Customer Agility, Smart Shopping Apps, and Its Implications: Customer Relationship Management Systems in Digital Age

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Abstract

Ubiquitous customer interactions are a strategic imperative for achieving firm’s customer agility in an environment in which the technology is ubiquitous whilst the customers are techno-savvy. This study conceptualizes, operationalizes and validates customer connectivity taking the example of deployment of smart mobile shopping apps and customers’ use of smart shopping apps in the context of contemporary consumer retail as a formative, multidimensional index. Based on customers; use of smart shopping apps, the study introduces the concept customer connectivity in relation to the past system use studies that in IS discipline and the notion of connectedness. The study then discusses the importance and implications of ubiquitous customer connectivity on a firm’s customer agility, highlighting the impact of ubiquitous interactions on customer perceptions in particular the customer expectations and the implications of customer expectations on their experiences and ultimate satisfaction.

The study conceptualizes ubiquitous customer connectivity based on customers’ use of smart mobile shopping apps in their routine shopping activities and developed its constructs through the system / technology use studies in IS literature. Our exercise conceptualized the ubiquitous customer connectivity through smart apps as a formative construct whilst its respective measures derived from prior system/technology use studies as reflective. Then we have employed the notion customer connectivity to the context of smart mobile shopping app in consumer retail using the lens of Expectation Confirmation Theory to empirically test its implications on customer (user) expectations, experiences and satisfaction in a field setting.

The study employed data gathered from 428 respondents, who are customers of two Australian retail organizations who launched customer focused smart apps for everyday shopping. The sample comprises both users and non-users of smart shopping apps of the two retailers. The analysis using polynomial regression together with response surfaces reveals that customers’ use of smart shopping apps does indeed influence customers’ expectations thus have implications on the perceived experience and satisfaction. Research also highlights that the process of formation of digital expectations that resulted due to customers’ use of smart apps are distinctively different to the formation of customer expectations in traditional product service
context. As such, the findings highlights that managing customer experiences is a critical component of a firm’s success since the management of customer expectations are difficult to attain thus remains decisive for customer satisfaction. Further, the findings suggest that rather the firms should focus on managing customer experiences as experience does completely mediates the relationship between digital expectations and satisfaction relationship.
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STATEMENT OF ORIGINAL AUTHORSHIP

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

QUT Verified Signature

Signature:

Date: ______________ 09/06/2015 ____________
The purpose of the first chapter is to provide a broad overview of the research. Thus, the chapter begins by introducing the background and motivation of the research prior outlining the context of this study and providing the theoretical background the anticipated contributions of this research. Then, in the following section of the chapter the key research questions, the purpose, specific aims and objectives of this study are explained in brief. The subsequently section outlines the significance, research scope, and key conceptual definitions that are used in this study. Then in the remaining section of this chapter briefly outlines the structure of this thesis including a succinct description of the five forthcoming chapters that follow.
RESEARCH BACKGROUND AND MOTIVATION

The advent of ubiquitous technologies such as smart mobiles, PDA’s, Internet, smart apps on smart devices, together with the growth of new generations of tech-savvy digital natives (Vodanovich, Sundaram, & Myers, 2010), have facilitated the inception of new digital business strategies in organizations. Accordingly, contemporary firms are investing heavily on multitude of digital technologies and trying to use digital technologies strategically to gain advantage over competition. When Sambamurthy, Bharadwaj, and Grover (2003) first introduced digital options in sensing and responding over a decade ago, they too have argued that ubiquitous technologies, of which mobile technology is the archetype of, present an unparalleled level of opportunities for firm’s to connect with their customers, enhancing the firms agile capabilities towards customer based opportunities (Chakravarty, Grewal, & Sambamurthy, 2013; Sambamurthy et al., 2003). Agility literature further discusses that a firm’s ability to sense-and-respond customer requirements in a timely and tailored manner is a strategic imperative in environmental turbidity (Overby, Bharadwaj, & Sambamurthy, 2006; Roberts & Grover, 2012a, 2012b). Thus, naturally, the contemporary firms are aiming for improved, ubiquitous and uninterrupted ‘customer connectivity’ for improved customer sensing and responding capabilities through the deployment of novel ubiquitous technologies. However, uninterrupted customer sensing and responding through ubiquitous customer interactions could have its own business implications for firms.

There has been many discussion around agility, role of IT in agility, use of technology, digital natives, adoption of technology and customer satisfaction for many years up until now. For example, Nazir and Pinsonneault (2012) demonstrated that firms use technology to integrate a firm’s internal sub units and with external environment for improved coordination and unfettered information accesss to achieve improved sensing and responding capabilities thus agility in environmental uncertainty. Similarly, Setia, Venkatesh, and Joglekar (2013) discussed how firms are able to effectively leverage digital technologies to improve competencies and enhance
localized firm dynamics for improved customer service performances. Vodanovich et al. (2010) discussed how ubiquitous technologies such as mobile phones and mobile apps have proliferated into the very fabric of everyday life of the individuals and has amplified the effectiveness of IT led firm - customer connectivity. Many others have discussed how the ubiquity of technologies help organizations to provide personalized product recommendations (T. C. Zhang, Agarwal, & Lucas, 2011), improve service quality (Pavlou & El Sawy, 2010) and optimize time and effort that customers required to put in when receiving a service (Xu, Benbasat, & Cenfetelli, 2011) from a firm. In parallel the past literature also discussed the criticality of firm-customer relationship in maintaining customer loyalty in mobile commerce (Lin & Wang, 2006; Walsh, Hennig-Thurau, Sassenberg, & Bornemann, 2010), where the literature recognizes customer loyalty as a key outcome of closer customer interactions in e-commerce context. As firms are increasingly deploying ubiquitous technologies and associated networks for improved customer sensing and responding, it is utmost critical for firms to understand the customer sensitivity and the business implications towards such intensified customer interactions. However, there is a paucity of research that investigates implications of extensive customer interactions and sensing through the ubiquitous technologies on customer perceptions. Specifically, such implications on customer perceptions could be significant in the retail and service sector firms, where the frequent customer engagement through ubiquitous technologies is comparatively much higher in those sectors compared to the other sectors. Whilst such implications potentially could influence the adoption and the success of customer focused strategic digital initiatives such as smart apps on smart mobiles and PDA’s, there is a dearth of research that investigates the association between customers’ adoption and use of such smart technologies, how customers’ use of such apps relates to a firm’s customer agility and/or the implications attached to the customers’ use of such apps. This provides the background and motivation for this study.
STUDY CONTEXT

The Australian retail industry sector provides the context to this research. Retailers in general have invested heavily in smart mobile apps to encourage their customers to mimic their daily routines (purchasing and purchase intentions) (Lamarre, Galarneau, & Boeck, 2012). As Narayanaswami, Kruger, and Marmasse (2011) noted, smart devices and applications are heavily influencing the customer-retailer landscape, making global shifts towards ‘everywhere – ubiquitous – retailing’, and ‘everywhere - ubiquitous sensing and responding’.

In Australia, the two main retailers (Woolworths with 41.1% of market share / $48.56 billion revenue, and Coles with 31% market share / $34.1 billion revenue in 2012) maintain a retail duopoly. They launched mobile apps in 2011 and currently over 3 million customers (~30% of total retail population) have downloaded these apps from Android® and Apple® markets. Both mobile apps provide customers the option of developing shopping lists, connecting to store locations, downloading and contributing to recipes. Furthermore, each mobile app is registered to a ‘loyalty card’ which includes customer details where the customer scans at the point of purchase. Consequently, the use of their mobile apps (linked with a loyalty card) provides woolworths and Coles the potential to understand shopping habits, potential shopping items and favoured store locations. As such, in 2013, Woolworths acquired a business intelligence company “Quantium” citing the importance of better analysing the shopping habits of Australians outside its stores (Kohler, 2013). This context highly similar to other customer-centered industries like book stores, airlines and hotels, thus allowing generalizability.
PURPOSE OF THE STUDY, RESEARCH PROBLEM AND KEY RESEARCH QUESTIONS

This study has several purposes. Key purposes of this study are to

(i) Provide a theoretical understanding of the logical relationship between customers use of smart apps, a firm’s customer agility, and associated business benefits to a firm

(ii) Facilitate a theoretical understanding of the impact of customer sensing that firms achieved through the customers’ use of smart apps on the customer’s expectations and perceptions

(iii) Empirically investigate the implications of customer’s use of smart apps on customer perceptions (perceived experience) and customer satisfaction

(iv) Conceptually understand how customer connectivity achieved through a customer’s use of smart app (such as smart shopping apps) could leads to firm-customer connectedness hence the digital connectedness

In doing so this study makes several contributions to the current body of knowledge as below. First, despite the popularity and wide deployment of customer focussed smart apps to connect with customers by the firms in many industries a clear comprehension of how such initiatives derive benefits or improve firm performance is rather bleak in current literature. Thus, this research provides a theoretical understanding of how customers’ use of smart apps relates to a firm’s customer agility thus how a firm could derive business benefits through such apps. Further, the study facilitates a understanding of the relationship between customers’ use of customer focussed smart apps with the customer expectations, perceived experience and ultimate satisfaction, which is absent in current literature. In doing so this study introduces the notion ‘digital expectations’ and discusses how the digital expectations are different to the expectations that have been discussed in the literature on traditional product service context. Further, the study conceptually elaborates the
Chapter 1: Introduction

relationship between customers’ use of smart apps, firm-customer connectedness hence its relatedness to the notion digital connectedness.

As the current understanding of the notion digital connectedness is zilch or very limited if any. Let alone comprehending the notion digital connectedness, but atleast a logical comprehension of how the notion digital connectedness is formed as a result of firm’s digital initiatives is essential at this juncture in time for several reasons. First, the new generation of customers seem to be innately techno-savvy and they are in general, let mobile technologies and associated apps to weave themselves into the very fabric of their everyday life mimicking their daily routines (Vodanovich et al., 2010). Therefore, the smart apps are facilitating the creation of a digital fabric of everyday life, creating digital thumb prints of individual customers in digital space. Thus, such digital thumbprints allow owners of such smart apps (i.e. respective firms) to sense the daily actions of the users of such apps (i.e. customers who use these smart apps in their daily routines, they are their ‘connected’ customers) through the resultant information footprints that come as a by-product. Hence, a clear comprehension of the notions, customers use of smart apps, firm-customer connectivity and digital connectedness has a significant value for both practice and academia. Secondly, at this point in time it is important for firms to understand how firm-customer interactions in digital space as in customers’ use of smart apps could create firm-customer connectivity and leads to digital connectedness, since such connectedness could act as a critical precursor of enacting a firm’s sensing and responding capabilities to realize positive organizational outcomes (e.g. customer satisfaction). Also, as a firm’s ability of sensing shifting customer needs and the ability of responding to such needs astutely with ease, speed and dexterity is recognized as one of the most critical strategic imperatives in hyper competitive environments. Hence a better comprehension of firm-customer connectivity achieved through smart devices and associated apps and the related implications of such connectivity on firms agility and on customer perceptions is necessary in this point in time. This study provides the significant first step towards this direction. In essence, the overarching research question of this research remains as the “the customers’ use of smart (shopping) apps, the implications of firm–customer
ubiquitous connectivity achieved through the customers’ use of smart apps on customer agility and customer perceptions”. In particular, this research aims to investigate the following key research questions.

- How customers’ use of smart shopping apps relates to a firm’s customer agility?
- How customers’ use of smart shopping apps drives customer expectations?
- How does customers’ use of smart shopping apps influence customer perceptions and satisfaction?
- How does a customer’s use of smart shopping apps leads to firm-customer digital connectedness?

**SIGNIFICANCE, SCOPE AND DEFINITIONS OF THE RESEARCH**

This research intend of making several significant contributions for both research and practice. First, in spite of wide employment of smart devices and smart apps by corporations globally to connect with techno savvy customers for ubiquitous sensing and responding to their needs wants and expectations with ease, speed and precision, there is a dearth of studies that discuss the link between this ubiquitous customer connectivity and a firm’s customer agility. For example, to the best of our knowledge, none to date have discussed the process that explains how customers’ use of smart apps relates to a firm’s customer agility and produce positive organizational outcomes. This research intends to explicate how customers’ use of smart apps promotes firm-customer ubiquitous connectivity relates to the two components of agility; sensing and responding through a pictorial process model.
Secondly, the implications of ubiquitous connectivity achieved through smart devices and associated apps (e.g. firm-customer connectivity through customers’ use of smart apps) is rarely been discussed in the current literature. However, it is important for both research and practice to comprehend such implications of ubiquitous customer connectivity attained through smart devices and smart apps especially with the renowned interest, wide deployment, and adoption of smart technologies of late. This research aim to develop an understanding of customer connectivity achieved through the customers’ use of smart apps and the related implications on the customers side (e.g. customer expectations, customer perceptions and customer satisfaction) in a field setting to fill this important gap in the literature.

Thirdly, as this research investigates how customer expectations influenced by the customers’ use of smart apps, one of the key objectives of this research is to facilitate a theory based explanation of the relationship between customers’ use of smart apps, formation of customer expectations as a result of their smart app use, and how such expectations influences customer perceptions and satisfaction. Thus we employ the lens of Expectation Confirmation Theory (Oliver, 1977; Oliver, 1980b) to comprehend understand such interactions. As such, this study explicates the differences between expectations formed as a result of smart app use (that we term as digital expectations), the process which digital expectations formed compared to the expectations in traditional product service context. Thus this research anticipates extending the original ECT (Oliver, 1977; Oliver, 1980b) to the context of digital expectations and confirmation.

Fourth, staying true to the non linearity assumptions of ECT in its original conception (See.. S. A. Brown, Venkatesh, & Goyal, 2011; Oliver, 1977; Oliver, 1980b), this study employs the polynomial regression and response surface methodology first, to test the hypothetical propositions and then to test the mediation in the analysis. Thus, this study aspire to make a methodological contribution to the field of IS research by introducing polynomial regression and response surface methodology in the analysis. This approach is significant to the field if IS as not many studies in the field have employed neither the non-linearity assumptions in the
analysis even though the underlying theoretical assumptions suggests non-linearity, nor they have employed the two aforementioned techniques in their analysis to address this issue.

