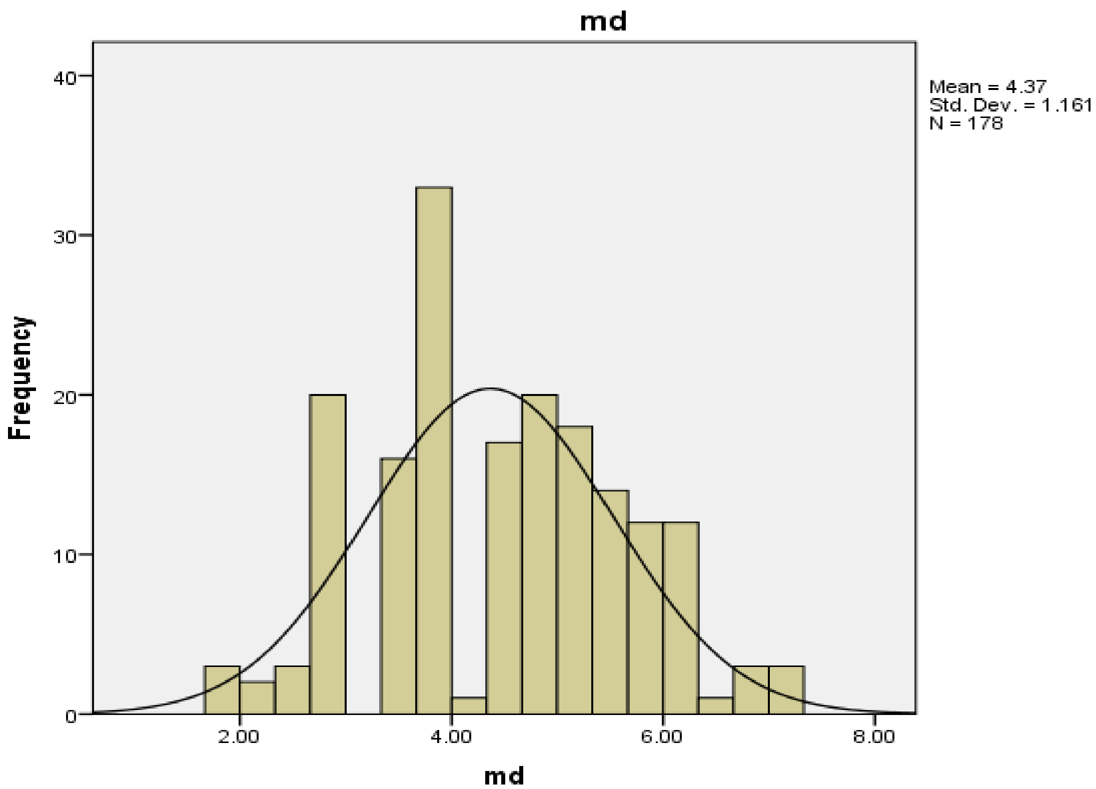
Product Meaningfulness



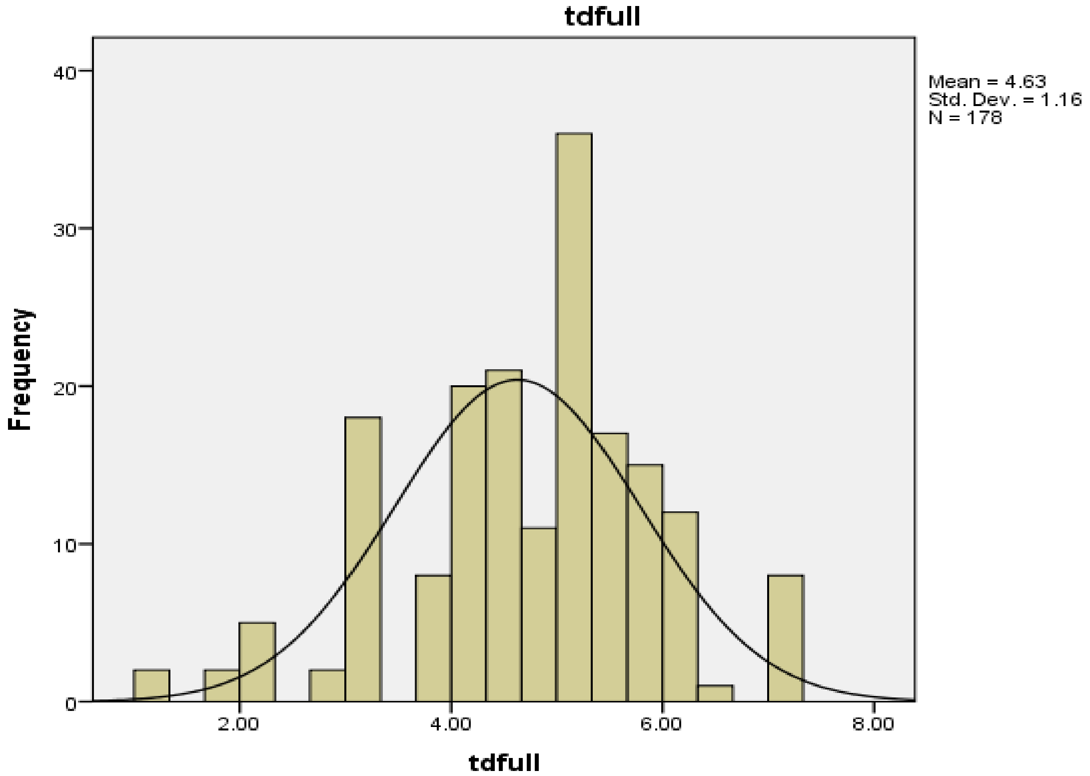
Product Superiority



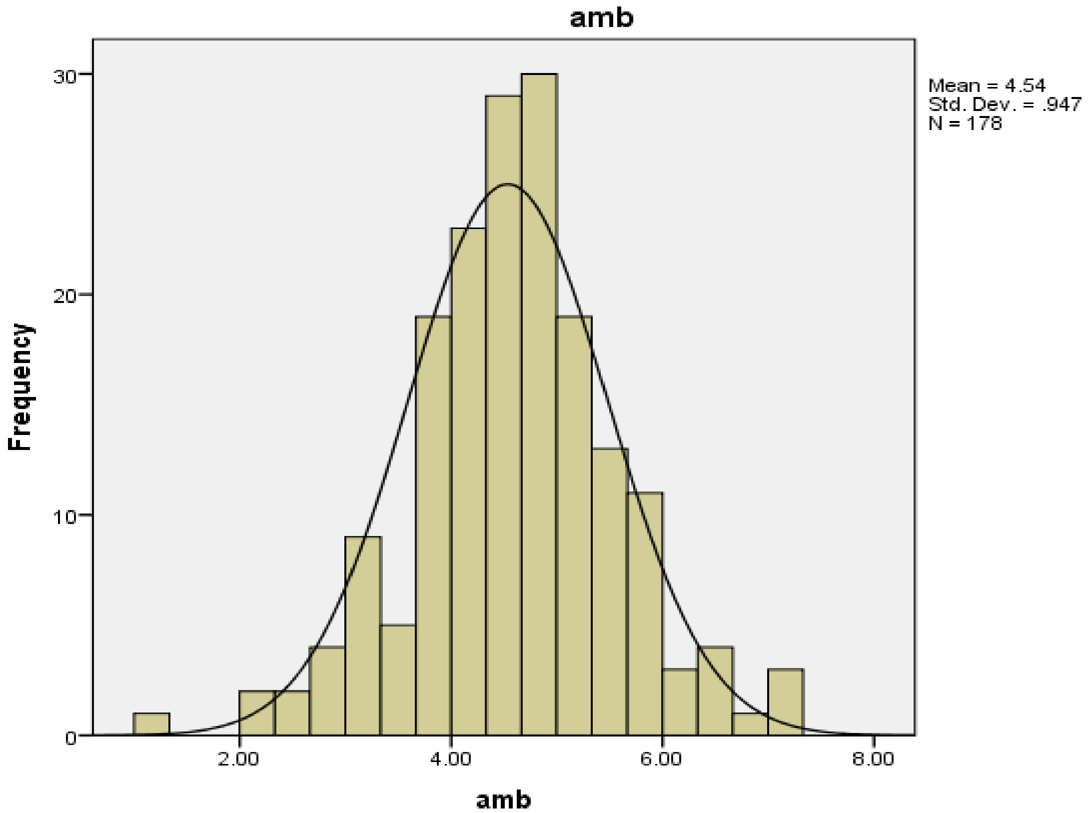
Marketing Discontinuity



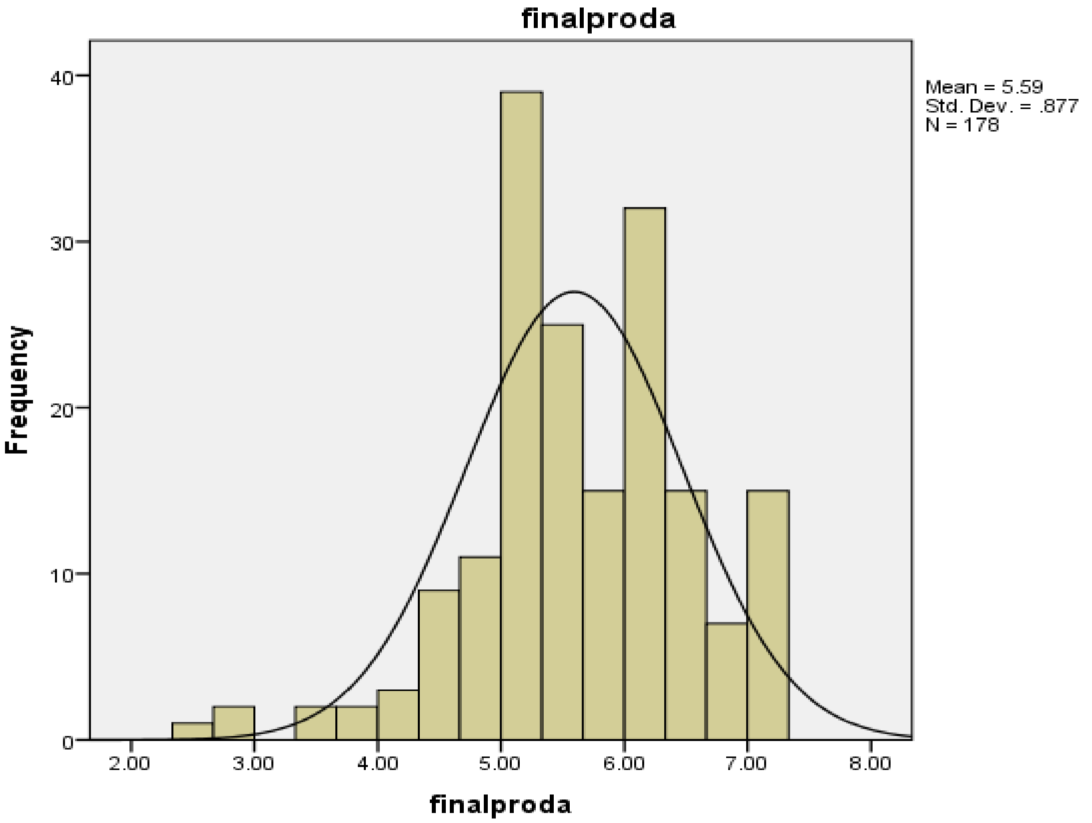
Technological Discontinuity



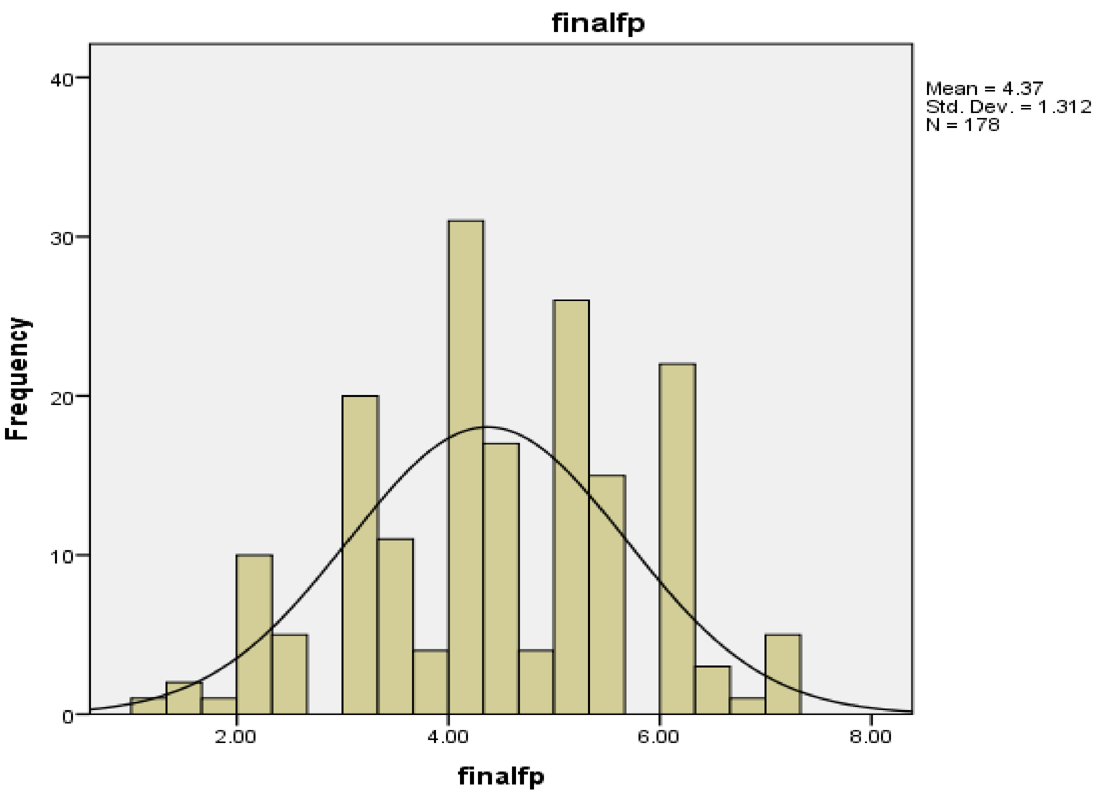
Ambidextrous Market Learning



Product Advantage

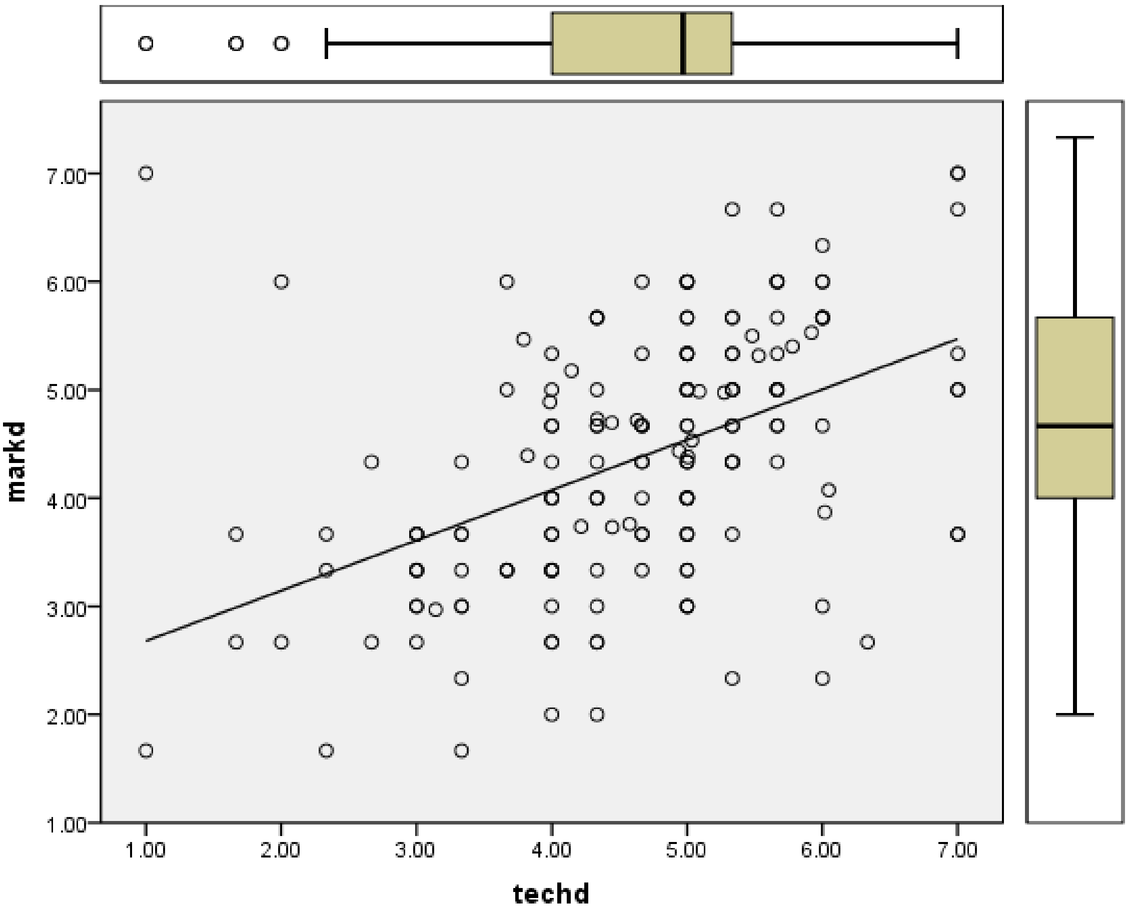


New Product Financial Performance

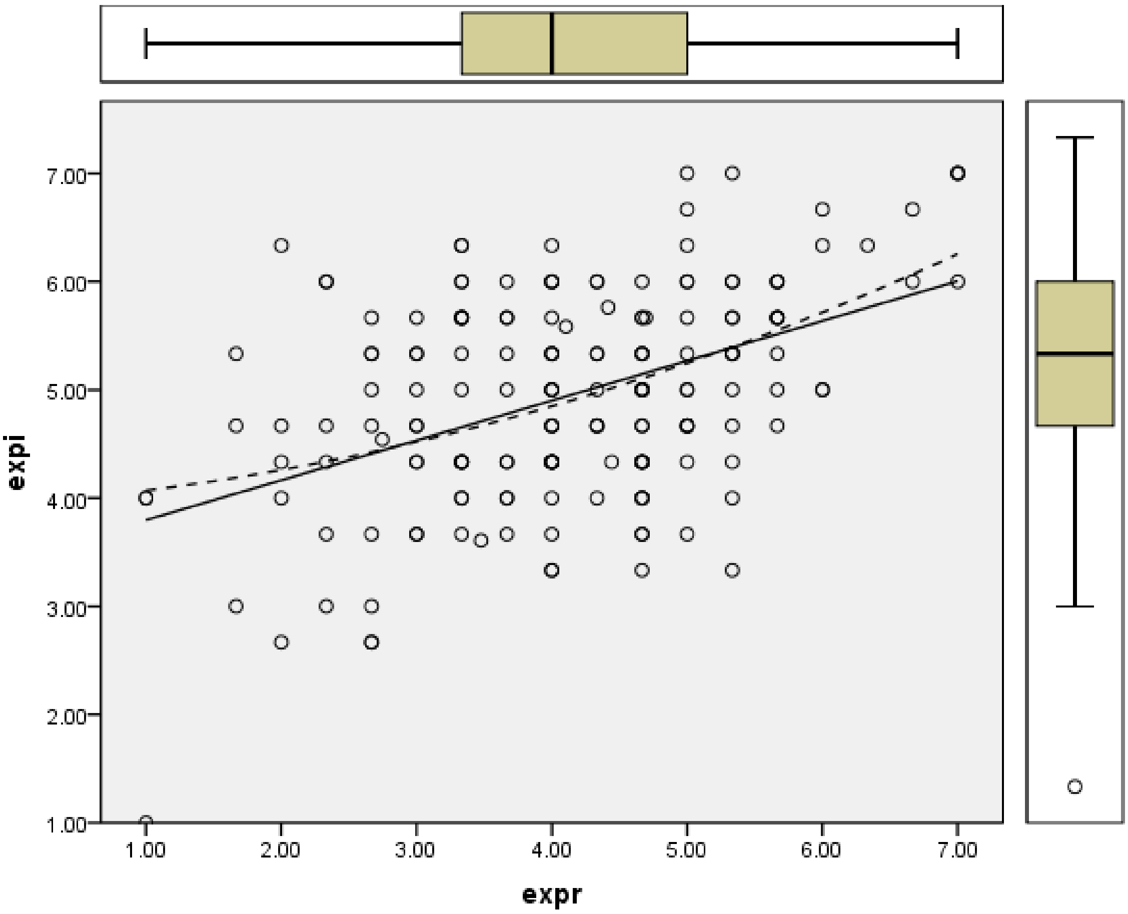


Appendix 7B: Scatterplots