Fifth, as literature reports he innately techno-savvy customers today are letting ubiquitous technologies to weave themselves into the very fabric of their everyday life, such actions (e.g. use of smart devices and associated applications in daily routines) allow astute organizations to sense their way of life. As such, the techno-savvy customers are providing avenues for firms’ to be truly agile on their requirements but, there is no clear comprehension of how customers use of digital technologies could initiate a psychological bond between the firm and the customer in the current literature. Thus, this research intends to provide a conceptual discussion to introduce the notion digital connectedness through the customers’ use of smart shopping apps. Thus, this research seek to conceptualize the notion digital connectedness through the customer connectivity achieved through their use of smart shopping apps. As such, we derive our research model of customers’ use of smart apps, digital expectations, customer experience and customer satisfaction based on the theoretical lens of expectation confirmation theory (ECT). Then, we follow the two staged approach proposed by A. Burton-Jones and Straub (2006) to develop our measures of the ‘smart app use’ that is relevant to this study. Following which we develop our measures for other constructs – customer expectations, customer experiences, and customer satisfaction following a comprehensive review of literature on the previous work on expectations, experiences, satisfaction, and business agility. The preliminary model below depicts a high level conceptualization of our research problem. It denotes the key focus of the study on the customers’ use of smart apps and the digital expectations, customer experiences and satisfaction through the employment of the expectation confirmation theory lens.
In this discussion we use following definitions to explicate key high level conceptual definitions that have been used in the model appeared in Figure 1 above. First, following A. Burton-Jones and Straub (2006) work on system use, in this research ‘customers’ use of smart shopping apps’ is conceptualized as going beyond generic use to the frequency and the depth of mobile app use that facilitate firm’s customer sensing. Hence, a customer using shopping related activities frequently on their mobile app has more connectivity to a firm and provides more sensing opportunities for the firm. Next, following Expectation-Confirmation Theory (Oliver, 1977; Oliver, 1980b) and the notions of (customer) agility (Roberts & Grover, 2012a) we defined digital expectations, perceived customer experiences and customer satisfaction as follows. According to ECT (Oliver, 1977; Oliver, 1980b), expectations explains the level of expectations that a customer has on a product or service prior to the purchase or consumption. Thus it reflects what a customer is expected from a product (or service) that he purchase (or consume). Based on this, in this discussion, we define the ‘digital expectations’ as; “the level of expectations that a customer forms about a firm’s responsiveness towards his/her unique shopping related needs and wants that is relevant to the firm, as a result of the custoers’ continuous use of smart shopping app”. Then, we define ‘customer experience’ as the “firm’s responsiveness towards a customer’s needs as perceived by the customer”. In other words, this signifies how customers perceive a firm’s responsiveness in relation to their needs and/or expectations that they have formed about a firm’s responsiveness. Next, we define customer satisfaction as the “level to which a customer is satisfied (or dissatisfied) on the actual shopping experience that s/he has received”.
UNIT OF ANALYSIS

Pinsonneault and Kraemer (1993) classified the unit of analysis into six different levels as follows.

1. Individual level
2. Work group level
3. Department level
4. Firm / organizational level
5. Application / system level
6. Project level

Given the focus and the objectives of this research the data should be gathered on the customers’ use of smart shopping apps and the implications of such connectivity have on an individual’s perceptions, the empirical data relating to the constructs in our conceptual model is gathered at the individual level. The unit of analysis that we use in this research is in line with the level of abstraction that the underlying theory, Expectation Confirmation Theory (ECT) suggest.

The individuals who respond to the survey represent both users and non-users of smart Coles or Woolworths mobile shopping apps. The non-users represent the current customers of either one the two retailers, Coles and Woolworths in Australia. In this discussion, the respondents who are non-users employed as the controlled sample for comparisons.
RESEARCH DESIGN

Research design is the logical plan that consists of key steps of a research project, such as problem definition, research model development, data collection, analysis and results (Black, 1999; Yin, 1984). The figure 2 below illustrates the key steps of this research project.

As shown above in figure 2, the design of this research has six main steps: 1) Research definition; 2) Literature review; 3) Theoretical/Conceptual model development; 4) Hypothesis development; 5) Data collection through a survey; and 6) Analysis of data and interpretation of findings. In Figure 2, the rectangular boxes represent the different stages of the research process. The arrows that link the boxes...
Chapter 1: Introduction

refer to the direction to which information flows in each process step. Other two boxes (See legend) represent outputs and the documents generated during the research process.
Chapter 1: Introduction

THESIS OUTLINE

This thesis is structured in the following manner. The significance of the research and research gaps were introduced in chapter 1. In addition, chapter 1 also introduced the key constructs of the study.

Next chapter, chapter two in this thesis reviews the key literature that is relevant to this study. Thus, the next chapter would provide a critical analysis of relevant key literature and the concepts, and the chapter aims to provide the information that facilitates the understanding of the rest of the thesis. Further the subsequent discussions therein provide an overview of the theoretical frameworks, models on this study builds upon. As such, the chapter would contain a critical analysis of prior research on the notions IS/System use, agility, expectation confirmation theory, expectations, experiences, satisfaction, customer relationship management systems and the benefits of contemporary customer relationship management systems in detail.

Next the main focus of the chapter three of this thesis is on research model development and the hypothesis. As such, discussion first introduces the background and context of the study. Then, based on prior system use related literature we develop and operationalized the ‘Use’ construct to denote the customers’ use of smart shopping app that we are interested in this research, before introducing the preliminary research model comprising digital expectations, perceived customer experience, and customer satisfaction using Expectation-Confirmation theory lens. Here, we first discuss deeply into the theoretical framework (i.e. Expectation-Confirmation Theory) in order to formulate our conceptual model, prior contextualizing and building our research model and proposing our hypothetical propositions.

Next, in chapter four we explain the research design and the methodology that we use in this research. Here, we focus on three main areas; (i) the operationalization
of the conceptual model that we have introduced earlier in the chapter three, (ii) development of measures for each construct in the research model, and (ii) the design and application of the method of data collection (i.e. survey method). In this section, the objectives of the data collection, appropriateness of the survey methodology, the process of the survey design, procedure of construct operationalization and the procedure of survey deployment are being discussed in detail. Further, the chapter introduces the steps that this research has employed to minimise the common method variance (CMV). Following which the ethical concerns of this research project is elaborated in the last section of the chapter.

Chapter five focuses on the data analysis, results and the discussion of the findings. As such the chapter systematically elaborates the empirical quantitative data analysis procedures and test of hypothesized relationships in detail. So, the first section of the chapter focuses on the data analysis design, methods and the procedures of data analysis. Second section of the chapter then reports and discusses the findings related to the descriptive statistics. Next, the third section of the chapter describes the testing of structural model, nomological validity including the testing of individual hypothesis and prior to the discussions of findings in detail. The chapter also reports and highlights the key findings of this research.

Chapter six of this thesis summarises the research findings and provides the concluding remarks of the research. First, the chapter revisits initial research questions and summarizes the research findings. Then the chapter discuss in detail on the theoretical contributions, theoretical implications, limitations of this research and the practical implications. Upon which the chapter concludes with the future research directions.
CHAPTER 2: LITERATURE REVIEW

This chapter reviews and reports a selection of literature relevant to this study. The literature review presented herein critically evaluates prior relevant work to provide a background of the key concepts researched in this study. Thus, the chapter has several key objectives as below:

(i) to determine and articulate the current level of knowledge in the domain of study and to assess where the further research is required,

(ii) to identify key issues that researched in this study and the corresponding ‘gaps’ in the existing literature,

(iii) to help identifying the most important characteristics of the notion ‘Agility’, and broader understanding of the role of IT, CRMS, customer connectivity through ubiquitous technologies and associated apps in achieving agility, and individuals use of technology / IS

(iv) to identify and introduce a theory that usefully relate to the research questions and aid clear explanation of the key constructs.

(v) to serve as a source of explanation of phenomena observed in conceptual model and testing hypotheses,

(vi) to formulate a logical and feasible approach to resolve the intended research questions and to formulate the conceptual arguments in a logical, critical and augmented way to find answers to the previously set research questions,

(vii) Last but not least to position the current research in relation to the previous research in the domain of study in order to clearly articulate and propose implications of the current research and areas of future potential research.
As such, this literature review structured as below.

(i) First, we analyse the current body of literature on ‘Enterprise Agility’ to broadly understand the basic theoretical foundations of the notion agility, current status of the agility research and the gaps in knowledge.

(ii) Then, the analysis focuses on the relationship between information technology (IT) and agility to discuss facilitating and restraining roles of IT on enterprise agility, prior moving into the discussion of digital business strategy, customer relationships and agility related phenomena in contemporary environment.

(iii) Thirdly, the review of literature centered on customer relationship management systems (CRMS) both traditional and contemporary prior discussing the benefits of contemporary ubiquitous CRMS to facilitate broader understanding of the relationships between use of ubiquitous technologies such as smart devices and apps in building and maintaining customer relationships, its relation to firm performance and implications relating to such relationships.

(iv) Next, we examined the extant body of literature on technology use to better comprehend the conceptualization of system/IS use, levels of system use, measures of system use and the types of system use measures in order to identify the use of smart app that is related to firm-customer connectivity and the measures of smart app use by customers that is relevant to this research.

(v) Following which we conclude the chapter with a detailed overview on the theoretical lens employed in this research – Expectation Confirmation Theory (ECT). In this section, the discussion specifically focused on the formation of expectations in traditional product / service context in order to understand the digital expectations and how digital expectations are different from traditional forms of expectations.
WHAT IS AGILITY?

Agility is the term that commonly used to describe the firms that are able to adapt to environmental turbulence and perform well in rapidly changing environments (Dove, 2002; Sambamurthy et al., 2003; Weill, Subramani, Broadbent, & Building, 2002). Thus, the highly turbulent and hyper competitive nature of the contemporary environment have drawn firm’s attention toward agility as a strategic capability (Chakravarty et al., 2013). Also, the business agility and speed to market have been recently ranked as top two management concerns in 2011-2012 globally (Jerry Luftman et al., 2012). Whilst, achieving sustained competitive advantage considered elusive and difficult in current business climate due to the hasty pace of globalization, continuously shifting customer demands, intensified competition and rapid technological advancements (Roberts & Grover, 2012b; Tallon & Pinsonneault, 2011), enterprise agility; a firm’s ability to sense and respond to rapid changes in its immediate operating environment remains an important and strategic imperative for business success in hyper-competition (Overby et al., 2006; Roberts & Grover, 2012a). As Overby et al. (2006) elaborate, the notion of agility is builds upon similar concepts in management literature that are pertaining to the firm success in environmental turbulence. For example, the notions or agility is closely related to the management theories of dynamic capabilities (Teece, Pisano, & Shuen, 1997), market orientation (Kohli & Jaworski, 1990; Narver & Slater, 1990), absorptive capacity (Cohen & Levinthal, 1990; Zahra & George, 2003), and strategic flexibility (Ansoff, 1980; Hitt, Keats, & Demarie, 1998). Whist, agility and the other marketing theories mentioned above all refers to the survival and success in environmental uncertainty, the notion of agility is distinctively different from the other concepts.

Definitions of Agility

Definition of agility is ambiguous and far from clear (Roberts & Grover, 2012b) where different researchers have defined agility using different terminologies (Atapattu & Sedera, 2013a), probably due to the contextual diversity (e.g. Umit S Bititci, Turner, & Ball, 1999; George S Day, 2000; Huang, Ouyang, Pan, & Chou, 2012; Nazir & Pinsonneault, 2012; Setia, Sambamurthy, & Closs, 2008; Sharifi & Zhang, 1999; Tallon & Pinsonneault, 2011) in which they have researched agility.
For example, S.L. Goldman, R.N. Nagel, and K. Preiss (1995) refers agility refers to a firm’s ability to sense opportunities for competitive actions marshal the necessary resources to seize such market opportunities, when Sambamurthy et al. (2003) defined agility as “a firm’s ability to detect opportunities for innovation and seize those competitive market opportunities by assembling requisite assets, knowledge, and relationships with speed and surprise” they recognized agility as a dynamic capability. Following which Overby et al. (2006) defined enterprise agility as “the ability of firms to sense environmental change and respond readily”. Recently, referring to the individual level customers, Roberts and Grover (2012b) defined a firm’s customer agility, as “the degree to which a firm is able to sense and respond quickly to customer-based opportunities for innovation and competitive action”. However, in spite of the differences in defining agility (Table 1), the different definitions mostly share some common attributes of agility between them (Table 2).

<table>
<thead>
<tr>
<th>Definition</th>
<th>Reference</th>
</tr>
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<tbody>
<tr>
<td>Comprehensive response to the business challenges of profiting from rapidly changing, continuously fragmenting, global markets for high-quality, customer-configured goods and services.</td>
<td>S.L. Goldman et al. (1995)</td>
</tr>
<tr>
<td>The capability of surviving and prospering in a competitive environment of continuous and unpredictable change by reacting quickly and effectively to changing market conditions driven by customer-designed products and services.</td>
<td>Cho, Jung, and Kim (1996)</td>
</tr>
<tr>
<td>The business’ ability to quickly adapt and change in response to rapidly changing environmental conditions.</td>
<td>U.S. Bititci, Trevor, and Ball (1999)</td>
</tr>
<tr>
<td>The ability of an enterprise to respond quickly and successfully to change.</td>
<td>McGaughey (1999)</td>
</tr>
<tr>
<td>Ability to cope with unexpected changes, to survive unprecedented threats of business environment, and to take advantage of changes as opportunities.</td>
<td>Sharifi and Zhang (1999)</td>
</tr>
</tbody>
</table>
The ability of a business to grow in a competitive market of continuous and unanticipated change, to respond quickly to rapidly changing markets driven by customer-based valuing of products and services.  


| The ability of an organization to thrive in a constantly changing, unpredictable environment. |
| G.S. Day (2000) |

| The ability of a firm to respond quickly and flexibly to its environment and to meet the emerging challenges with innovative responses. |
| Bessant, Francis, Meredith, Kaplinsky, and Brown (2001) |

| The ability to manage and apply knowledge effectively, so that an organization has the potential to thrive in a continuously changing and unpredictable business environment. |
| Dove (2002) |

| The ability to detect opportunities for innovation and seize those competitive market opportunities by assembling requisite assets, knowledge and relationships with speed and surprise. |
| Sambamurthy et al. (2003) |

| The ability to respond to unanticipated change (response ability) but also to act proactively with regard to change (knowledge management). |
| Arteta and Giachetti (2004) |

| The ability of firms to sense environmental change and respond readily |
| Overby et al. (2006) |

| Being able to swiftly change businesses and business processes beyond the normal level of flexibility to effectively manage unpredictable external and internal changes. |
| Oosterhout, Waarts, and Hillegersberg (2006) |

| An organization's ability to (1) discover new opportunities for competitive advantage; (2) harness the existing knowledge, assets, and relationships to seize these opportunities; and (3) adapt to sudden changes in business conditions. |
| Setia et al. (2008) |
The ability to detect and respond to opportunities and threats with ease, speed and dexterity.

Tallon and Pinsonneault (2011)

The degree to which a firm is able to sense and respond quickly to customer-based opportunities for innovation and competitive action.

Roberts and Grover (2012a, 2012b)

the ability to sense and respond to opportunities and threats with ease, speed, and dexterity

Nazir and Pinsonneault (2012)

A firm’s ability to sense opportunities for competitive action and marshal the necessary resources to seize those market opportunities.

Chakravarty et al. (2013)

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sense / sensing change</td>
<td>Atapattu and Sedera (2013b); Overby et al. (2006); Roberts and Grover (2012a)</td>
</tr>
<tr>
<td>Response / responding readily/quickly</td>
<td>Atapattu and Sedera (2013b); Overby et al. (2006); Roberts and Grover (2012b); Sambamurthy et al. (2003)</td>
</tr>
<tr>
<td>Detect / anticipate</td>
<td>Levinson (2004); Sambamurthy et al. (2003)</td>
</tr>
<tr>
<td>Competitive market opportunities / market threats/ evolving market condition</td>
<td>Levinson (2004); Nazir and Pinsonneault (2012); Sambamurthy et al. (2003)</td>
</tr>
<tr>
<td>Seize with speed and surprise, fast response to,</td>
<td>Levinson (2004); Weill et al. (2002)</td>
</tr>
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</table>
readily implement

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<tr>
<th>Quick/ speed/ rapid</th>
<th>Bessant et al. (2001); Cho et al. (1996); McGaughey (1999); Nazir and Pinsonneault (2012); Oosterhout et al. (2006); Overby et al. (2006); Sambamurthy et al. (2003); Yahaya Y Yusuf et al. (1999)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Respond efficiently and effectively</td>
<td>Ambrose and Morello (2004)</td>
</tr>
<tr>
<td>Ease, dexterity</td>
<td>Nazir and Pinsonneault (2012); Overby et al. (2006)</td>
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Table 2: Attributes of enterprise agility

As evident in Table 2, enterprise agility is commonly decomposed into two components: sensing and responding. The two components sensing and responding or their synonyms are the commonest attributes appear in prior academic and business literature. According to Dove (2002), sensing component of agility defines the firm’s intellectual ability (knowledge component) to find appropriate things (i.e. opportunities or threats available in its environment) to act on, whilst responding component defines a firm’s physical ability to act where it refers to the firm’s ‘response ability’. Overby et al. (2006) refers to environmental changes as to the changes precipitated by competitors’ actions, consumer preference changes, regulatory or legal changes, economic shifts, and technological advancements. When sensing symbolize the ‘awareness’ component, responding signifies the ‘execution’ component of agility.

**Sensing Component of Agility**

Nazir and Pinsonneault (2012) lamented a firm’s sensing capability as the exploration or acquiring of knowledge about threats or opportunities from the environment. Thus, sensing component of agility refers to the firm’s ability to scan its environment for actionable opportunities and threats. Prior research on enterprise agility highlighted the value of capturing new knowledge regarding the environmental
factors that influences the firm in order for a firm to be able to make sense of such changes (Nazir & Pinsonneault, 2012).

Whilst, sensing remains one of the key components of achieving agility, a firm may require various different types of capabilities to sense diverse varieties of environmental changes, such as shifting competitors’ actions, changes in consumer preferences, economic shifts, regulatory and legal changes, and technological advancements (Overby et al., 2006). For example to detect consumer preference changes a firm might need capabilities on strong customer affiliations, when tracking economic shifts or competitor actions require strong market intelligence capabilities. Consequently, to sense impending technological advancements and to leverage them to gain first mover or competitive advantage, a firm might need strong technical capabilities such as IT and research and development. Alternatively, to sense imminent regulatory and legal changes that are relevant to a firm, firm need to possess strong capabilities relating to industry/trade associations and government relations. However, possessing such capabilities are of an utmost important for firms to be ambidextrous and reasonably agile in every situation, relative importance of each capability may possibly vary across firms, industries, time and its operating environment.

As literature suggest, firms in technology intensive industries, such as communications, office equipments, entertainment and electronics, capabilities that enable them utilizing the novel technologies early in their (new technology) life cycle are of utmost important (Overby et al., 2006). However, once the technology get matured and become available as a commodity a firm might need a different set of capabilities to sense the changes and re-model their pricing, positioning and marketing capabilities. As Overby et al. (2006) states, despite the relative importance of different types of environmental changes could vary across firms and industries, most of such changes are likely to be relevant at some point for every firm in the contemporary environment.
Chapter 2: Literature Review

Literature on competitive dynamics (Chi, Ravichandran, & Andrevski, 2010) too have discussed the role of value networks in achieving greater sensing capabilities. Further, Braunscheidel and Suresh (2009) shows that firm’s are able to survive better in tumultuous environments when they are well connected with the partners as they more easily acquire and share information and knowledge thus, are able to continuously evolve and improve their business to adapt in to new situations. Further, research suggest that firms that maintain closer connections with external partners are able to sense potential environmental threats and opportunities better through transferring relevant knowledge between them (Hoyt, Huq, & Kreiser, 2007; Sánchez & Pérez, 2005). As such, a firm’s ability to scan its environment and sense the relevant threats and opportunities is a critical element of being agile in environmental uncertainty where it allows firms to keep up with trends and opportunities thus are competitive.

Responding Component of Agility

Responding component of agility refers to a firm’s ability to respond to an already sensed threat or an opportunity with ease, speed and dexterity (Overby et al., 2006) and describe a firm’s action execution. Roberts and Grover (2012b) described a firm’s responsive as its ability to adapt to and perform well in rapidly changing environments by capitalizing on opportunities on hand. As Overby et al. (2006) explain, once a firm sense an environmental change, a variety of responses that they can make. For example the scope of the response can differ (Dove, 2002), where a firm might carry out a complex move such as embarking on a new undertaking, a simple move such as adjusting an existing undertaking or might just wait and might not be doing anything about it (Ferrier, Smith, & Grimm, 1999).

As Overby et al. (2006) elucidate, all types of actions that a firm carry out as responses likely to be influenced by the assortment of operating and strategic capabilities that the firm owns. For example, a firm’s ability to carry out new product launches (new ventures), add new features to the products (adjust existing ventures)
likely to be influenced by the firm’s ‘product development capabilities’, whilst a firm’s ability to implement IT-enabled offerings such as hardware or software products (in technology industries) or electronic commerce solutions (firms in other industries) quickly and efficiently will dependent upon the firms system development capabilities (Overby et al., 2006). A firm’s ability to adjust existing ventures by shifting production to match a pending change in demand influenced by the firm’s supply-chain and production capabilities. Also, a firm’s ability to utilize its resources flexibly allows the firm to shift its resources to areas of need (i.e. improvisation), thus, it helps them either embark on new ventures or adjust existing ventures. Also, a firm’s ability to integrate units within the firm electronically, likely to enable a firm’s overall ability of process coupling and knowledge exploitation (Nazir & Pinsonneault, 2012), as it allows better coordination between units and makes them more adaptive to one another (Malhotra, Gosain, & El Sawy, 2007).

By decomposing agility into its two fundamental components – sensing and responding, Overby et al. (2006) presented a 2 x 2 matrix with sensing capability on the X-axis and responding capability on the Y-axis to classify firms into four distinctive groups. Each of the four cells in the matrix represents four different firm profiles with unique combinations of sensing and responding components. Alternatively, following similar lines Forrester Research (2013) too have presented four distinct groups of firms in a 2x2 matrix, based on their awareness of the opportunities and threats and their ability to execute. The 2 x 2 matrix present in Figure: 3 below represents a combined view of the four distinct types of firms mentioned in the aforementioned two matrices.
**Quadrant 1**: This quadrant represents the firm’s that are agile thus exhibit well-honed sensing and responding capabilities (Overby et al., 2006). Hence firms in this quadrant usually possess strong sensing capabilities such as well-developed capabilities in market intelligence, industry relations, government relations and research and development capabilities, and strong responding capabilities such as strategic and operational capabilities, product development, systems development, supply chain, and resource utilization skills etc., therefore the firm is able to detect changes in its environment caused by technological and economic shifts, regulatory or legal changes and seize opportunities in a timely manner (Overby et al., 2006). The firms in this quadrant both be aware that the change is happening in its environment and execute on appropriate decisions quickly to respond, where Forrester Research (2013) label them as ‘Formidable’.
As stated in Overby et al. (2006), Wal-Mart in early 2000’s provide a good example of how a firm sense and respond quickly to the changes in the environment. In early hurricane season in Florida, Wal-Mart has shown its ability to leverage its strong IT and data analysis capabilities to sense which disaster-related products were in the greatest demand, both predictable items such as flashlights and batteries as well as less predictable items such as beer and strawberry Pop-Tarts. Then they have shown their superior supply chain and distribution capabilities, by delivering additional disaster-related inventory to stores in affected areas to respond to this unusual spike in demand (Hays, 2004).

**Quadrant 2:** This quadrant represents the firm’s with well-honed responding capabilities thus, with weak sensing capabilities (Overby et al., 2006). Whilst they possess flexible capabilities to rapidly retool existing products, change production volumes, customize service offerings, supply chain, and resource utilization skills, they fail to notice any emerging opportunities because they unable to sense relevant environmental changes. As such, it is possible for firms to have stronger responding capabilities despite not being able to sense the correct opportunities to pursue. This lack of a sensing capability may be due to several factors. Lack of integration, over-reliance on outsourcing, external relations or market intelligence to atrophy, competitive complacency makes it difficult for such firms to sense relevant environmental change. Such complacencies may cause when firms become comfortable in their current strategic positions, causing them to ignore signals of change in the competitive landscape (Ferrier et al., 1999).

As Overby et al. (2006) mentions, Cisco Systems circa 2001 provides an example for a firm with strong responding capabilities,
but with weak capabilities to sense critical environmental changes. Even though Cisco consistently recognized for its quick responsiveness to customer demands due to its strong supply chain capabilities (Poirier & Bauer, 2000), but they failed to sense the downturn in the market for networking equipment in 2001, whilst their competitors managed to downgrade their forecasts and reduce inventories accordingly (Berinato, 2001). As they report, that led Cisco to write-off a $2.2 billion inventory in the third quarter of 2001. As critics contend Cisco’s flexible responding capabilities probably may have exacerbated the situation by streamlining their ability to acquire inventory in order to respond to demand that never materialized (Berinato, 2001; Overby et al., 2006). As the firms in this quadrant characterized with poor awareness due to lack of sensing capabilities but with fast executions due to strong responding capabilities, they may execute dangerously short-sighted strategic decisions thus Forrester Research (2013) label such firms as ‘Dangerous’.

**Quadrant 3:** Contrasting to the quadrant 2 above, some firms possess well-honed sensing capabilities but with weak responding capabilities (Overby et al., 2006), thus they show strong awareness but execute poorly. As Overby et al. (2006) elucidates it is possible to have firms that are able to sense environmental change relevant to their business (high awareness /sensing) but fail to respond to it in an agile manner (low responding / execution). In such cases, well-developed sensing capabilities allow them to detect environmental change and identify emerging opportunities correctly in timely manner but unable to respond to such opportunities as they cannot adjust their strategy, reconfigure the production, mobilize the appropriate resources for better execution of the tasks. Unnecessary bureaucracy, too much analysis (analysis-paralysis), risk-aversion, poorly integrated processes and agency problems
can slow down the strategic decision making process and miss the opportunities thus, causing such firms to fail to act on emerging opportunities in timely fashion. Thus, Forrester Research (2013) labelled this type of firms as “paralysed”.

As Overby et al. (2006) reports, Xerox’s Palo Alto Research Centre (‘PARC’) is an example from the 1970s for a firm with strong sensing capabilities, but with weaker capabilities to respond to the opportunities it sensed. They sensed imminent industry changes and innovated product such as the graphical user interface, the mouse, and Ethernet but, due to various issues, including conflicting strategies and issues with the U.S. Justice Department, they did not market these innovations (Smith & Alexander, 1988). In other words, although Xerox was able to sense opportunities created by changes in customer demand, but was unable to respond to them in a profitable manner.

Quadrant 4: This quadrant is characterized by low sensing and low responding capabilities thus with lesser awareness as well as lesser execution abilities. As Overby et al. (2006) states it is possible for firms to lack not only the ability to sense environmental change but also to lack the ability to respond readily to such changes. The deficiencies we have discussed above in quadrant 2 and 3, apples to this quadrant where Forrester Research (2013) labelled such firms as “Clueless”.

As previous literature reports Woolworth’s US in 1990’s provides an example for such firms following its final U.S. store closings in 1997. Woolworth’s initially failed to sense the growth of suburbs in the U.S. during that time hence, the shifts of its target market’s shopping activities from the places where most of their stores were located. As Woolworth’s failed to re-locate their store locations accordingly, there was a mismatch between its merchandise and
the needs of the customers who continued to shop ‘downtown’ thus, leaving Woolworth’s in jeopardy. They recognized this shift late and attempted to convert their lunch counters into coffee bars, and adjust the mix of merchandise with more high-volume items such as health and beauty aids (Zinn, 1991) but lacked the necessary marketing capability to rebrand itself thus responses were ineffective, ultimately leading to the store closures (Brancaccio, 1997).

As aforementioned discussion explains, ‘sensing’ represents the knowledge component of agility (Overby et al. 2006) and reflects the firm’s ability to find appropriate opportunities and/or threats to act upon (Dove 2001). ‘Responding’ describes the firm’s ability to act quickly and accurately on opportunities and/or threats (Dove 2001; Overby et al. 2006). As the 2 x 2 matrix above suggest sensing and responding together explain how firms respond to opportunities and threats with speed, ease and dexterity (Overby et al. 2006). These two capabilities (Overby et al. 2006; Roberts and Grover 2012a; Roberts and Grover 2012b) are complementary, yet distinctively different (Roberts and Grover 2012a) thus possessing of both capabilities are required for achieving agility. However, just simply possessing the capabilities of sensing and responding themselves do not provide agility leading to competitive advantage, but the two capabilities need to be aligned (Overby et al., 2006; Roberts & Grover, 2012a).

Agility Alignment

As illustrated in Overby et al. (2006), the agility alignment in general answers the question on whether a firm senses opportunities in areas where it possesses the capabilities to respond, or whether it senses opportunities beyond which the firm is
able to respond. Here they explain that, the firm is aligned if they seldom waste their capabilities, either by possessing responding capabilities that lie unused or by sensing opportunities that cannot be seized. In other words, the firm only senses those opportunities to which it can respond, or the firm develops capabilities that are useful only for those opportunities it could sense. In contrast, non-aligned firms may hold responding capabilities that do not apply to the opportunities they sense, or they do not own responding capabilities to support the breadth of opportunities that they sense. As discussed above, a firm can sense more, but may choose to only respond to a subset of what it has sensed. Sensing essentially provides intelligence and the awareness which can help a firm’s responsive actions. As such, a firm might have built capabilities to acquire customer preferences but may not have the capacity to act upon this information.

Prior research on agility alignment (Roberts & Grover, 2012a) proposed that a firm’s agility impacts its performance; but, to gain optimum effect of agility on firm performance, the firm needs to align its sensing and responding capabilities (Haeckel, 1999; Overby et al., 2006; Teece, 2007). Overby et al. (2006) suggested that the enterprise agility should be measured as a function of its sensing and responding capabilities, and they oppose measuring enterprise agility as a direct measurement. In other words, to create an overall measurement, the two capabilities of sensing and responding should be measured individually and separately and then combined to get the actual agility assessment. Therefore, the overall agility score will be dependent on the functional relationship linking the two sensing and responding sub-scores (or the alignment) (Overby et al., 2006). Further, they stated that agility alignment is better described by the degree to which the two sense-response capabilities are aligned in a continuous, rather than a binary scale. The core idea of alignment is not that the firm is merely aligned or non-aligned, but that the alignment is attained somewhere in a continuum between the two.

Alignment in general refers to “the degree to which the needs, demands, goals, objectives, and/or structures of one component are consistent with the needs, demands, goals, objectives, and/or structures of another component” (Nadler &
Tushman, 1983). As Roberts and Grover (2012a) discussed, in the context of customer agility, alignment refers to the degree to which the structures and objectives of a firm’s customer sensing capability should be consistent with the structures and objectives of its customer responding capability. Researchers recommend considering multiple specifications as competing theories or models suggest, when considering the most appropriate perspective of alignment for a given research question (Venkataraman, 1989). Roberts and Grover (2012a), for example, studied agility alignment based on sense-response alignment with matching and mediation perspectives from firms’ perspective with the sense, response and firm performance data obtained from the marketing managers of firms.