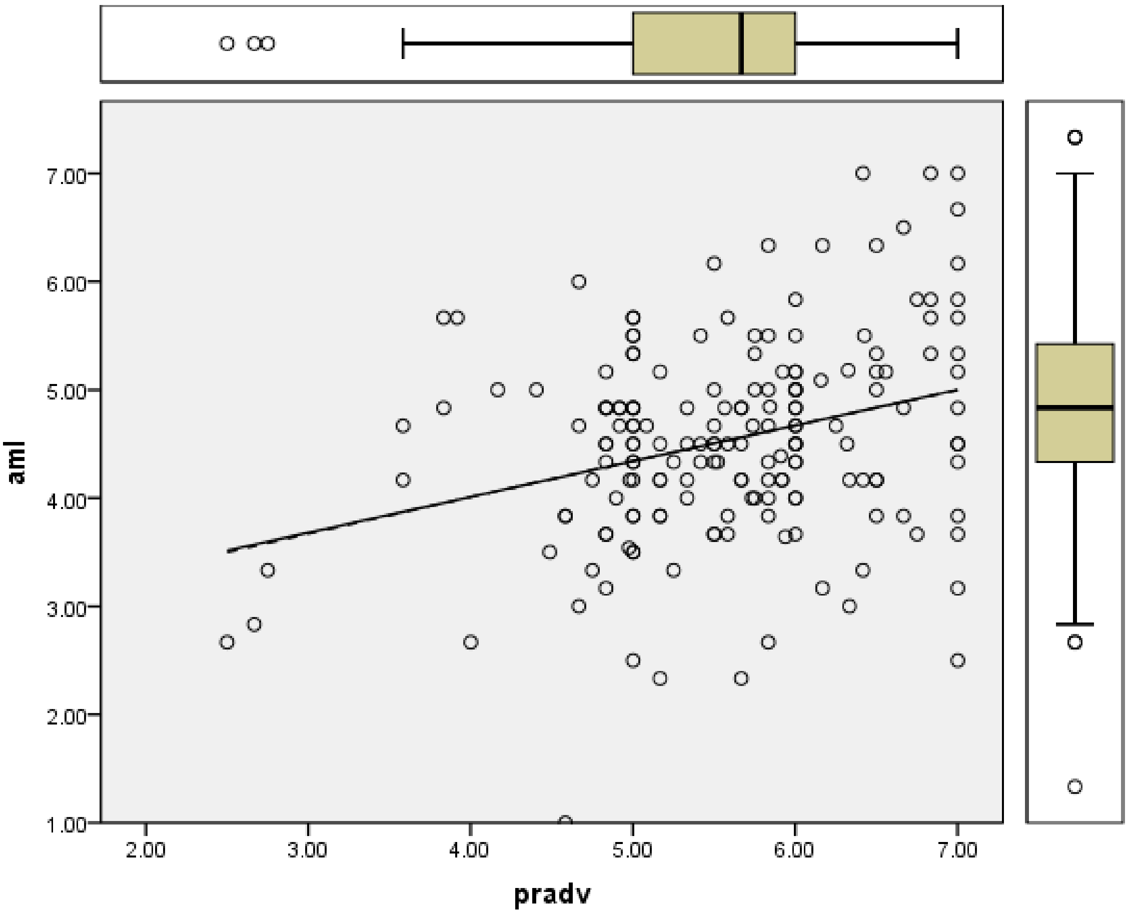
Scatterplot between Marketing Discontinuity and Technological Discontinuity



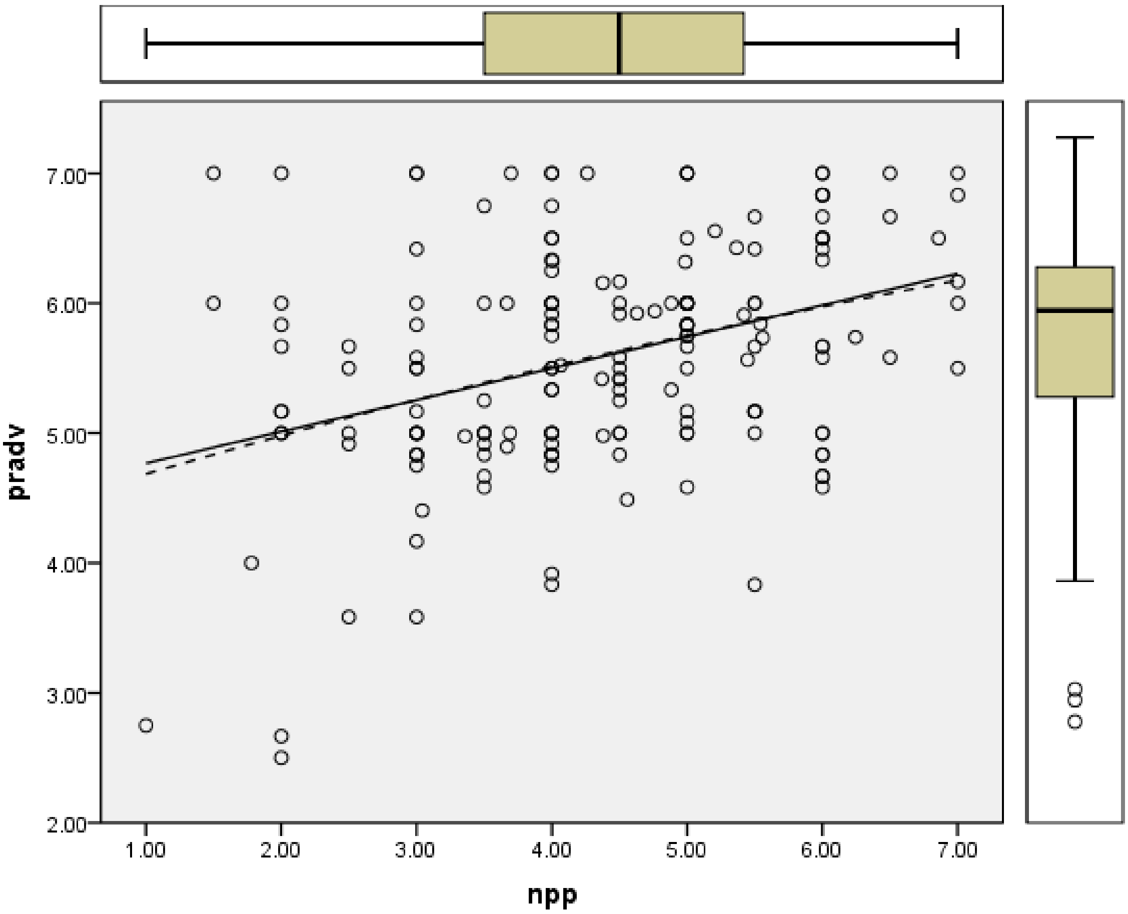
Scatterplot between Exploratory Market Learning and Exploitative Market Learning