**Alignment as Matching**

Matching refers to the theoretical match between two related variables wherein the basic tenet is that the stronger the match between a firm’s sensing capability and responding capability, the greater the effect of firm’s agility on an appropriate criterion variable (Overby et al., 2006; Roberts & Grover, 2012a). Accordingly, firms are likely to extract greater value from their agility when they are aligned in their sensing and responding activities. Well-documented case study of BMW (Roberts & Grover, 2012a) provides clear evidence for this argument, as they were able to sense emerging customer needs by involving lead users in the idea generation towards the product innovation activities, and they responded quickly to the new ideas by implementing them in upcoming products.

As proposed by Overby et al. (2006) taking the matching perspective, the agility score for agile firms can be expressed as the minimum of the sensing and responding scores when the two capabilities are in synch (or aligned 100%). This supports the notion that, while a firm can neither sense nor respond to all opportunities, it is capable of responding to those that it senses (or vice versa):
Enterprise Agility score $\text{Aligned} = \min \left( \text{Sensing score}, \text{Responding score} \right)$

On the contrary, for non-agile firms, the score is calculated as the product of the sensing and responding scores as its sensing and responding capabilities are not in sync. What it shows is that, what the firm senses and what the firm is able to respond to, do not always match up; thereby, limiting the number of opportunities the firm can seize:

Enterprise Agility score $\text{Non-Aligned} = \text{Sensing score} \times \text{Responding score}$

At one extreme, misalignment can cause severe negative consequences (Strandholm, Kumar, & Subramanian, 2004). As discussed earlier in this literature review in the case of Woolworths in the US in 1990’s, Xerox in 1970’s and Apple’s decision to position the Newton as a mass-market product in early 2000’s (Roberts & Grover, 2012a) provide good examples for such negative consequences of sense-response mis-alignment. In aforementioned cases, the firms either sense the wrong opportunities or simply fail to sense the correct opportunities. All these practical cases share the common notion that the consequences of misalignment and alignment of a firm’s sensing and responding capabilities could be decisive and extremely critical for their competitive position in the market.

Alignment as Mediation

Roberts and Grover (2012a) specifies that, the existence of an intervening mechanism between an antecedent variable and the dependent variable as the mediation perspective. As Venkataraman (1989) elucidates, the main difference visible in the mediation perspective, compared to the matching perspective, is that the mediation view of alignment is anchored to a particular criterion variable. Hence, while the matching perspective provides insights regarding the combinations of
different levels of sense and response capabilities, the mediation perspective provides insights into the sense-response-performance process (Roberts & Grover, 2012a).

Conceptually, the mediation perspective entails looking into how the conception of agility works from a process perspective (Roberts & Grover, 2012a). Referring to the dynamic capabilities view, focusing on competitor dynamics, Teece (2007) elucidated that “a firm’s ability to manage competitor threats and to reconfigure itself is dependent upon its investment activity, which is in turn dependent on its ability to sense an opportunity”. Further, as Roberts and Grover (2012a) mentioned in their recent study on the sense-response-performance context, a firm’s performance is primarily dependent on its ability to respond to market opportunities (Hult, Ketchen, & Slater, 2005), which in turn is inherently dependent on the firm’s ability to sense the opportunities. However, the superior sensing ability cannot be effectively leveraged for value creation if a firm is weak in its responding capabilities (Overby et al., 2006; Roberts & Grover, 2012a).

**Customer Agility**

As Overby et al. (2006) conceptualization of agility of the firm applies to sensing and responding capabilities for the entire firm, they argued that enterprise agility is distinct from forms of agility that are specific to certain processes such as agility in software engineering, or the ones operate at different levels of analysis such as a network of firms. However, it is possible for a firm to display its agility in many different areas such as customer-based processes, supply chain interactions, and day-to-day operations (Huang et al., 2012; Roberts & Grover, 2012b; Sambamurthy et al., 2003; Y.Y. Yusuf et al., 1999) thus extant agility literature spans over number of different contexts taking different study perspectives (see..Table: 3). Our analysis of past literature affirms that despite the contextual diversity, agility studies in the past all shares the firm’s viewpoint of agility, and none to date assessed firm’s agility from other perspectives such as of customers.
<table>
<thead>
<tr>
<th><strong>Source</strong></th>
<th><strong>Study context</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Overby et al. (2006)</td>
<td>Conceptual work on organizational agility from integration perspective.</td>
</tr>
<tr>
<td>Goldman et al. (2007)</td>
<td>Discuss how organizations become agile in competitive environments.</td>
</tr>
<tr>
<td>Tallon &amp; Pinnsonneault (2011)</td>
<td>Strategic IT alignment and agility, survey of 241 IT and business executives.</td>
</tr>
<tr>
<td>Chakravarty et al.</td>
<td>Role of IT competencies shaping organizational agility</td>
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</tbody>
</table>
Focusing on the customer agility, Roberts and Grover (2012b) defined customer agility as the “degree to which a firm is able to sense and respond quickly to customer-based opportunities for innovation and competitive actions”. In their study, by referring to the “customer based”, Roberts and Grover (2012b) indicates the opportunities that originate from individual customers, communication between customers or the interactions between customers and the firm such as co-creation of ideas and sharing knowledge in online environments. Whilst previous research best viewed agility as an organizational capability – set of routines and processes that produces a particular output, and implies sensing and responding (See Table: 1 and 2) customer agility viewed as having well developed and better orchestrated customer sensing capability and customer responding capability.

Considering the fact that customer agility is most critical in dynamic unpredictable environments than in more stable predictable environments, dynamic capabilities view is used to further understand customer agility (Roberts & Grover, 2012a, 2012b). Whilst, organizational decision making under uncertainty bounded rational they ‘satisfy’ rather than ‘optimize’ in searching or selecting solutions to problems (J.G. March & Simon, 1958), thus firm’s require keep re-configuring their existing capabilities (Roberts & Grover, 2012a). As Roberts and Grover (2012a) explicates, as per Teece’s (2007) notion of dynamic capabilities view, in agility, firms (1) sense and shape opportunities and threats, (2) seize market opportunities, and (3) maintain their competitive stance by reconfiguring and combining the firms tangible and intangible assets. As Roberts and Grover (2012a) suggests dynamic capabilities view provides an appropriate way to frame customer agility, since agility captures, suggest he sensing and seizing (responding) components of dynamic capabilities. Sensing in dynamic capabilities discussion is mainly refers to the scanning, learning, and interpretive activity (Rapp, Trainor, & Agnhotri, 2010; Teece, 2007) that
involves researching, probing customer needs, understanding latent demand, and assessing related competitive dynamics (Roberts & Grover, 2012a; Teece et al., 1997). On the contrary the customer responding component concerns mobilization of firms existing processes or/and services (Jayachandran, Hewett, & Kaufman, 2004; Teece, 2007) thus, implies improvisation (Pavlou & El Sawy, 2010). As such, even though dynamic capabilities view appropriate to frame customer agility, enterprise agility is distinctively different from dynamic capabilities view (Overby et al., 2006). Therefore, it is imperative to understand the distinctive difference between agility in relation to similar notions; the discussion next compares enterprise agility and the concepts that are similar to agility.

Concepts Similar to Agility

The sensing component of agility relates to the broader conceptualization of environmental change (Overby et al., 2006) thus, it allows enterprise agility to focus on wider range of change drivers that operates in highly turbulent volatile environments compared to the similar concepts that focuses on specific change drivers such as technological opportunism (Srinivasan, Anderson, & Ponnavolu, 2002) in management field (it only deals with a specific change driver). Likewise there are other theories similar to firm agility, that pertain to firm success in turbulent environments, such as market orientation (Kohli & Jaworski, 1990; Narver & Slater, 1990), dynamic capabilities (Teece et al., 1997), absorptive capacity (Cohen & Levinthal, 1990; Zahra & George, 2003) and strategic flexibility (Ansoff, 1980; Grewal & Tansuhaj, 2001) but are distinctively different from firm agility in significant ways.

For example, market orientation reflects an organizations ability of generating market intelligence pertaining to the current and future customer needs throughout the organization, dissemination of such intelligence across its departments, and adding organization-wide responsiveness to it (Kohli & Jaworski, 1990). Thus, market intelligence includes information about customers, competitors, and other factors such
as technology and regulatory developments and concerns all of the drivers of ‘environmental change’ included in the notion of firm agility. Correspondingly, both agility and market intelligence explicitly include responsiveness to market intelligence and environmental change. However, as Overby et al. (2006) explains, the two concepts differentiate themselves slightly, as market orientation is greatly rooted in information processing (i.e. information is gathered, disseminated across departments, and acted upon), whilst the notion of agility is not necessarily as contingent on information processing. In the notion of agility, it is possible for firms to act in an agile manner with no dissemination of information across its departments. On the other hand, agility might get hindered when information dissemination across departments takes time thus, it may actually delay the speedy responsiveness making firms less agile (Overby et al., 2006).

Teece et al. (1997) defined the ‘dynamic capabilities’ as a firm’s capabilities that are able to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. A basic tenet of dynamic capabilities view is that a firm needs to continuously adapt their capabilities for them to maintain their advantage over competition (Overby et al., 2006). As such, the concept of dynamic capabilities is relevant to all types of firm processes thus, is a broader concept. Whilst both dynamic capabilities shares many of the same concepts, in particular its relevance to rapidly changing environments, agility is a significantly different, because agility includes only those processes relevant for sensing and responding to environmental change thus, agility is being enabled by a specific subset of dynamic capabilities (Overby et al., 2006).

Zahra and George (2003) has re-conceptualized ‘absorptive capacity’ as a set of routines and processes that a firm follow to acquire, assimilate, transform, and exploit knowledge to produce a dynamic organizational capability. Since the acquiring and the exploiting dimensions of absorptive capacity refer to the firm’s ability to gather and make sense of externally generated knowledge and ability to use the newly acquired and assimilated knowledge respectively (Overby et al., 2006), they reflect notions similar to sensing and responding in firm agility. However, the absorptive
capacity predominantly refers to a firms’ ability to manage knowledge (i.e., by acquiring, assimilating, transforming, and exploiting it), whereas the notion agility conceived as a firms’ ability to manage change (i.e., by sensing and responding to it). Thus, the two concepts are fundamentally different as absorptive capacity operates on a continuous and relatively predictive environment but, the notion agility is best viewed as applying to episodic events precipitated by uncertainty (Overby et al., 2006).

Grewal and Tansuhaj (2001) has defined ‘strategic flexibility’ as a firm’s ability to manage political and economic risks by responding promptly to threats and opportunities with either in a reactive or proactive manner. According to Michael E. Porter (1987), strategic flexibility predominantly refers to the strategic issues where the focal point is about the businesses that a firm is in and how it creates and maintains competitive advantage in those chosen businesses. Firms that are strategically flexible tend to have flexible resource pools and diverse portfolios of strategic options, thus allowing them to manage unexpected issues effectively (Ansoff, 1980). Agility on the other hand applies to both strategic and operational issues (Overby et al., 2006). For example, a firm may need to handle strategic issues such as those created by competitor moves or changing customer preferences as well as handle operational issues such as those created by new regulations (e.g. a new federal law) in an agile manner in order to be competitive. Whilst, strategic issues are fundamentally and distinctively different from operational or tactical issues (Michael E Porter, 1996), and the notion agility refers to both strategic and operational issues, it is fundamentally different from strategic flexibility where The conception of agility envelops and extends strategic flexibility. Overby et al. (2006) explained that firm agility concerns both proactive as well as reactive moves (Dove, 2001) as well as both strategic and operational moves.

Whilst, several firm capabilities including market intelligence, supply chain, production, and resource utilization in combination enables firm’s agility in many different areas as discussed above, information technology (IT) plays a pivotal role in enabling sensing and responding capabilities (Overby et al., 2006).
AGILITY: SENSING, RESPONDING AND THE ROLE OF IT

Past literature has extensively discussed the role of IT in sensing and responding (Bradley & Nolan, 1998; Nazir & Pinsonneault, 2012; R. L. Nolan, 1998; Overby et al., 2006; Roberts & Grover, 2012b; Sambamurthy et al., 2003; Weill & Broadbent, 1998). Sambamurthy et al. (2003) stated that IT influences a firm’s performance by influencing three key firm capabilities agility, digital options and entrepreneurial alertness. Subsequently, Overby et al. (2006) discussed the role of IT on achieving agility in two different ways (1) directly and (2) indirectly through the creation of digital options.

IT capability directly related to sensing and responding in number of different ways. For example, in order for a firm to anticipate or sense changes relevant to their business that are brought about specifically due to advances in IT, the firm must have an adequate level of IT capability (Overby et al., 2006). As mentioned in Kalakota and Robinson (2001), for a firm to sense the possible opportunities created by the emerging technologies such as interactive HTML pages, smart mobile devices and associated apps and other electronic commerce strategies before many of their competitors, the firm needs to possess strong IT capabilities. Also, firms needs adequate levels of IT capabilities if they were to utilize IT for responding to opportunities both in IT-driven industries (Sambamurthy et al., 2003) as well as in other industries (A. S. Bharadwaj, 2000) as they often require frequent modification and enhancement to supporting information systems. In addition, as Haeckel (1999) elucidate IT capability directly supports firms sensing and responding through its sheer ability process enormous volume of information quickly, as the amount of information that a firm need to process in day to day basis simply outstrips human capacity to process it. As Overby et al. (2006) explicate, the complexity of responses that a firm should make and the speed of which need to carry out for timely implementation in contemporary highly turbulent environments would be near impossible without the support of IT in the form of communication, infrastructure and automation. Thus, IT enables firms to make sense out of voluminous information and carry out complex timely responsive actions, what would otherwise overwhelm them.
R. A. Nolan and Haeckel (1993) referred this firm’s inability to manage the sense making and action in extreme turbulence without IT as ‘managing by wire’.

As Barua, Kriebel, and Mukhopadhyay (1995) lament most of the business value of IT stems from its complimentary nature to business processes, Overby et al. (2006) states that the indirect relationship of IT and agility probably be even more pronounced than the direct relationship between IT and agility. In essence, IT provides the infrastructure for other business functions and processes (Lewis & Byrd, 2003), such as product development, manufacturing, and supply chain and which in turn enables firm agility. Thus, at the same time a firm’s IT capabilities have a direct impact on firms sensing and responding, IT also has an indirect effect on sensing and responding by influencing on firm processes. As literature suggest IT provide digital options (Sambamurthy et al., 2003), thus creates IT-enabled capabilities in the form of digitized work processes and knowledge systems to enhance the reach and richness of a firm’s knowledge and its processes (Nazir & Pinsonneault, 2012; Overby et al., 2006). Digital options has the potential to integrate an enterprise internally as well as externally to enhance a firm’s sensing and responding capabilities in unique ways (Nazir & Pinsonneault, 2012) thereby making the firm more agile towards changes in its operating environment. The Figure: 4 illustrate the two forms-directly and indirectly, that IT enhances a firm’s agility as described above.

As seen in Figure: 4, IT enables firm agility by streamlining their processes and providing decision makers with unfettered access to mission critical information from both within as well as outside the firm (Nazir & Pinsonneault, 2012). Taking the
electronic integration view, they have demonstrated that the link between IT and agility depends on the degree to which IT applications work as a functional whole with other internal and/or external IT applications (i.e. degree of electronic integration) achieved in a firm. Whilst earlier literature suggest digital options enhances the reach and richness of firm knowledge and processes (Overby et al., 2006; Sambamurthy et al., 2003), Nazir and Pinsonneault (2012) laments that electronic integration make the efficient and effective communication and sharing of specialized knowledge a possibility, among distinct components both within a firm and with its business partners and customers.

In addition, H. Barki and Pinsonneault (2005) further elaborates that electronic integration also supports coordination of processes both within and outside the organization. Thus, Nazir and Pinsonneault (2012) argued that, the way a firm employ electronic integration to access and utilize knowledge and to integrate processes play an important mediating role in the relation between IT the firm’s agility. Thus, to explain the relationship between IT and the two key components of agility - sensing and responding through the mediation of knowledge exploration, knowledge exploitation, and process coupling, Nazir and Pinsonneault (2012) proposed a 2 x 2 matrix combining the two forms of integration – internal and external (Figure 5).
As evident in Figure 5, the matrix involving electronic integration (Nazir & Pinsonneault, 2012) provide an explanation that is complementary to the four types of firm’s introduced by Overby et al. (2006) classification. Thus, it provides a unique combination of integration types providing explanation of differential effects that each type of integration have on firm agility. Firms that represent four distinct groups would have different levels of internal and external electronic integration based on their portfolio of IT applications (Nazir & Pinsonneault, 2012).

Digital options (Sambamurthy et al., 2003) provide the medium to enhance the firm’s reach to knowledge bases that are external to the firm and obtain rich knowledge that are critical for business decision making. Such IT applications essentially enable outside-in capabilities (Wade & Hulland, 2004) and permit firms to better anticipate market requirements by effectively managing its external relationships and improves firm’s ability in understanding its market (G.S. Day, 2000; Wade & Hulland, 2004). For example, firms that are well connected easily acquire
and share information and knowledge, consequently they are able to continuously evolve and improve their business processes (Braunscheidel & Suresh, 2009). Further, Hoyt et al. (2007) evidenced that firm’s who constantly communicate and make close relationships with suppliers are better equipped to sense information about potential environmental threats and opportunities. Sánchez and Pérez (2005) too have suggested that knowledge transfers with external partners improve firm flexibility.

Literature suggests that integration externally through digital options enhances firms sensing in three distinct ways (J. S. Brown & Duguid, 1998; Carlile, 2002; Malhotra et al., 2007). First, it enables boundary spanning thus increasing the firm’s access to new knowledge domains belongs to its partners (Nazir & Pinsonneault, 2012). Next, it provide different perspectives on environmental problems and opportunities thus improves decision makers understanding of trends and issues in the market place (Aranda & Molina-Fernández, 2002) thus, challenges the dominant mindset and opens up the minds to notice new opportunities and minimize suboptimal resolutions (Nazir & Pinsonneault, 2012). Third, it improves the firm’s capability of sensing environmental threats and opportunities (Nazir & Pinsonneault, 2012; Nonaka, 1994; Okhuysen & Eisenhardt, 2002) thus promotes unconventional methods to understanding consumer preferences (Von Krogh, Nonaka, & Aben, 2001).

On the contrary, high levels of internal integrations between sub units achieved through the digital options, enables the firm to attain greater responsiveness to its environmental changes by achieving better coordination among its activities (Gattiker & Goodhue, 2005; Malhotra et al., 2007; Nazir & Pinsonneault, 2012; Truman, 2000). Such internal amalgamation essentially enables the firm’s inside-out capabilities (Day, 1994; Wade & Hulland, 2004). As Nazir and Pinsonneault (2012) states, internal electronic integration enables knowledge exploitation and process coupling among firm’s internal units of a firm thus improving firm’s responding capability.

Knowledge exploitation refers to the transferring and making use of knowledge that already exist within the firm (Von Krogh et al., 2001). As discussed in Nazir and
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Pinsonneault (2012) internal electronic integration facilitate firms knowledge exploitation thus firm’s responding capabilities in two ways. First, it enables standardized communication protocols and data schemas (H. Barki & Pinsonneault, 2005) thus support shared meanings, common language among different organizational units, and help easy knowledge transfers between them (R. M. Grant, 1996). This organization wide standardization in turn helps converting complex and tacit knowledge of procedures into explicit knowledge and eases knowledge transfer among the units (Nazir & Pinsonneault, 2012; Nonaka, 1994), thus allowing different and complementary components of organizations to be orchestrated, more responsive to each other and to behave as a unified whole (H. Barki & Pinsonneault, 2005). Second, it brings together the perspectives of different organizational units thus helping the firm to respond to the opportunities and threats more effectively with the application of specialized expert knowledge in various organizational units (R. M. Grant & Baden-Fuller, 1995).

Process coupling refers to the inter-meshing of processes between organizational sub units (Saraf, Langdon, & Gosain, 2007), such a way that it standardizes the routines and operating procedures to allow coordination among units to enable handling of anomalous circumstances easy (Nazir & Pinsonneault, 2012; Robicheaux & Coleman, 1994). Thus, reconfiguration of processes together with standardized communication routines (Malone et al., 1999), allow different units to tailor their processes to each other and make them adaptive to each others' requirements (Nazir & Pinsonneault, 2012). Antonio, Richard, and Tang (2009) too have states that internal process coupling able to combine and utilize internal resources to improve the firm’s flexibility. Taken together, literature informs that tight internal coupling of firms processes are able to better synchronize and adapt their process activities, thus, becomes more agile (Nazir & Pinsonneault, 2012).

Both Nazir and Pinsonneault (2012) and Roberts and Grover (2012b) decomposed the IT infrastructure into two components – knowledge based and process based to describe how IT relates to two key components of agility sensing and responding. In doing so Roberts and Grover (2012b) taking the “tool” view of IT
Chapter 2: Literature Review

artefact, conceptualized IT as a “driver” and/or “magnifier” that firms can utilize for their specific requirements such human resources related needs, increase operational efficiencies, information processing and manage relationships. As a driver IT act as an exogenous force that influence the behavior of firms and the individuals whilst as a magnifier IT amplifies existing routines and behaviors to improve firm performance (Roberts & Grover, 2012b). As explained therein for example, IT as a tool for information processing alter the flows of information whilst magnifying feedback and learning within organizations.

Since sensing involves scanning, creating, learning, and interpretation (Teece, 2007) to identify opportunities firms needs to search and explore regularly, across technologies and markets, both in its vicinity and remote (James G March, 1991; Roberts & Grover, 2012b), firms needs to constantly monitor their customers shifting needs and wants to strengthen firm’s customer sensing capability. As explained in Roberts and Grover (2012b), in new product development context, IT help firms sensing of customer based opportunities from customer generated content as a driver and as a magnifier as follows. For example, web based tools such as suggestion forms and design toolkits, allows customers to generate, propose and refine new ideas for products and services and stimulates customer based knowledge creation. So IT drives customers’ behavior. On the other hand IT – analytical tool, supports sensemaking thus detect the patterns from customer generated content thereby increase or magnifies visibility of customers’ voice.

Once an opportunity is sensed, it must be addressed with an appropriate responsive action/s. As Dove (2002) asserts a firm’s response ability depends primarily on the coordination and execution of firm’s operational processes. Improved information flow, reduction of potential bottlenecks and well-coordinated operational processes essentially enables a firm’s responsiveness (Roberts & Grover, 2012b). Similarly, as they further elaborate, for a firm to respond accurately to customer based opportunities a they should have a better coordinated functions and processes. As such internal and external coordination influences a firm’s ability to respond (Nazir &
Pinsonneault, 2012; Roberts & Grover, 2012b), thus IT can facilitates (or constrain) firm’s operational process execution and responsiveness (Wanda J Orlikowski, 1992).

As discussed above IT influences agility both directly as well as indirectly in several ways. IT enables several firm capabilities relating to sensing and responding components of firm agility, including market intelligence, supply chain, production, and resource utilization (Overby et al., 2006). Past research have investigated both how certain characteristics of IT enables individual elements of sensing and responding (Nazir & Pinsonneault, 2012) and how broad IT construct affect the individual elements of sensing and responding (Overby et al., 2006; Sambamurthy et al., 2003). However, IT not only be complementary but that itself could be pejorative and hinder agility unless is not deployed or managed properly (Overby et al., 2006). For example, monolithic IT architectures (of older generations of IT) may make it difficult for firms to adjust their process to changing conditions thus limiting the range of responses available to firm making the firm non-agile (Daniel & Wilson, 2003; Overby et al., 2006). Also, IT systems may store data in the formats that are difficult to retrieve and interpret thus limiting the visibility by or the systems themselves becomes incompatible with other systems thus limiting the process reach (Overby et al., 2006). As Overby et al. (2006) explains such issues mainly stems from inappropriate investment decisions, management of IT and other resources or inapt IT planning, implementation, and maintenance (A. S. Bharadwaj, 2000; Overby et al., 2006; Weill & Broadbent, 1998).

**CUSTOMER AGILITY AND DIGITAL STRATEGY**

During last decade or so, the business infrastructure has become digital during with the advancements in information, computing, communication and connectivity technologies (A. Bharadwaj, El Sawy, Pavlou, & Venkataraman, 2013) providing more digital options for firms to utilize in sensing-responding. With the emergence of these pervasive and ubiquitous digital technologies business strategies, business processes, firm capabilities, products, services and key inter-firm relationships in extended business networks all have been transformed remarkably. At the same time sensing and responding became a strategic imperative. As such, contemporary firms
are looking to build production-side as well as delivery side (both product and service) competencies to leverage these technologies in their digital business strategic initiatives (Setia et al., 2013) whilst deploying these technologies for improved sensing opportunities.

Meanwhile, the new generations of consumers are innately techno-savvy and let ubiquitous technologies, networks, and associated systems to weave themselves into the very fabric of their everyday life (Vodanovich et al., 2010). Thus, the advent of mobile computing, together with the growth of tech-savvy digital natives (Vodanovich et al., 2010), have facilitated digital business strategies in organizations. Consequently, contemporarily firms are using their IT competencies to create digital options (Chakravarty et al., 2013; Sambamurthy et al., 2003) to sense-and-respond to customer requirements in a timely and tailored manner. Techno-savvy customers on the other hand are eager to mimic their daily routines in appropriate digitized environments, and allow firms to sense customer needs. Digital environments allow firms to access customers’ daily routings via the information footprints they leave as a by-product during their regular digital interactions with the firm. Similarly, as researchers affirm firms also can effectively leverage digital technologies to improve firms customer responsiveness by improving customer side competencies and enhancing localized firm dynamics (Setia et al., 2013). As such firms are aiming heightened ‘digital connectivity’ with their techno-savvy customers to further strengthen their customer agility – sensing and responding, with the deployment of smart mobile devices and associated apps in their digital business strategic initiatives. In other words, firms are progressively utilizing customer focused digital options in their customer focused strategic initiatives such as in customer relationship management systems aiming better and ubiquitous firm-customer connectivity for better customer relationships.

**SENSING, RESPONDING AND UBIQUITOUS CUSTOMER MANAGEMENT SYSTEMS**

I. J. Chen and Popovich (2003) described Customer relationship management (CRM) as a combination of people processes and technologies that seeks to
understand a company’s customers. CRM is an integrated customer relationship management approach and primarily focuses on customer retention and relationship development. Consequently, firms implement relationship marketing principles using strategic and technology-based customer relationship management (CRM) applications (I. J. Chen & Popovich, 2003) widely known as Customer Relationship Management Systems (CRMS). Following which, Reinartz, Krafft, and Hoyer (2004) described CRMS as business processes and enabling technologies that focus on improving and managing relationships with customers in the areas of sales, marketing, customer support and service.

As Fickel (1999) point out CRMS link both customer facing functions - front office (e.g. sales, marketing and customer service) and supporting functions - back office (e.g. financial, operations, logistics and human resources) with the company’s customer “touch points”. These customer touch points can include a combination of corporate web site/s, online trading, mailers both online and off-line, Social media/networking sites, smart-apps, point of sales interactions, interactions over the phone such as in telemarketing and call centers, advertising and promotions, face-to-face interactions and so on, with the aid of multitude of technologies (I. J. Chen & Popovich, 2003). Often, these touch points are controlled by a separate IT system – CRMS and it integrates all the touch points to provide a common view of the customer (Eckerson & Watson, 2000).

Firms invest on different types of systems anticipating different types of outcomes (Aral & Weill, 2007). For example, Enterprise Resource Planning systems are used for back-office core business functions such as finance, HR, manufacturing, whilst CRMS are used to develop collaborative links with customers and manage customer relationships (Peter B Seddon, Shanks, & Willcocks, 2003). As outlined in Dale L. Goodhue, Wixom, and Watson (2002) CRMS has two main functions – analytical and operational, where the analytical side typically maintains, analyses and make sense of historical customer data while the operational side focuses on the customer interactions and capturing of customer data from multiple customer touch points. As explained in Dale L. Goodhue et al. (2002), front end of the operational
side of the CRMS (i.e. customer touch points) are linked to the operational data store (back end) whilst the front end of the analytical side (i.e. analytical tools and applications) are linked to the main data warehouse (back end) (see Figure 6). Operational side of the CRMS captures data from all customer touch points integrates them and then stores them in the data warehouse. Current data is usually maintained in operational data store to support operational applications, and when the data ages, they are passed from the operational store to the main data warehouse (Dale L. Goodhue et al., 2002). On the analytical side, the historical data were maintained in the main warehouse and are utilized by both general analytical tools and applications to make use of the data to find patterns, opportunities or threats (sensing) and to create and execute appropriate responsive actions (responding).

As observable in CRMS technical architecture (Dale L. Goodhue et al., 2002), the primary purpose of CRMS is to sense individual customers unique requirements through collecting insights through the regular customer interactions via multiple customer touch points. Thus main benefit that firms anticipate from CRMS is to improve their understanding of each customers unique requirements and thus enabling firm’s ability to develop timely responses to their customers unique needs (Rapp et al., 2010). Whilst CRMS has the ability to congregate information gathered through multiple customer touch points to generate ‘360 degree view’ of the customer (Dale L. Goodhue et al., 2002). As such in CRMS, many applications are supplying and using customer information thus providing better and reliable understanding of unique customer needs.
The convergence of pervasive technologies, techno-centric customers and the emergence of digitized technologies, overabundance of user friendly smart devices and associated applications are providing immense opportunities for organizations to interact with their customers almost every time ubiquitously (Atapattu & Sedera, 2012). As such, rapid uptake of digital complimentary assets (Rosemann, Andersson, & Lind, 2011) and smart mobile applications are revolutionizing the CRMS. As researchers suggest contemporary CRMS enables innovative practices of communicating with customers and provide benefits (Coltman, Devinney, & Midgley, 2011; Jayaganesh, Shanks, & Carlsson, 2004; Shanks, Jagielska, & Jayaganesh, 2009) but at the same time such initiatives stresses organizations to be more agile and more responsive to the changing and demanding nature of customer needs in very little or no time. Thus, to better understand the benefits and the consequences of contemporary CRMS, we next investigate the benefits of ubiquitous customer engagements in contemporary CRMS.