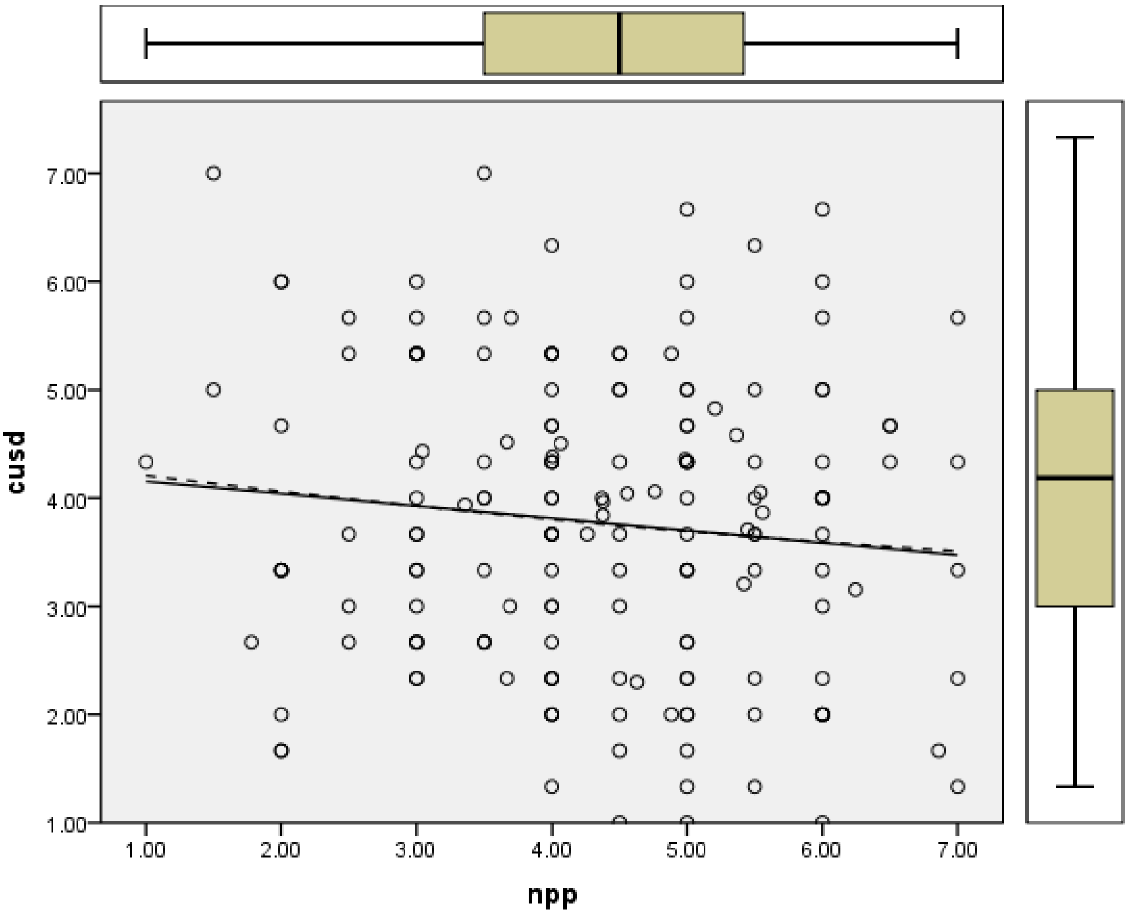
Scatterplot between Ambidextrous Market Learning and Product Advantage



Scatterplot between Product Advantage and New Product Financial Performance

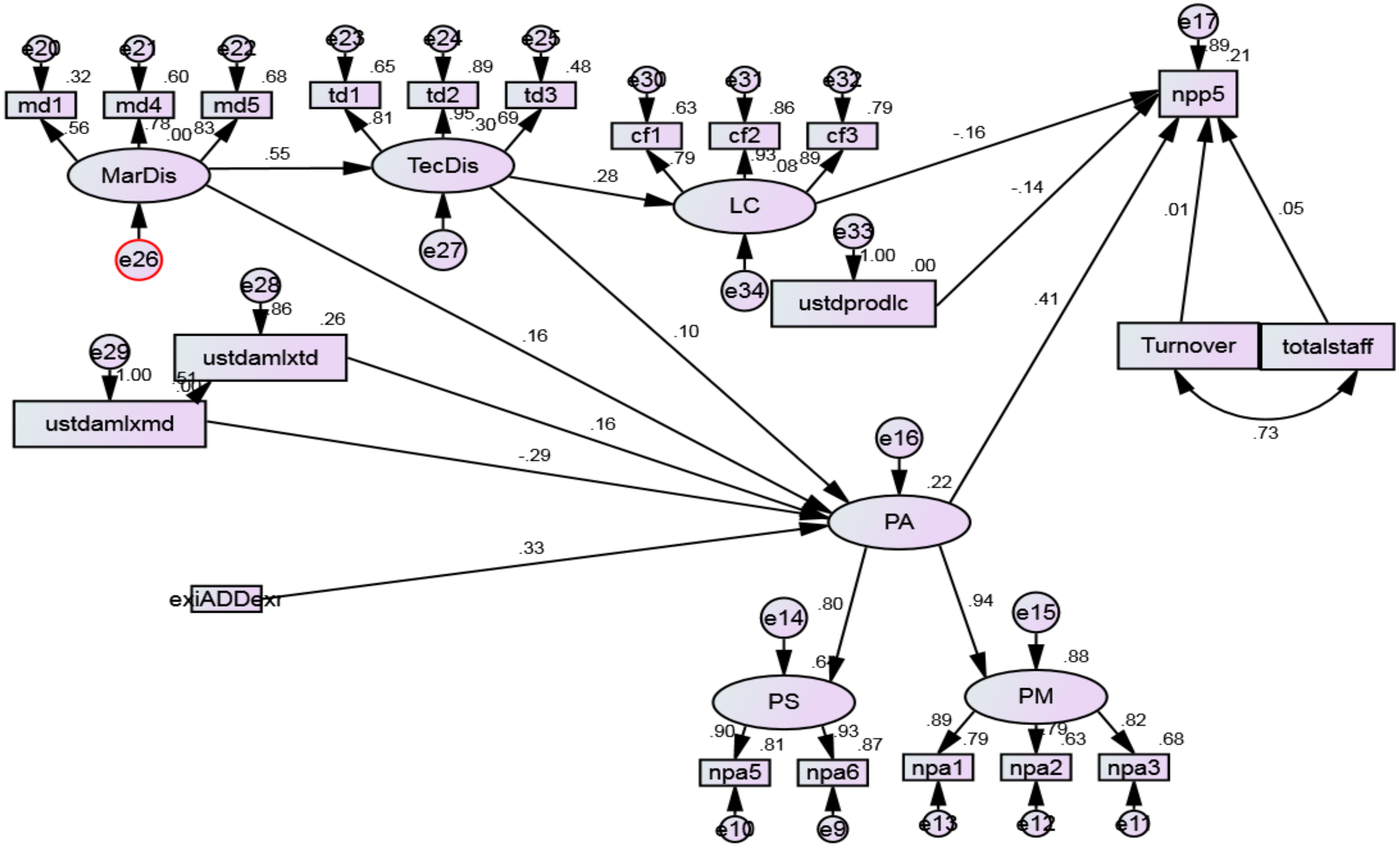


Scatterplot between Customer Discontinuity and New Product Financial Performance



Appendix 7C: Additive, Subtraction and Multiplicative AML Model

Additive Term



Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ustdamlxmd	<---	e29	.750				
ustdamlxtd	<---	e28	.680				
TecDis	<---	MarDis	.766	.153	5.005	***	par_14
ustdamlxtd	<---	ustdamlxmd	.593	.074	7.972	***	par_23
PA	<---	MarDis	.168	.122	1.374	.170	par_11
PA	<---	TecDis	.074	.077	.963	.335	par_12
PA	<---	ustdamlxtd	.088	.048	1.841	.066	par_13
PA	<---	ustdamlxmd	-.177	.058	-3.063	.002	par_22
PA	<---	exiADDexr	.132	.032	4.068	***	par_24
PS	<---	PA	1.000				
PM	<---	PA	1.044	.142	7.336	***	par_4
ustdprodlc	<---	e33	.700				
LC	<---	TecDis	.359	.104	3.432	***	par_19
npa6	<---	PS	1.000				
npa5	<---	PS	1.016	.065	15.653	***	par_1
npa3	<---	PM	1.000				
npa2	<---	PM	.879	.074	11.807	***	par_2
npa1	<---	PM	1.003	.075	13.409	***	par_3
npp5	<---	PA	.751	.145	5.173	***	par_5
npp5	<---	e17	.796				
npp5	<---	totalstaff	.041	.088	.462	.644	par_6
md1	<---	MarDis	1.000				
md4	<---	MarDis	1.542	.222	6.935	***	par_7
md5	<---	MarDis	1.761	.269	6.551	***	par_8
td1	<---	TecDis	1.000				
td2	<---	TecDis	1.226	.096	12.724	***	par_9