### CONTEMPORARY CRM SYSTEMS, SYSTEMS BENEFITS AND AGILITY

Firm’s today are investing heavily and transforming their traditional mode of customer relationship management systems into more contemporary robust CRM systems equipped with multitude of ubiquitous digital technologies to connect with their customers ubiquitously and pervasively, expecting more benefits. In other words
firms are trying to be more agile towards individual customers’ unique needs by sensing requirements that are unique to the individual customers through ubiquitous connectivity attained via novel ubiquitous technologies. Thus, the next section herein attempts to understand the benefits that contemporary firms are able to achieve through the contemporary CRM systems powered by ubiquitous technologies.

A wide range of sources including academic papers, commercial press and vendor associated social media available between 2005 and 2012, are being considered for deriving a comprehensive list of contemporary CRMS benefits as described belows. The main academic outlets canvassed for this study includes the top tier IS journals and conferences. In addition popular CRM vendors, SAP, Microsoft and Oracle based YOUTUBE video clips and web-community based resources such as SAP Sapphire presentations were considered since they have the potential of providing most up to date information. Inclusion of Science-Direct data base ensured the search results incorporate CRM studies from multiple disciplines while inclusion of commercial sources such as vendor portals and YOUTUBE ensured the most novelty and contemporary updates. The main key words employed in the academic search were restricted to a title, abstract, body text search of the term “CRM” and its alternatives. The commercial sources were scanned using advertorials and powerpoint presentations. Moreover, several key academic papers (Richards & Jones, 2008; Shanks et al., 2009; Shayon, 2011; White & Nteli, 2004) and a PhD dissertation (Tallon & Pinsonneault, 2011) provided much needed scope for the study. Shanks et al., (2009) make a substantial contribution to our understanding of their listing of CRM benefits – which this exercise heavily rely upon.

The archival analysis yielded a total of 62 unique organizational benefits of contemporary CRMS as a result of ubiquitous and uninterrupted customer connectivity. The 62 benefits were then categorized according to classifications employed in Shanks et al (2009). Shanks et al (2009) has 14 sub categories, while our classification extends to 17 sub categories. To reduce personal bias, two researchers

1 MISQ, ISR, JMIS, EJIS, JAIS, ISJ, JIT, JSIS, CAIS, DSS & I&M, ICIS and ECIS
synthesized and categorized the CRMS benefit statements separately (with inter-coder reliability over 90%) based on the framework provided by Shanks et al (2009).

Similar to Shanks et al. (2009), following Anthony’s (1965) classification of employee cohorts, we too have classified the contemporary CRMS benefits in to a framework comprises of operational, tactical and strategic employee cohorts (See Tables 4, 5 and 6). The employee cohorts classification (Anthony, 1965) recognizes the levels on the timeframe for the decision making, level of judgment, impact of a single action as the basis, thus, the classification herein recognizes the different types of users of the system and the potential system impact on each employee cohort’s area of work in an organization. Whilst the operational benefits in Table 4 pertain to day-to-day business operations, many of them triggers related benefits at both tactical and strategic level benefits (Atapattu & Sedera, 2012; Shanks et al., 2009). Benefits for tactical level management listed therein Table 5, relates to the medium level planning and facilitates tactical strategies thus relates to the middle level management. Correspondingly, they are related to the operational level benefits listed in Table 4, but may trigger at strategic level benefits. Strategic level benefits listed in Table 6, relates to the top most level of the organization and are concerned with long term organizational vision and goals and are innately relate to the lower level operational and tactical level benefits (Shanks et al., 2009). More importantly, as portrayed in the Tables 4, 5 and 6 are the benefits corresponding to the three different levels in the organizations where all of them reflects the inherent relationships that CRMSs have on firm’s sensing and responding capabilities.
<table>
<thead>
<tr>
<th>Benefits (sub categories)</th>
<th>Benefit items</th>
<th>Sources</th>
<th>Relatedness to Agility</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Improved customer data management (ABCDEF*)</td>
<td>1.1 Improved accuracy of customer information</td>
<td>ABCDF*</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.2 Improved completeness of customer information</td>
<td>ABCF*</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.3 Decrease in the duplicate records</td>
<td>BCEF*</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.4 Reduction in time taken to access complete customer information</td>
<td>ABF*</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.5 Increase in the timeliness of the information</td>
<td>ABDE*</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.6 Improved customer data history</td>
<td>ABF*</td>
<td>✓</td>
</tr>
<tr>
<td>2. Improved process management (ABD*)</td>
<td>2.1 Reduction in number of redundant processes</td>
<td>ABCD*</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.2 Increase in efficiency at different stages of managing the customer</td>
<td>ABCDF*</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.3 Increase in efficiency in assignment of tasks</td>
<td>ABCD*</td>
<td>✓</td>
</tr>
<tr>
<td>Improved customer service (BDF*)</td>
<td>3.1. Increased number of resolutions at first point of contact</td>
<td>ABDE*</td>
<td>✓</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th>4. Empowerment of staff (BCD)</th>
<th></th>
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<tbody>
<tr>
<td>3.2. Reduced handling time for enquiries</td>
<td>ABDE</td>
<td>✓</td>
</tr>
<tr>
<td>3.3. Increased access to high quality information at the point of customer contact</td>
<td>ABF</td>
<td>✓</td>
</tr>
<tr>
<td>4.1. Increased conversion rate of prospects</td>
<td>BF</td>
<td>✓</td>
</tr>
<tr>
<td>4.2 Increased staff satisfaction level</td>
<td>B</td>
<td>✓</td>
</tr>
<tr>
<td>4.3. Improved employee productivity</td>
<td>CDF</td>
<td>✓ ✓</td>
</tr>
<tr>
<td>4.4. Reduction in administration of sales staff</td>
<td>BCD</td>
<td>✓</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
<th>5. Improved productivity (ABDEF)</th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td>5.1. Reduction in lost opportunity costs</td>
<td>BF</td>
<td>✓</td>
</tr>
<tr>
<td>5.2. Reduction in costs for lead generation, marketing, customer service and sales</td>
<td>ABCDE</td>
<td>✓</td>
</tr>
<tr>
<td>5.3. Increase in the number of customers handled per sales representative</td>
<td>ABE</td>
<td>✓</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>6. Enabling of real-time responsiveness to trends (BCEF)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>6.1. Increase in number of cross-sales</td>
<td>BCDF</td>
</tr>
<tr>
<td>6.2. Increase in number of up-sales</td>
<td>BCDF</td>
</tr>
<tr>
<td>6.3. Earlier detection of trends</td>
<td>BCEF</td>
</tr>
<tr>
<td>6.4. Increased number of effective campaigns</td>
<td>BCE</td>
</tr>
</tbody>
</table>

**Sources**:  
B: MISQ, ISR, JMIS, EJIS, JAIS, ISJ, JIT, JSIS, CAIS, DSS, I & M, ICIS and ECIS  
C: JIT journal paper by Coltman et al., (2011)  
D: IMM journal paper by Richards & Jones (2008)  
E: PACIS conference paper by Wang & Sedera (2011)  
F: Advertorials on YouTube, LinkedIn and SAP Sapphire
**Table 4: Operational level benefits of contemporary CRMS**

<table>
<thead>
<tr>
<th>CRMS Management Level Benefits</th>
<th>Benefit items</th>
<th>Sources</th>
<th>Relatedness to Agility</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Improved facilitation of market segmentation (BF)</td>
<td>1.1. Increase in campaign response rates</td>
<td>BEF</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.2. Increase in identification and utilization of business opportunities</td>
<td>ABC</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.3. Increase in target marketing driven revenue</td>
<td>BCF</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.4. Increase in profitability of market segments</td>
<td>ABC</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.5. Increase in number of target marketing initiatives</td>
<td>BCE</td>
<td>✓</td>
</tr>
<tr>
<td>2. Facilitation of key account management (BF)</td>
<td>2.1. Increase in average customer lifetime value</td>
<td>BEF</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.2. Increase in number of customers with high life time value</td>
<td>BCF</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.3. Reduction in number of customers with credit risk</td>
<td>BC</td>
<td>✓</td>
</tr>
<tr>
<td>3. Improved channel management (BCDF)</td>
<td>3.1. Increase in number of transactions through cost-effective channels</td>
<td>ABC</td>
<td>✓ ✓</td>
</tr>
<tr>
<td></td>
<td>3.2. Increase in the number of customers</td>
<td>BF</td>
<td>✓</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Section</th>
<th>Benefit Description</th>
<th>Source(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.3.</td>
<td>Improved internal communication, information sharing and integration</td>
<td>CD</td>
</tr>
<tr>
<td>3.4.</td>
<td>Reduction in channel cost per sale</td>
<td>ABC</td>
</tr>
<tr>
<td>4.1.</td>
<td>Improvements in monitoring KPI’s</td>
<td>BEF</td>
</tr>
<tr>
<td>4.2.</td>
<td>Improvements in reporting at customer rather than at account level</td>
<td>ABF</td>
</tr>
<tr>
<td>4.3.</td>
<td>Increase in the number of relevant reports available</td>
<td>BDE</td>
</tr>
<tr>
<td>5.1.</td>
<td>Improved streamlined business processes</td>
<td>ACDF</td>
</tr>
</tbody>
</table>

Sources*:  

Table 5: Managerial level benefits of contemporary CRMS
## CRMS Strategic level benefits

<table>
<thead>
<tr>
<th>Benefits (sub categories)</th>
<th>Benefit items</th>
<th>Sources</th>
<th>Relatedness to Agility</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. Improved customer satisfaction (ABDEF)</strong></td>
<td>1.1. Improved value perception</td>
<td>BF</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.2. Increase in period of customer loyalty</td>
<td>BEF</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.3. Increase in the number of repeat customers</td>
<td>BC</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.4. Reduced number of complaints</td>
<td>B</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>1.5. Increase in word-of-mouth recommendations</td>
<td>BF</td>
<td>✓</td>
</tr>
<tr>
<td><strong>2. Improved business performance (ABCDEF)</strong></td>
<td>2.1. Increase in profit</td>
<td>ABCDE</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.2. Increase in share of wallet</td>
<td>BCF</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.3. Increase in customer retention</td>
<td>BCDEF</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.4. Increase in revenue per customer</td>
<td>BCD</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.5. Increase in sales</td>
<td>ABDE</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.6. Increase in gross margin and market share</td>
<td>DF</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.7. Decrease in the time required to realize ROI from marketing activities</td>
<td>DF</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>2.8. Increased market competitiveness</td>
<td>ACDEF</td>
<td>✓ ✓</td>
</tr>
<tr>
<td></td>
<td>2.9. Increase in the number of customers</td>
<td>BCE</td>
<td>✓</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>3. Improved value added partnerships (BC)</th>
<th>3.1. Improved support on worldwide growth</th>
<th>DF</th>
<th>✓</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3.2. Increase in internal and external value added linkages</td>
<td>BC</td>
<td>✓ ✓ ✓</td>
</tr>
</tbody>
</table>

| 4. Improved innovative use of customer relationships (BC) | 4.1. Increase in CRM system driven innovations | BCDF | ✓ |

| 5. Improved organizational infrastructure (AC) | 5.1. Improved organizational architecture | AC | ✓ |
|                                             | 5.2. Improved organizational human analytic capability | AC | ✓ |
|                                             | 5.3. Improved organizational IT infrastructure | AC | ✓ |
|                                             | 5.4. Improved organizational business architecture | AC | ✓ ✓ |

| 6. Improved organizational emphasis on strategy (ACE) | 6.1. Improved organizational emphasis on strategy | ACEF | ✓ |

**Sources**:  

**Table 6**: Strategic level benefits of contemporary CRMS
Our exercise of mapping each benefit item in relation to sensing, responding and overall firm performance reveals that majority of operational level CRMS benefits are related to sensing and responding capabilities, whilst the higher level managerial and strategic level benefits are predominantly reflects the firm’s performance (i.e. outcomes / impact of having lower level operational benefits). As such, CRMS inherently enables a firm’s customer sensing and responding capabilities thus enacting firm’s customer agility thus delivering better firm performance. Also, creating and maintaining customer connectivity becomes the most critical starting point in CRMS benefits realization process as it initiates customer sensing and responding thus prompting the firm’s customer agility. As a result, the contemporary firm’s are deploying multitude of pervasive digital technologies such as smart apps in smart devices for ubiquitous digital customer connectivity for everywhere sensing and responding expecting organizational benefits. As in this discussion, our focus is on the firm-customer connectivity relating to the customers’ use of smart apps for shopping related activities and the firm’s customer agility we next look in to the system / IS use related literature in order to comprehend customers’ use of smart apps.

IS / IT USE IN INFORMATION SYSTEMS RESEARCH

IT /system usage has a long history in IS research (Barkin & Dickson, 1977). One of the key themes of IT/IS use was the antecedents to usage, where many models of antecedents were present in the literature (F.D. Davis, Bagozzi, & Warshaw, 1989; Hong, Thong, & Tam, 2006; B. Szajna, 1993; Bernadette Szajna, 1996; Taylor & Todd, 1995; Venkatesh & Davis, 2000; Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, Chan, Hu, & Brown, 2011; Venkatesh, Thong, & Xu, 2012). Another stream of research have discussed the impact of IS/IT usage on the performance of the users (Doll & Torkzadeh, 1988; Dale L Goodhue, 1995; Magid Igbaria & Tan, 1997; Lucas & Spitler, 1999; B. Szajna, 1993). Meanwhile some others have studied the usage construct itself (A. Burton-Jones & Gallivan, 2007; A. Burton-Jones & Grange, 2013; A. Burton-Jones & Straub, 2006; P.B. Seddon, 1997; Trice & Treacy, 1988).

As A. Burton-Jones and Straub (2006) reports, use of technology or the use of systems (i.e. System use) has been one of the most mature research streams in IS
Chapter 2: Literature Review

discipline, it has been discussed in four main streams of IS for quite some time (see Figure 6).

**IS success**

* e.g. DeLone and McLean (1992), Goodhue (1995), Lucas and Spiltler (1999)

![IS success diagram](image)

**IS acceptance**

* e.g. Davis (1989), Straub et al. (1995), Venkatesh et al. (2003)

![IS acceptance diagram](image)

**IS for decision making**

* e.g. Barkin and Dickson (1977), Szajna (1993), Yuthas and Young (1998)

![IS for decision making diagram](image)

**IS implementation**

* e.g. Lucas (1978), Ginzberg (1981), Hartwick and Barki (1994)

![IS implementation diagram](image)

Figure 6: Early conceptualizations of the system / IT usage construct

As depicted above in Figure 6, system use has been a popular and extensively discussed construct in earlier studies of IS success (DeLone & McLean, 1992, 2003; Petter & McLean, 2009) and technology acceptance and use by individuals (Susan A. Brown, Venkatesh, & Goyal, 2012; F.D. Davis et al., 1989; Venkatesh, Brown, Maruping, & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh et al., 2012). In these studies the usage construct has measured as an independent variable, mediating variable or the dependent variable. However, the
usage measures across various disciplines and various contexts generally have deployed similar usage measures despite the diversity of the focus and the context (see A. Burton-Jones & Straub, 2006 for a review). Commonly used usage measures in the field include: duration of use, use or non-use, heavy use or light use, frequency of use, extent of use, tasks supported and features used. Also, the system usage has been measured in two main perspectives; as the use of information from the system or the use of the system (A. Burton-Jones & Straub, 2006). Burton-Jones (2005) analysed 48 articles in major IS journals that have used ‘system usage’ as a construct during 1977 and 2005 to understand the different perspectives of IS usage constructs that have been used in the prior IS literature. Based on his work, Burton-Jones and Straub (2006) reports the broader dimensions, individual measures and the type (independent or dependent) of usage measures as below (Table 7).