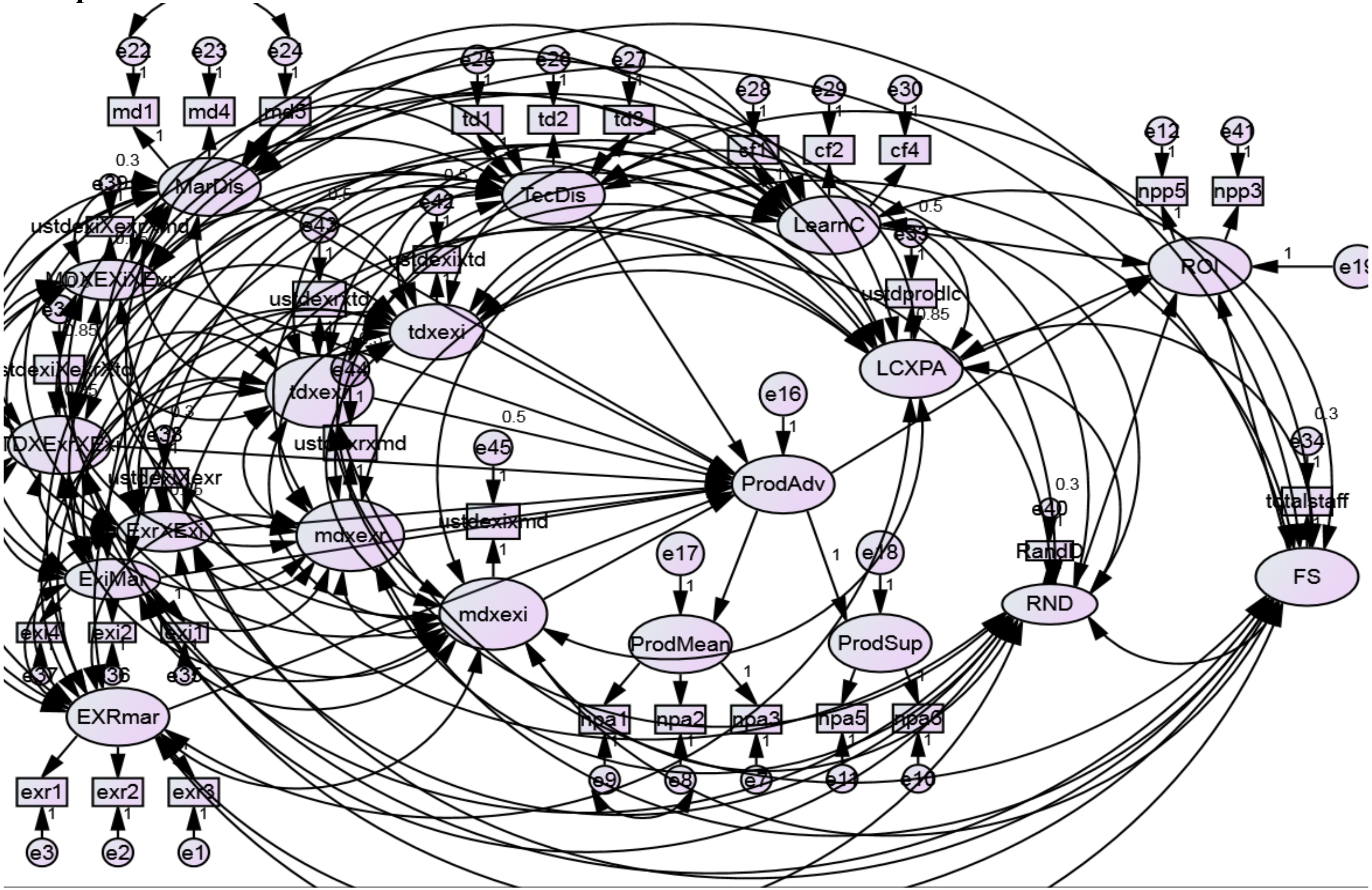
			Estimate	S.E.	C.R.	P	Label
td3	<---	TecDis	.984	.100	9.846	***	par_10
cf1	<---	LC	1.000				
cf2	<---	LC	1.186	.086	13.829	***	par_15
cf3	<---	LC	1.049	.079	13.276	***	par_16
npp5	<---	LC	-.175	.080	-2.180	.029	par_17
npp5	<---	ustdprodlc	-.147	.073	-1.999	.046	par_18
npp5	<---	Turnover	.008	.058	.141	.888	par_20

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
ustdamlxmd	<---	e29	1.000
ustdamlxtd	<---	e28	.858
TecDis	<---	MarDis	.546
ustdamlxtd	<---	ustdamlxmd	.514
PA	<---	MarDis	.157
PA	<---	TecDis	.098
PA	<---	ustdamlxtd	.165
PA	<---	ustdamlxmd	-.288
PA	<---	exiADDexr	.327
PS	<---	PA	.802
PM	<---	PA	.937
ustdprodlc	<---	e33	1.000
LC	<---	TecDis	.283
npa6	<---	PS	.934
npa5	<---	PS	.898
npa3	<---	PM	.823
npa2	<---	PM	.792

			Estimate
npa1	<---	PM	.890
npp5	<---	PA	.409
npp5	<---	e17	.890
npp5	<---	totalstaff	.047
md1	<---	MarDis	.564
md4	<---	MarDis	.775
md5	<---	MarDis	.826
td1	<---	TecDis	.806
td2	<---	TecDis	.946
td3	<---	TecDis	.690
cf1	<---	LC	.793
cf2	<---	LC	.929
cf3	<---	LC	.888
npp5	<---	LC	-.159
npp5	<---	ustdprodlc	-.139
npp5	<---	Turnover	.014

Multiplicative Term



Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ProdAdv	<---	MarDis	.133	.114	1.162	.245	par_11
ProdAdv	<---	TecDis	.069	.085	.803	.422	par_12
ProdAdv	<---	TDXExrXExi	-.092	.052	-1.758	.079	par_16
ProdAdv	<---	EXRmar	-.085	.108	-.789	.430	par_21
ProdAdv	<---	ExiMar	.482	.146	3.314	***	par_24
ProdAdv	<---	MDXEXiXExr	.127	.057	2.229	.026	par_25
ProdAdv	<---	ExrXExi	.153	.049	3.137	.002	par_26
ProdAdv	<---	tdxexi	-.037	.165	-.227	.820	par_30
ProdAdv	<---	tdxexr	.209	.172	1.219	.223	par_31
ProdAdv	<---	mdxexr	-.256	.132	-1.947	.051	par_32
ProdAdv	<---	mdxexi	-.222	.157	-1.418	.156	par_33
ProdMean	<---	ProdAdv	1.057	.122	8.671	***	par_6
ProdSup	<---	ProdAdv	1.000				
ROI	<---	ProdAdv	.741	.139	5.316	***	par_7
ROI	<---	LearnC	-.183	.079	-2.314	.021	par_15
ROI	<---	LCXPA	-.173	.085	-2.030	.042	par_17
ROI	<---	FS	.083	.067	1.237	.216	par_20
ROI	<---	RND	.051	.044	1.154	.249	par_28
exr3	<---	EXRmar	1.000				
exr2	<---	EXRmar	1.296	.195	6.654	***	par_1
exr1	<---	EXRmar	1.585	.229	6.911	***	par_2
npa3	<---	ProdMean	1.000				
npa2	<---	ProdMean	.786	.076	10.314	***	par_3
npa1	<---	ProdMean	.918	.073	12.497	***	par_4
npa6	<---	ProdSup	1.000				

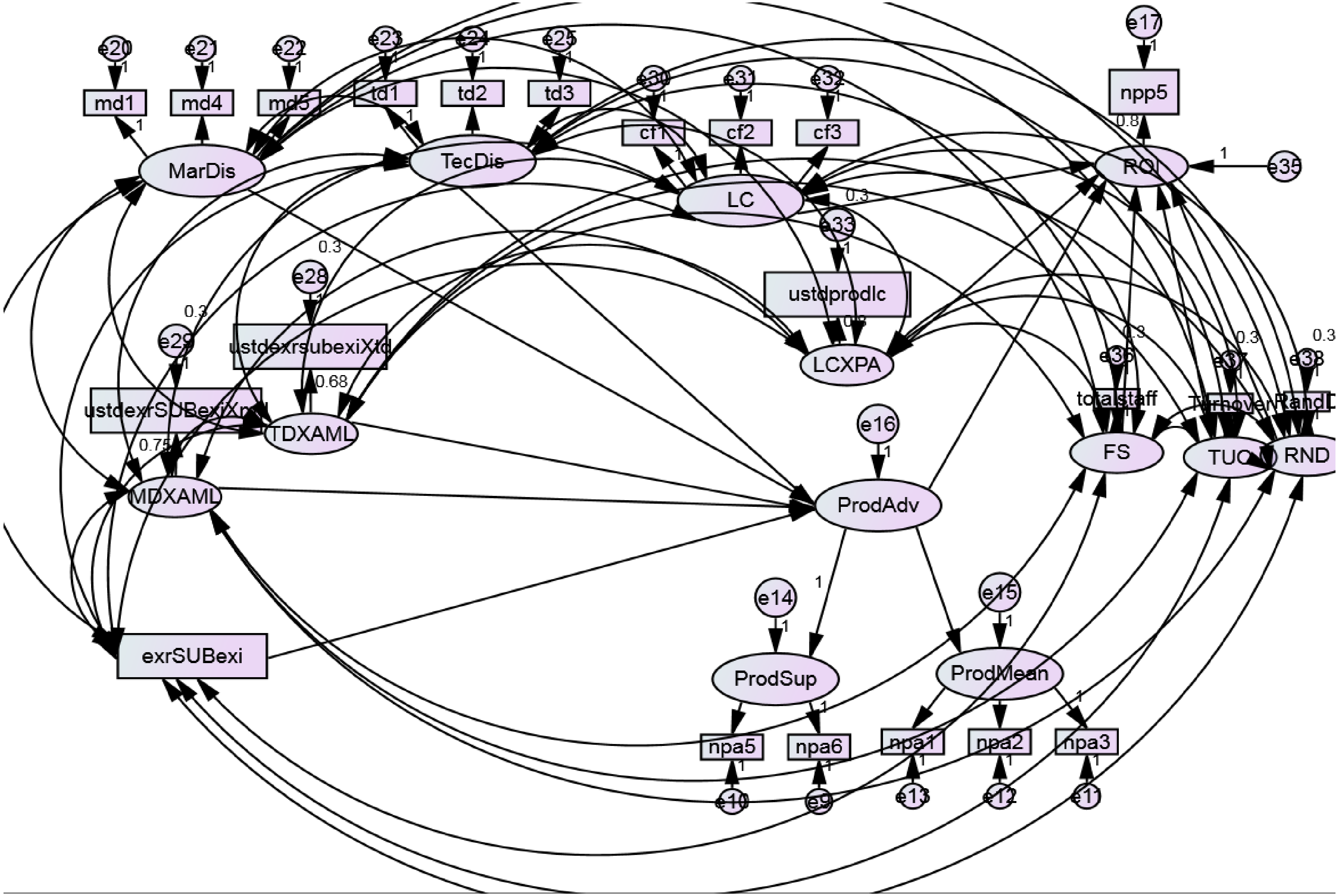
			Estimate	S.E.	C.R.	P	Label
npa5	<---	ProdSup	1.002	.062	16.053	***	par_5
npp5	<---	ROI	1.000				
md1	<---	MarDis	1.000				
md4	<---	MarDis	1.300	.213	6.093	***	par_8
td1	<---	TecDis	1.000				
td2	<---	TecDis	1.208	.094	12.817	***	par_9
td3	<---	TecDis	.988	.099	9.960	***	par_10
cf1	<---	LearnC	1.000				
cf2	<---	LearnC	.933	.086	10.832	***	par_13
cf4	<---	LearnC	.604	.086	7.048	***	par_14
ustdexiXexrXtd	<---	TDXExrXExi	.850				
ustdexiXexrXtd	<---	e31	.850				
ustdprodlc	<---	LCXPA	.850				
totalstaff	<---	FS	1.000				
exi1	<---	ExiMar	1.000				
exi2	<---	ExiMar	1.428	.175	8.165	***	par_22
exi4	<---	ExiMar	1.068	.173	6.170	***	par_23
ustdexiXexr	<---	ExrXExi	.850				
ustdexiXexrXmd	<---	MDXEXiXExr	.850				
RandD	<---	RND	1.000				
md5	<---	MarDis	1.635	.227	7.210	***	par_27
npp3	<---	ROI	.841	.098	8.578	***	par_29
ustdexixtd	<---	tdxexi	1.000				
ustdexrxtd	<---	tdxexr	1.000				
ustdexrxmd	<---	mdxexr	1.000				
ustdexixmd	<---	mdxexi	1.000				

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
ProdAdv	<---	MarDis	.133
ProdAdv	<---	TecDis	.086
ProdAdv	<---	TDXExrXExi	-.262
ProdAdv	<---	EXRmar	-.088
ProdAdv	<---	ExiMar	.435
ProdAdv	<---	MDXEXiXExr	.366
ProdAdv	<---	ExrXExi	.337
ProdAdv	<---	tdxexi	-.054
ProdAdv	<---	tdxexr	.370
ProdAdv	<---	mdxexr	-.420
ProdAdv	<---	mdxexi	-.284
ProdMean	<---	ProdAdv	.945
ProdSup	<---	ProdAdv	.828
ROI	<---	ProdAdv	.441
ROI	<---	LearnC	-.195
ROI	<---	LCXPA	-.168
ROI	<---	FS	.094
ROI	<---	RND	.093
exr3	<---	EXRmar	.579
exr2	<---	EXRmar	.682
exr1	<---	EXRmar	.869
npa3	<---	ProdMean	.861
npa2	<---	ProdMean	.741
npa1	<---	ProdMean	.849
npa6	<---	ProdSup	.942

			Estimate
npa5	<---	ProdSup	.894
npp5	<---	ROI	.956
md1	<---	MarDis	.636
md4	<---	MarDis	.738
td1	<---	TecDis	.810
td2	<---	TecDis	.937
td3	<---	TecDis	.697
cf1	<---	LearnC	.896
cf2	<---	LearnC	.826
cf4	<---	LearnC	.533
ustdexiXexrXtd	<---	TDXExrXExi	.955
ustdexiXexrXtd	<---	e31	.296
ustdprodlc	<---	LCXPA	.844
totalstaff	<---	FS	.941
exi1	<---	ExiMar	.671
exi2	<---	ExiMar	.864
exi4	<---	ExiMar	.536
ustdexiXexr	<---	ExrXExi	.940
ustdexiXexrXmd	<---	MDXEXiXExr	.963
RandD	<---	RND	.976
md5	<---	MarDis	.865
npp3	<---	ROI	.838
ustdexixtd	<---	tdxexi	.853
ustdexrxtd	<---	tdxexr	.895
ustdexrxmd	<---	mdxexr	.881
ustdexixmd	<---	mdxexi	.823

Subtractive Term



Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ProdAdv	<---	MDXAML	-.070	.056	-1.253	.210	par_52
ProdAdv	<---	TDXAML	.059	.044	1.342	.180	par_53
ProdAdv	<---	MarDis	.232	.131	1.773	.076	par_54
ProdAdv	<---	TecDis	.117	.088	1.325	.185	par_55
ProdAdv	<---	exrSUBexi	-.058	.054	-1.068	.285	par_57
ProdSup	<---	ProdAdv	1.000				
ProdMean	<---	ProdAdv	.985	.152	6.463	***	par_4
ROI	<---	ProdAdv	.898	.179	5.005	***	par_11
ROI	<---	LCXPA	-.173	.091	-1.911	.056	par_12
ROI	<---	FS	.064	.161	.395	.693	par_13
ROI	<---	TUO	.014	.100	.137	.891	par_14
ROI	<---	RND	.047	.054	.868	.385	par_15
ROI	<---	LC	-.247	.107	-2.308	.021	par_56
npa6	<---	ProdSup	1.000				
npa5	<---	ProdSup	1.015	.065	15.720	***	par_1
npa3	<---	ProdMean	1.000				
npa2	<---	ProdMean	.877	.074	11.918	***	par_2
npa1	<---	ProdMean	1.009	.074	13.722	***	par_3
md1	<---	MarDis	1.000				
md4	<---	MarDis	1.518	.219	6.935	***	par_5
md5	<---	MarDis	1.714	.245	6.989	***	par_6
td1	<---	TecDis	1.000				
td2	<---	TecDis	1.226	.096	12.719	***	par_7
td3	<---	TecDis	.990	.100	9.891	***	par_8
cf1	<---	LC	1.000				
cf2	<---	LC	1.184	.085	13.986	***	par_9