<table>
<thead>
<tr>
<th>Broader dimension</th>
<th>Individual measures</th>
<th>Measured as IV</th>
<th>Measured as DV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Usage as a measure of information from the system</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Extent of use</strong></td>
<td>Number of searches or reports requested</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td><strong>Nature of use</strong></td>
<td>Types of reports requested, general versus specific use</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td><strong>Frequency of use</strong></td>
<td>Frequency of reports requested, number of times discuss information</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td><strong>Usage as a measure of the use of a system</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Method of use</strong></td>
<td>Direct versus indirect</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td><strong>Extent of use</strong></td>
<td>Number of systems, sessions, displays, functions, or messages; user’s report of whether they are a light / medium / heavy user</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
Table 7: Analysis of system usage measures employed in early IS research

As A. Burton-Jones and Straub (2006) reports, the usage measures that have been listed in Table 7 above have been developed atheoretical manner where there is a theoretical lacuna since only very few has discussed how theory informs their choice of usage measures. As A. Burton-Jones and Straub (2006) further elaborate, except Barkin and Dickson (1977) none has presented a strong theoretical basis the choice of system usage, appropriate empirical indicators or their relatedness to the other constructs. In most cases the measures of system usage were chosen because of their appearance in past empirical investigations rather than for valid theoretical reasons. Whilst, majority of studies simply select one or two types of usage measures from the many available (Andrew Burton-Jones, 2005), there is no accepted definition of system usage present in the IS literature (A. Burton-Jones & Straub, 2006) until recently.

| Proportion of use | Percentage of times use the system to perform a task | ✓ |
| Duration of use | Connect time, hours per week | ✓ | ✓ |
| Frequency of use | Number of times use a system (periods are: daily, weekly, etc.) | ✓ | ✓ |
| Decision to use | Use or not use (binary variable) | ✓ |
| Voluntariness of use | Voluntary or mandatory use (binary variable) | ✓ |
| Variety of use | Number of business tasks supported by the system | ✓ | ✓ |
| Specificity of use | Specific versus general use | ✓ |
| Appropriateness of use | Appropriate versus inappropriate use | ✓ | ✓ |
| Dependence of use | Degree of dependence on use | ✓ | ✓ |
A. Burton-Jones and Straub (2006) proposed a two staged approach to alleviate these issues. They defined the system usage as an activity that involves three elements:

1) a user, i.e. the subject using the system,
2) a system, i.e. the object being used, and
3) a task, i.e. the function being performed.

Following which A. Burton-Jones and Straub (2006) define individual-level system usage as an individual user’s employment of one or more features of a system to perform a task. In doing so, as highlighted in A. Burton-Jones and Straub (2006), this definition distinguishes and delineates the system usage construct from related (proxy) but distinct other constructs such as information usage, users decision to use a system, dependence on a system, adoption, quality of use, appropriate use. Rather, the A. Burton-Jones and Straub (2006) does not evaluate the system usage but instead it quantifies and measures the system usage itself.

Further, upon defining the usage of a system in terms of three components; a user, a system and a task, the usage measures can be classified into six distinct groups / types. As such A. Burton-Jones and Straub (2006) has summarized and categorized different types of usage measures that have been used in the past studies, based on the richness of the measures used, type of the measure used, domain of content measured (measures that reflect usage versus measures that reflects its nature involving the systems, user and /or task), with examples and references for each grouping as shown in Table 8 below.
### Table 8: Types of Measures (Rich and Lean) of System Usage (Adopted from A. Burton-Jones and Straub (2006))

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>Presence of use</td>
<td>Extent of use</td>
<td>Extent to which the system is used</td>
<td>Extent to which the user employs the system</td>
<td>Extent to which the system is used to carry out the task</td>
<td>Extent to which the user employs the system to carry out the task</td>
</tr>
<tr>
<td>Domain of content measured</td>
<td>Usage</td>
<td>Usage</td>
<td>Usage</td>
<td>Usage</td>
<td>Usage</td>
<td>Usage</td>
</tr>
<tr>
<td>Example</td>
<td>Use / Non use</td>
<td>Duration: Extent of use</td>
<td>Breadth of use (number of features)</td>
<td>Cognitive absorption</td>
<td>Variety of use (number of subtasks)</td>
<td>None to date (difficult to capture via a reflective construct)</td>
</tr>
</tbody>
</table>

As visible in Table 8, the measures of system usage could be as diverse as very lean to very rich. So that the measures could be as simple as presence of use as in Alavi and Henderson (1981) or lean as in Venkatesh and Davis (2000). Lean measures generally tries to capture the entire activity of usage in an omnibus measure such as use/non use, extent of use or duration of use (A. Burton-Jones & Straub, 2006). Despite the convenience use of such measures could be problematic as they are inexact, and do not refer to the aspect of usage that is most relevant to the study context hence it may not be clear to a respondent what part of the usage activity that the measure is actually attempt to measure. Dubin (1978) called such measures as ‘summative units’ and cautioned about their employment and appropriateness in empirical investigations. As explained by A. Burton-Jones and Straub (2006) employment of rich measures could alleviate such issues as rich measures (column 3,4, 5 and 6 in Table 8) incorporate the nature of the usage activity. Whilst all rich measures incorporate nature of usage activity, not all rich measures incorporate the three basic component of use; system, user, task the same way. Based on this, A. Burton-Jones and Straub (2006) further classified rich measures into four different categories as in table 8, hence a researcher has the flexibility to choose relatively rich...
measures that is most suitable for a given study. Some studies may only be interested on the extent of system usage but not about the user or the task being performed. For some studies, they may be only interested on the degree to which a user employs a system or the degree to which the system is employed to a task. None of the measures are superior on its own but one must select the type of the measures that are relevant and superior to the study context by looking at the study objectives, theory and methods. This means that despite the definition ‘system usage’ can be attributed with a precise definition comprising a broad range of content including user, system and task, only a subset of which could be relevant in a specific study. Whilst it is only a subset which is relevant to a study context required to be measured for a study, the measures that are relevant could and should be different from study to study. Thus, a researcher should select the usage measures that capture the most relevant content for a specific content (content valid yet contextualized) (A. Burton-Jones & Straub, 2006). In order to select a content valid yet contextualized systematic usage measures for a given study A. Burton-Jones and Straub (2006) has proposed a two steps that a researched should follow for measures selection upon defining the system usage in the study context.

First, a researcher needs to select the elements of usage that are most relevant to the research context and the research model. Next, the elements that tie closed to the other constructs in the research / theoretical model needs to be selected for the selected elements of usage in order to develop the content valid contextualized measures that are most suitable for the given study. As A. Burton-Jones and Straub (2006) further elaborate, this approach allows a researcher to focus on just one or two elements and justify the selection based on the context of their study. As they further states, this approach also allows a cumulative progress of system usage by allowing researchers to work on different elements and measures of usage thus allowing a disciplined diversity achieved through a procedure supported by a theoretical basis.

System use has also been discussed at different levels of the organizations (A. Burton-Jones & Gallivan, 2007). In addition to the clear conception of system usage and the different types of system usage measures (A. Burton-Jones & Gallivan, 2007;
A. Burton-Jones & Straub, 2006), the multilevel nature of system usage too is important for deeper understanding of system usage construct. Majority of the extant studies have mainly focussed on only a single level of analysis; individual, group or firm- mainly the individual level. In their discussion of multilevel nature of system usage, A. Burton-Jones and Gallivan (2007) discusses the importance of considering several levels of system usage in an organization simultaneously to understand natural, complete and integrated view of the system use in practice. Also, the comprehension of multilevel phenomena of system usage allows readers and researchers both understand about ‘collectives’ using information systems. When looking back into past research the individual level research is conceptually looked at system usage as an individual behaviour (e.g. F.D. Davis et al., 1989), an individual cognition (e.g. A. Burton-Jones & Straub, 2006) or an individual affect (e.g. Webster, 1998). Similarly the past system usage that studied group level usage has conceptually looked system usage either as an aggregation of individual behaviours (e.g. Easley, Devaraj, & Crant, 2003) or a pattern of individual behaviours, cognitions, and affect (e.g. G. DeSanctis & Poole, 1994). The past studies looked at firm level system usage conceptualize the system usage as an aggregation of individual behaviours (e.g. Devaraj & Kohli, 2003) or an intra (and/or inter) organizational behaviour (e.g. Massetti & Zmud, 1996).

Subsequently, Po-An Hsieh, Rai, and Xin Xu (2011) has conceptualized extended use to study how firms extract business value from already implemented information systems in order to understand individuals richer, deeper engagement with technology termed as extended use. In doing so they explained how individuals engage in post adaptive use of a system – learn and apply as many functions of an available system to support their work (Po-An Hsieh et al., 2011). As they explain whilst, sensemaking refers to the individuals developing cognitions, an individual’s use of technology remains a cognitive process where the users first construct meaning of the technology prior making the interaction with the technology (Weick, 1990, 1993). As this making of cognition and subsequent interactions provides a useful lens to investigate an individual’s use of a technology subsequent to the adoption, Po-An Hsieh et al. (2011) have employed this lens to understand the employees ‘routinely
use’ of already implemented information system. The system usage herein refers to the users’ deeper and extended engagement with more of the functional features of a system (Hsieh & Wang, 2007; Po-An Hsieh et al., 2011) to support their work.

Furthering on similar lines A. Burton-Jones and Grange (2013) have introduced the notion effective use (A. Burton-Jones & Grange, 2013), referring to the argument, to obtain benefits from a system, system use alone is not sufficient (P.B. Seddon, 1997) but the use must be effective. In doing so, A. Burton-Jones and Grange (2013) have defined effective as ‘using a system in a way that helps attain the goals for using the system’. In this definition, they have simply shifted the emphasis of ‘task’ to a ‘goal directed activity’, where system use is shifted from ‘use’ to ‘using the system to perform a goal directed activity’ and ‘attaining the relevant goal using the system’. In their discussion the goal for effective use refers to whatever the end point (desired end point) the system is used to attain. Whilst different stakeholders could have different view regarding the goals thus the goals could be of relatively objective notions the effective use and performance also could and should be relatively diverse. So the researchers can focus on effective use of a system from different stakeholder perspectives.

USE OF TECHNOLOGY, EXPECTATIONS AND EXPERIENCE

Based on met expectations research (L. W. Porter & Steers, 1973) in the fields of organizational behaviour and consumer psychology, S.A. Brown, venkatesh, Kuruzovich, and Massey (2008) studied the relationships between expectations, experiences and system satisfaction in the context of new information system implementation using technology acceptance model. Over the years met expectations have been studied to predict many different outcomes in many different fields including, organizational behaviour (e.g. Greenhaus, Seidel, & Marinis, 1983), consumer behaviour (e.g. Cadotte, Woodruff, & Jenkins, 1987) and information systems (e.g. Susan A. Brown et al., 2012; S.A. Brown et al., 2008; Ginzberg, 1981; B. Szajna & Scamnell, 1993). Majority models in aforementioned studies share the notion that initial expectations serves as the basis on which subsequent judgements are formed, yet the theoretical viewpoints are varied as different studies have
discussed the deviations of outcomes from initial expectations in terms of direction (positive or negative) and size (large or small) (S.A. Brown et al., 2008). A review of literature revealed many different models of expectation, confirmation and an outcome variable (usually the satisfaction), whilst in IS literature mainly discussed six competing models of expectation-confirmation-satisfaction models (see, Susan A Brown, Venkatesh, & Goyal, 2014; S.A. Brown et al., 2008). Based on the theoretical expositions S.A. Brown et al. (2008) have introduced three different models namely disconfirmation model, ideal point model, and experience only model. Further expanding this three basic models with the help of prior organizational behaviour, organizational psychology and marketing literature, Susan A Brown et al. (2014) have further extended the three basic model they have introduced earlier into six different models of expectation confirmation namely, assimilation model, contrast model, generalized negativity model, assimilation-contrast model, experiences only model, and expectations only model.

Each of the aforementioned models were supported by prior empirical investigations in many different research domains (Susan A Brown et al., 2014). As they report, the assimilation model is supported by service quality literature (e.g. Boulding, Kalra, Staelin, & Zeithaml, 1993), whilst contrast model is supported by realistic job preview related literature (e.g. Dugoni & Ilgen, 1981) when the support for generalized negativity model provided by social psychology literature (e.g. Carlsmith & Aronson, 1963). The assimilation-contrast model is supported by marketing literature (e.g. R. E. Anderson, 1973; Coughlan & Connolly, 2001) whilst personal psychology literature (e.g. P Gregory Irving & Meyer, 1994) supports the two simpler models expectation only and the experience only models. This suggest that the relationships between expectations, experiences and outcomes could be diverse where Susan A Brown et al. (2014) have attributed these differences to the context of the study. However, number of models that we have mentioned above can be seen in the prior expectation confirmation studies within the context of IS. For example, S. Staples, I. Wong, and P. B. Seddon (2002) study in IS has supported the contrast model of Expectation-Confirmation. Meanwhile, both Lankton and McKnight (2012) and B. Szajna and Scamell (1993) supports the assimilation model,
whilst Susan A. Brown et al. (2012) supports modified version of assimilation-contrast model. Similarly, several other studies in IS have supported the general negativity model that have been mentioned earlier (see, Ginzberg, 1981; Tan, Wei, Sia, & Raman, 1999; Venkatesh & Goyal, 2010). Additionally, when F. D. Davis and Venkatesh (2004) support expectation only model, S.A. Brown et al. (2008) support modified version of the experience only model. Whilst a majority of such studies focussed on the technology acceptance and IS use by individuals, next, we focuses on Susan A. Brown et al. (2012) to understand the relationship between expectations-experiences and technology use.