			Estimate	S.E.	C.R.	P	Label
cf3	<---	LC	1.036	.077	13.419	***	par_10
npp5	<---	ROI	.800				
ustdprodlc	<---	LCXPA	.800				
ustdexrsubexiXtd	<---	TDXAML	.680				
ustdexrSUBexiXmd	<---	MDXAML	.750				
totalstaff	<---	FS	1.000				
Turnover	<---	TUO	1.000				
RandD	<---	RND	1.000				

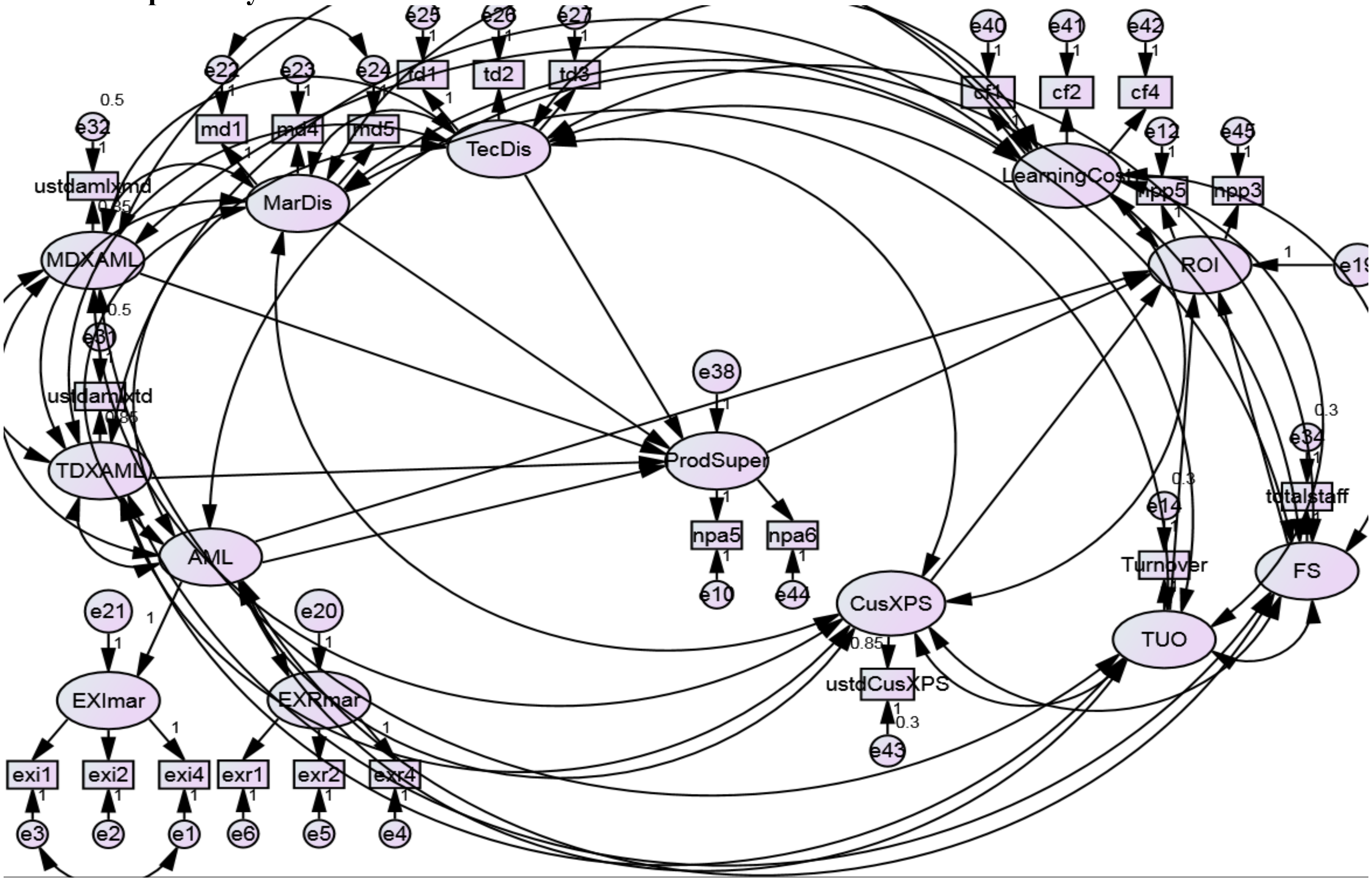
Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
ProdAdv	<---	MDXAML	-.152
ProdAdv	<---	TDXAML	.161
ProdAdv	<---	MarDis	.211
ProdAdv	<---	TecDis	.146
ProdAdv	<---	exrSUBexi	-.085
ProdSup	<---	ProdAdv	.830
ProdMean	<---	ProdAdv	.913
ROI	<---	ProdAdv	.534
ROI	<---	LCXPA	-.194
ROI	<---	FS	.072
ROI	<---	TUO	.024
ROI	<---	RND	.086
ROI	<---	LC	-.234
npa6	<---	ProdSup	.936
npa5	<---	ProdSup	.900

			Estimate
npa3	<---	ProdMean	.826
npa2	<---	ProdMean	.794
npa1	<---	ProdMean	.896
md1	<---	MarDis	.574
md4	<---	MarDis	.777
md5	<---	MarDis	.818
td1	<---	TecDis	.804
td2	<---	TecDis	.945
td3	<---	TecDis	.693
cf1	<---	LC	.797
cf2	<---	LC	.932
cf3	<---	LC	.882
npp5	<---	ROI	.769
ustdprodlc	<---	LCXPA	.910
ustdexrsubexiXtd	<---	TDXAML	.938
ustdexrSUBexiXmd	<---	MDXAML	.921
totalstaff	<---	FS	.941
Turnover	<---	TUO	.975
RandD	<---	RND	.976

Appendix 7D: Model(s) with Product meaningfulness and Product Superiority

Product Superiority



Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ProdSuper	<---	AML	.388	.153	2.539	.011	par_14
ProdSuper	<---	TDXAML	.285	.122	2.333	.020	par_15
ProdSuper	<---	MDXAML	-.434	.156	-2.773	.006	par_16
ProdSuper	<---	MarDis	.259	.154	1.687	.092	par_17
ProdSuper	<---	TecDis	-.015	.109	-.136	.892	par_18
EXImar	<---	AML	1.000				
EXRmar	<---	AML	.808	.235	3.438	***	par_5
ROI	<---	TUO	.049	.080	.614	.539	par_6
ROI	<---	FS	-.074	.133	-.558	.577	par_13
ROI	<---	ProdSuper	.347	.121	2.879	.004	par_19
ROI	<---	LearningCost	-.203	.079	-2.575	.010	par_22
ROI	<---	CusXPS	-.073	.077	-.948	.343	par_23
ROI	<---	AML	.638	.232	2.744	.006	par_61
exi4	<---	EXImar	1.000				
exi2	<---	EXImar	1.070	.179	5.988	***	par_1
exi1	<---	EXImar	.904	.144	6.274	***	par_2
exr4	<---	EXRmar	1.000				
exr2	<---	EXRmar	.978	.125	7.817	***	par_3
exr1	<---	EXRmar	1.145	.140	8.163	***	par_4
npa5	<---	ProdSuper	1.000				
npp5	<---	ROI	1.000				
Turnover	<---	TUO	1.000				
md1	<---	MarDis	1.000				
md4	<---	MarDis	1.381	.230	5.993	***	par_7
md5	<---	MarDis	1.629	.230	7.079	***	par_8
td1	<---	TecDis	1.000				

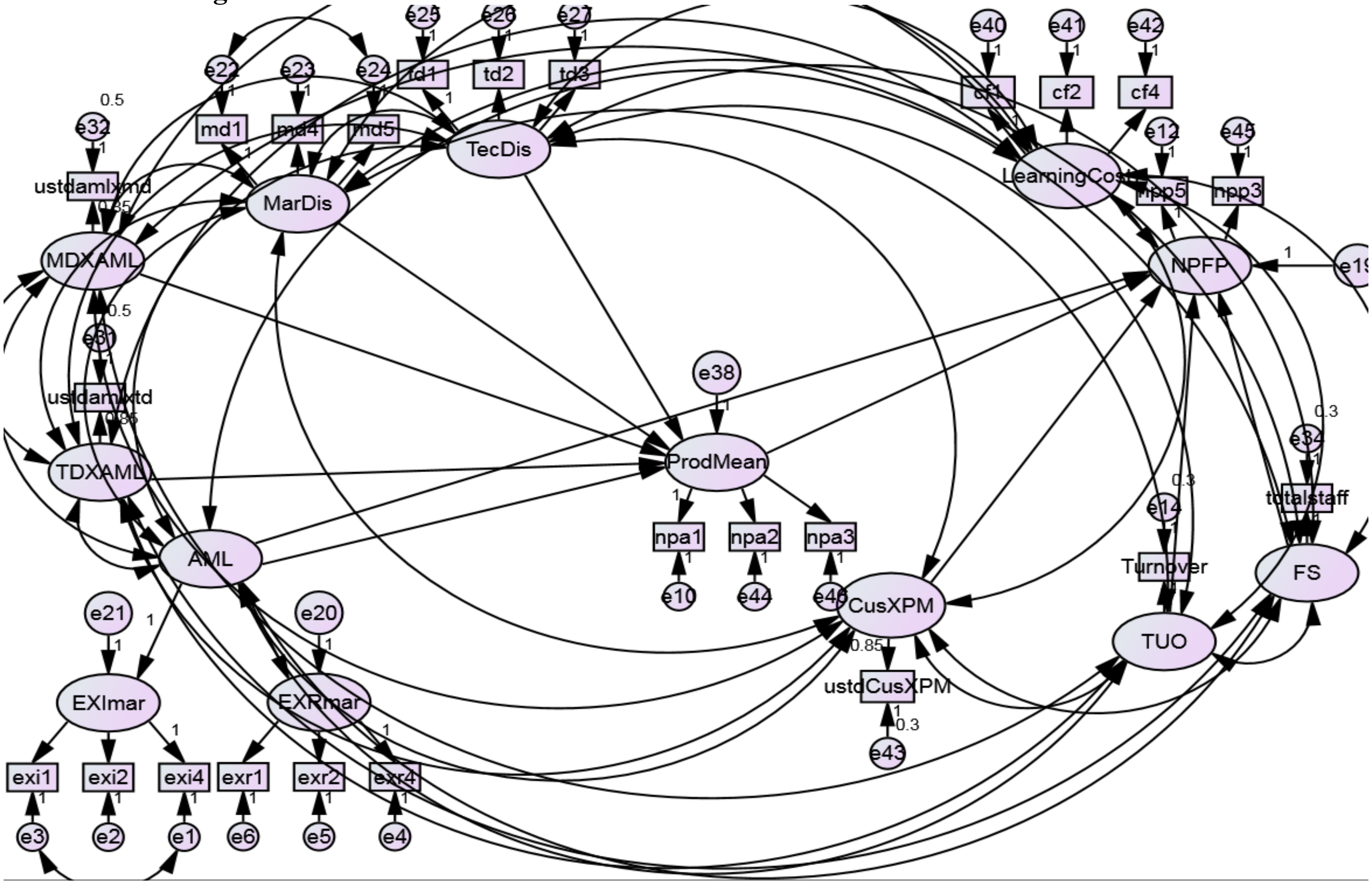
			Estimate	S.E.	C.R.	P	Label
td2	<---	TecDis	1.230	.097	12.730	***	par_9
td3	<---	TecDis	.986	.100	9.847	***	par_10
ustdamlxtd	<---	TDXAML	.850				
ustdamlxmd	<---	MDXAML	.850				
totalstaff	<---	FS	1.000				
cf1	<---	LearningCost	1.000				
cf2	<---	LearningCost	.996	.102	9.739	***	par_20
cf4	<---	LearningCost	.644	.091	7.095	***	par_21
ustdCusXPS	<---	CusXPS	.850				
npa6	<---	ProdSuper	1.025	.097	10.614	***	par_60
npp3	<---	ROI	.817	.095	8.596	***	par_62

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
ProdSuper	<---	AML	.319
ProdSuper	<---	TDXAML	.435
ProdSuper	<---	MDXAML	-.542
ProdSuper	<---	MarDis	.212
ProdSuper	<---	TecDis	-.015
EXImar	<---	AML	.898
EXRmar	<---	AML	.562
ROI	<---	TUO	.086
ROI	<---	FS	-.083
ROI	<---	ProdSuper	.243
ROI	<---	LearningCost	-.205
ROI	<---	CusXPS	-.074
ROI	<---	AML	.366

			Estimate
exi4	<---	EXImar	.607
exi2	<---	EXImar	.784
exi1	<---	EXImar	.734
exr4	<---	EXRmar	.682
exr2	<---	EXRmar	.702
exr1	<---	EXRmar	.857
npa5	<---	ProdSuper	.882
npp5	<---	ROI	.970
Turnover	<---	TUO	.975
md1	<---	MarDis	.618
md4	<---	MarDis	.761
md5	<---	MarDis	.837
td1	<---	TecDis	.804
td2	<---	TecDis	.947
td3	<---	TecDis	.690
ustdamlxtd	<---	TDXAML	.869
ustdamlxmd	<---	MDXAML	.821
totalstaff	<---	FS	.941
cf1	<---	LearningCost	.864
cf2	<---	LearningCost	.851
cf4	<---	LearningCost	.548
ustdCusXPS	<---	CusXPS	.907
npa6	<---	ProdSuper	.955
npp3	<---	ROI	.826

Product Meaningfulness



Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ProdMean	<---	AML	.425	.143	2.973	.003	par_14
ProdMean	<---	TDXAML	.263	.109	2.421	.015	par_15
ProdMean	<---	MDXAML	-.363	.138	-2.630	.009	par_16
ProdMean	<---	MarDis	.176	.132	1.334	.182	par_17
ProdMean	<---	TecDis	.032	.097	.332	.740	par_18
EXImar	<---	AML	1.000				
EXRmar	<---	AML	.709	.211	3.359	***	par_5
NPFP	<---	TUO	.014	.080	.174	.862	par_6
NPFP	<---	FS	-.005	.132	-.041	.967	par_13
NPFP	<---	ProdMean	.417	.144	2.900	.004	par_19
NPFP	<---	LearningCost	-.160	.077	-2.085	.037	par_22
NPFP	<---	CusXPM	-.096	.083	-1.158	.247	par_23
NPFP	<---	AML	.476	.207	2.301	.021	par_61
exi4	<---	EXImar	1.000				
exi2	<---	EXImar	1.108	.178	6.219	***	par_1
exi1	<---	EXImar	.904	.144	6.280	***	par_2
exr4	<---	EXRmar	1.000				
exr2	<---	EXRmar	.978	.126	7.784	***	par_3
exr1	<---	EXRmar	1.157	.143	8.122	***	par_4
npa1	<---	ProdMean	1.000				
npp5	<---	NPFP	1.000				
Turnover	<---	TUO	1.000				
md1	<---	MarDis	1.000				
md4	<---	MarDis	1.324	.222	5.967	***	par_7
md5	<---	MarDis	1.615	.226	7.150	***	par_8
td1	<---	TecDis	1.000				

			Estimate	S.E.	C.R.	P	Label
td2	<---	TecDis	1.211	.094	12.858	***	par_9
td3	<---	TecDis	.986	.099	9.937	***	par_10
ustdamlxtd	<---	TDXAML	.850				
ustdamlxmd	<---	MDXAML	.850				
totalstaff	<---	FS	1.000				
cf1	<---	LearningCost	1.000				
cf2	<---	LearningCost	.998	.104	9.604	***	par_20
cf4	<---	LearningCost	.643	.091	7.060	***	par_21
ustdCusXPM	<---	CusXPM	.850				
npa2	<---	ProdMean	.884	.069	12.847	***	par_60
npp3	<---	NPFP	.793	.096	8.306	***	par_62
npa3	<---	ProdMean	.963	.075	12.763	***	par_63

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
ProdMean	<---	AML	.406
ProdMean	<---	TDXAML	.440
ProdMean	<---	MDXAML	-.497
ProdMean	<---	MarDis	.161
ProdMean	<---	TecDis	.037
EXImar	<---	AML	.968
EXRmar	<---	AML	.526
NPFP	<---	TUO	.024
NPFP	<---	FS	-.006
NPFP	<---	ProdMean	.263
NPFP	<---	LearningCost	-.160
NPFP	<---	CusXPM	-.091

			Estimate
NPFP	<---	AML	.286
exi4	<---	EXImar	.597
exi2	<---	EXImar	.797
exi1	<---	EXImar	.721
exr4	<---	EXRmar	.678
exr2	<---	EXRmar	.699
exr1	<---	EXRmar	.862
npa1	<---	ProdMean	.901
npp5	<---	NPFP	.984
Turnover	<---	TUO	.975
md1	<---	MarDis	.633
md4	<---	MarDis	.747
md5	<---	MarDis	.851
td1	<---	TecDis	.810
td2	<---	TecDis	.939
td3	<---	TecDis	.695
ustdamlxtd	<---	TDXAML	.869
ustdamlxmd	<---	MDXAML	.821
totalstaff	<---	FS	.941
cf1	<---	LearningCost	.864
cf2	<---	LearningCost	.852
cf4	<---	LearningCost	.546
ustdCusXPM	<---	CusXPM	.898
npa2	<---	ProdMean	.811
npp3	<---	NPFP	.814
npa3	<---	ProdMean	.807

References

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