Following the perceived usefulness construct, a primary construct of technology acceptance model (TAM; F.D. Davis et al., 1989), Susan A. Brown et al. (2012) have developed a conceptual model to understand the expectation-experience gap and the relevant implications on technology use by individuals in the context of information systems based on the assimilation-contrast model of expectation-confirmation. As further explained in Venkatesh and Goyal (2010), in doing so, the research has focussed on expectations and experiences that are associated with usefulness and control for the effect of ease of use. As conceptualized therein, a user’s expectations (i.e. a user’s perceptions of a system’s usefulness) is developed during their initial exposure to the system (i.e. pre-implementation, training sessions and/or at the time of kickoff, as at this point in time users tend to evaluate how the system play a role in their jobs. Thus, the users are cognitively forming perceptions on how the system is going to be useful in their jobs during this pre-usage stage. If the system performs at the level that they have expected it to be performed (or better), when actually they start using the system they will use it. Lamenting on assimilation-contrast model (R. E. Anderson, 1973), in this discussion Susan A. Brown et al. (2012) have discussed the changes to the outcome variable in relation to the magnitude and the direction of deviation from the point of agreement (the point where the expectations are met). In doing so, the study has explained the variation of outcome variable in relation to the magnitude of deviation in two categories – small / within the level of tolerance deviations and large / substantial deviations that falls outside the level of tolerance. The study suggests that as the magnitude of the difference between expectation and
experience decreases the effect on outcome variable is consistent with expectations. This suggests that when expectation-experience discrepancy is at minimum levels, the use increases as expectations increases. Also, the analysis suggests that when experience exceeds expectations (positive disconfirmation) have a positive effect on individual’s system use, but as experience falls behind expectations (negative disconfirmation) have a negative effect on individual’s system use. Thus, Venkatesh and Goyal (2010) provides insights into how the magnitude and the direction of confirmation influences an outcome variable – the technology use in the context of IS.

Similarly, the relationship between use of a technology and a user’s expectations relating to the use of that particular technology has been discussed widely in number of different fields. For example, in Niederhauser and Perkmen (2010) discussed how teachers use of technology for instructional purposes influences their anticipated outcome expectations. In doing so the study explain how the utilizing of a technology for instructional teaching purposes could relate to a teachers outcome expectations / anticipated outcomes in three perspectives – performance, self-evaluative and social following Social Cognitive Theory (Bandura, 1986). Thus, they have discussed outcome expectations relating to (i) the belief that using a technology would make ones teaching more effective / someone a more effective teacher (ii) the belief that the experience of using a technology in teaching would derive personal satisfaction, and (iii) belief that the use of a technology would create positive and favourable perception among peers. Similar to the main body of current literature on expectation-confirmation research in IS, this research also discusses the relationship between use of technology and the usefulness of technology in an individual’s job related activities.

Meanwhile Sangle and Awasthi (2011) have investigated consumer’s expectations from mobile customer relationship management services in banking context to understand the primary concerns of the primary concerns of a banking customer when they use mobile banking services. This study examined the users expectations in broad nine themes; personal innovativeness, capability, perceived usefulness, perceived ease of use, context, perceived value, perceived risk, perceived
cost and perceived trust. Thus, the study was focusing on the factors underlying the decision to use a mobile CRM app. The items to measure aforementioned were derived from the studies in other related areas such as adoption of mobile commerce, mobile internet, mobile services and internet banking (Sangle & Awasthi, 2011). The findings of the study revealed that perceived utility (i.e. the utility that customers expect from mobile CRM) considered the most important factor for mobile CRM success. The study further identified that the expectations relating to ease of use, context, compatibility, cost, risk, and personal innovativeness as the other factors that influences the success of mobile CRM app. The study further highlights that customer expectorations relating to the service aspect is more dominant than the technical aspects for a successful adoption of mobile CRM.

As evident in the review of literature above, existing work on user expectations have predominantly focused on the user’s expectations relating to the utility of the technology (see..Susan A. Brown et al., 2012 for a review; Susan A Brown et al., 2014; S.A. Brown et al., 2008; Niederhauser & Perkmen, 2010; Sangle & Awasthi, 2011). They seldom discussed the expectations that emerge as a result of using a system. For example, in the context of mobile CRM, a customer’s use of mobile CRM in banking context could have an influence on the customers’ expectation of service quality that s/he receives from the bank, banking products that s/he receives from the bank or the type of special promotions that s/he receives from the bank. A study of this form of expectations is contemporarily important as both employment of customer focussed smart apps and the popularity of smart devices and associated apps are on the rise in recent times. As such next this discussion focuses on the literature pertaining to firm’s deployment of smart devices and apps in customer interactions for generating customer intelligence.

**CUSTOMER INTELLIGENCE AND THE ROLE OF SMART APPS**

A firm’s ability to know its customers expressed as well as latent needs through continuous generation of customer intelligence has long being considered a strategic imperative for achieving competitive advantage (Slater & Narver, 2000). However,
the generation of intelligence traditionally has been treated as a generic firm activity until recently. Customer intelligence is generated only when an actionable insights relating to the customer focussed activities (meaning) is given to the collected customer data (Glazer, 1991; Slater & Narver, 2000). As Petrič and Pinter (2002) mentions still the customer intelligence is mainly developed through the traditional market research techniques such as surveys, focus groups, sales force feedback, customer visits, concept testing and voice of the customer programs. As they further explain while these techniques are able to generate customer insights relating to their articulate needs, these techniques fails to identify the customers latent needs adequately. Some other non-traditional ways of acquiring customer intelligence includes customers’ use of services and products in context, embed smart technologies and engaged with customers ubiquitously and allow replication of their very fabric of life in digitized world, provide customers with tools to manage their daily product and service consumption routines, and engage with customers in social platforms. For example smart phones and PDA’s are rapidly becoming the main device that inately intertwined into the humans lives as they could paly the dual role as a communication device as well as the central computer (Scheufele, Shanahan, & Lee, 2001).

As Scheufele et al. (2001) explicate the smart mobiles and PDA’s emergence as one of the popular choices for key computing and communicating tool in everyday life has been emerged due to the inherent smart characteristics that is been embedded in these devices. For example these smart devices often equipped with accellerometers, gyroscopes, digital compases, microphones, inbuilt GPS, camera and internet connectivity. Whilst these utensils provide number of diverse options and capabilities for the users of such devices they provide a rich set of sensors for firms to capture the user related intelligence. Collectively these sensors are enabling variety of applications such as shopping apps, games, mobile banking, VOIP communication, flight booking, travel management apps, health apps, weather maps and social networking. There are number of different technological advances that have been came to the fore recently are opening up these new user sensing applications.
For example, the new phones now can be programmed for real-time sharing of user activity on social networks, monitoring of user behaviour, keeping track of the user's wellbeing, tracking the user's carbon footprint with the availability of cheaper embedded sensor technologies (Scheufele et al., 2001). Consequently, when the phone vendors are offering a variety of apps through the app stores, the third party programmers too are developing and shipping a variety of different smart applications to the market daily. When these parties are offering new applications to larger populations globally, and masses of technosavvy smart device users are embracing these smart apps in millions, far beyond the numbers what was previously possible. Thus, the daily engagements on such smart apps by millions of users creates unprecedented volumes of user-specific data available for firms. Thus, firms are now able to infer the user-specific intelligence through their use of smart apps.

In this study, we focus on the customers' use of smart apps and the subsequent expectations that s/he forms as a result of using the smart app. Further, this study intends to understand the relationship between expectations that form as a result of customers' use of smart apps, their evaluation of met expectations following the actual experience and the satisfaction. As such in this discussion we employ the Expectation Confirmation Theory (Oliver, 1977; Oliver, 1980b) lens to investigate the customers' use of smart apps, implications of customers' use of smart apps on customer expectations and perceptions, and their satisfaction.

**EXPECTATION-CONFIRMATION THEORY**

The instigation of expectation confirmation theory (ECT) can be traced back to consumer behavior and marketing research streams (Oliver, 1977; Oliver, 1980a). The theory presumes that satisfaction is a function of prior expectations and a posteriori disconfirmation² (Oliver, 1980a; Susarla, Barua, & Whinston, 2003). Oliver (1980a) elaborated on the process which consumers go through in forming repurchase intentions using the ECT framework (Figure 7).

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² Also labeled “confirmation” in the extant literature where the theory is called “expectation-confirmation” or “expectation-disconfirmation”, interchangeably.
As explained by Oliver (1980b), first, consumers form initial expectations of a specific service or a product prior to purchase. Then, they agree and consume/use that service or the product and they form perceptions about its performance based on the experience following its initial consumption. Third, they evaluate its perceived performance against their original expectations and determine the extent to which their expectation is confirmed. Subsequently, based on the level of (dis) confirmation and the expectation upon which the (dis) confirmation was based, they form (dis) satisfaction or affection (or revulsion). Finally, the consumers form a repurchase intention when they are satisfied, and dissatisfied consumers discontinue use.

In marketing literature, expectations are associated with number of different standards, from which a customer’s subjective predictions being the most common (Parasuraman, Zeithaml, & Berry, 1985). As such a customer’s subjective predictions – the customer’s expectations could be at diverse levels thus; in literature, a customer’s expectations have been interpreted in numerous ways. For example, expectations have been seen as minimum tolerable emotional state (Zeithaml, Berry, & Parasuraman, 1993), highest ideal standard (Tse & Wilton, 1988), desired level (Swan & Trawick, 1980), experience based norms (Woodruff, Cadotte, & Jenkins, 1983), realistic level of evaluation (Spreng, Mackenzie, & Olshavsky, 1996) or subjective belief (Olson & Dover, 1979). As such, the levels of expectations that a customer could form could be diverse from expecting ideal, excellent levels to worst imaginable. Santos and Boote (2003) have summarised the possible levels of expectations that a customer could form into nine different groups in the form of a
hierarchy from highest to the lowest as follows. The ‘ideal’ is the highest level of expectations that a customer has, followed by the ‘should’ - what the customer feel ought to happen, the ‘desired’ – what the customer wants to happen, the ‘predicted’ – what the customer thinks will happen, the ‘deserved’, the ‘adequate’, the ‘minimum tolerable’, the ‘intolerable’, and the least being the ‘worst imaginable’. Whilst the expectation serves as the base line which actual experience is evaluated against, customers always gauge the level of experience against the different levels of expectations that s/he pursue to form the satisfaction or dissatisfaction. As such, the level of expectation that the actual customer experience commensurate with defines the level of satisfaction.

For example, if the actual experience equates to a customer’s ideal level of expectations, then the customer get delighted and forms highest level of satisfaction due to the resultant extremely positive disconfirmation. Similarly, if the customer’s actual experience commensurate with his/her predicted level of expectations, the level of satisfaction is not that great as it represent a marginal yet positive disconfirmation. If the customer’s actual experience falls behind and commensurate with his intolerable or worst imaginable levels of expectations, the customer get dissatisfied due to the resultant negative disconfirmation (see Figure 7).
Figure 8: Hierarchy of customer expectations with expectations as the ideal standard for experience evaluation (adopted from Santos and Boote (2003))

The following figure (Figure 9) further elaborates the two types of expectation-experience indifferences, expectation-experience equations, different levels of cognition performances and a customer’s different levels of post experience affective states.
Chapter 2: Literature Review

Following its original conception, the predictive ability of the ECT theory is demonstrated across a number of different contexts. A stream of literature that follows affirms that satisfaction is a key determinant of repurchase decisions (Oliver, 1980a), and continuance intentions (Anol Bhattacherjee, 2001; Susan A. Brown et al., 2012; Venkatesh & Goyal, 2010). A common theme in the ECT literature is that satisfaction is a function of the magnitude and direction of disconfirmation, whereby the customers are satisfied in the case of positive disconfirmation whilst dissatisfied in the case of negative disconfirmation. The variation in satisfaction is also higher as the degree of disconfirmation increases (Venkatesh & Goyal, 2010). The initial conceptualization (Oliver, 1980a) of ECT posits that prior expectations and disconfirmation are the only determinants of satisfaction, whereas some subsequent research (J. G. A. Churchill & Surprenant, 1982) shows that actual experience exerts effects independently on satisfaction in addition to the impact it makes via disconfirmation, whilst according to some others (Susan A. Brown et al., 2012), experience is the sole determinant of satisfaction.

In the IS literature, Ginzberg (1981) examined the impact of unrealistically high user expectations on satisfaction in the information systems context and found that the users with realistic prior expectations were more satisfied than the users with
unrealistic prior expectations. In another study, D. S. Staples, I. Wong, and P. B. Seddon (2002) argued that unrealistically high expectations will result in a lower level of perceived benefit when compared to realistic expectations. Further, some researchers in IS used ECT to examine how and why the attitudes and beliefs towards IT use changed over time when the users gained experience with a particular system (Anol Bhattacherjee, 2001; Bhattacherjee & Premkumar, 2004). They found that satisfaction with the system usage was the strongest predictor of intention to continue. Furthermore, they highlighted the role of disconfirmation and satisfaction in driving the change in attitudes and beliefs over time, which shows why it is important for an organization to be continuously responsive to their customer needs all the time.

Recent work on ECT focuses on the methodological and analytical shortcomings associated with prior ECT research (Venkatesh & Goyal, 2010). Venkatesh and Goyal (2010) recently discussed the issues relevant to the direct measurements and the analytical limitations associated with the use of linear models. Drawing from cognitive dissonance theory, realistic job preview, and prospect theory they proposed a polynomial model of expectation-(dis)confirmation in information systems to better understand expectation-(dis)confirmation in IS and to deal with the shortcomings associated in prior ECT research (see APPENDIX B). A more recent work by Susan A. Brown et al. (2012) further demonstrated that the employment of polynomial modelling and response surface methodology presented a better explanation of the relationships between expectations, experiences and use in information systems. In this discussion, we employ ECT to investigate two tripartite relationships, (1) customers’ use of smart shopping apps, customer expectations, customer satisfaction and (2) customers’ use of smart shopping apps, customer experience and customer satisfaction.

**CHAPTER SUMMARY AND CONCLUSION**

Our objective of this literature review was to critically evaluate the prior work that are related to this study in order to understand the background and key concepts that are related to this study. As such, we have critically analysed the existing body of
literature relating to agility, technology use, business intelligence and met expectations thus have achieved several objectives as follows.

First, we discussed the basic theoretical foundations of agility in relation to its origins and similar concepts in order to understand the differences and the similarities between the notions. Then the analysis of literature was focused on prior agility discussions to understand the key attributes of enterprise agility and the different conceptualizations and the different definitions. Following which we have discussed the two key components of agility – sensing and responding, then alignment of the two components sensing and responding and its relation to firm performance, prior discussing the four distinctive types of firms based on a firm’s agility orientation, the facilitating and restraining roles of IT in achieving agility in environmental dynamism. Then the discussion has focused on the emergence of digital natives, popularity of ubiquitous digital technologies and digital business strategy to discuss their influence on sensing and responding in contemporary business environments. In doing so, we have discussed the principles and objectives of customer relationship management systems and the deployment of smart technologies in CRMS for ubiquitous sensing and responding. Next, we have analysed CRMS benefits related literature to better understand the relationship between CRMS and enterprise agility. The resultant CRMS benefits framework reflected the sensing and responding components of agility and the firm performance outcomes that are usually associated with enterprise agility. Following which we have analysed the literature relating to the technology use construct, conceptualizing system use by individuals and prior applications of system use construct in IS research, prior discussing the relationship between customers’ use of smart apps, generation of customer intelligence and expectations. Following which the discussion elaborated the notion of expectation confirmation theory in order to facilitate the conceptual discussion of customers’ use of smart shopping apps and its implications. Finally we discussed the notion expectation-confirmation in detail to conclude the chapter.
CHAPTER 3: RESEARCH MODEL DEVELOPMENT

This chapter begins with a discussion of the conceptual model that was introduced in chapter 1. The study context, key constructs of the conceptual model and the arguments presented herein then lead to the a-priory research model and the subsequent hypothetical propositions development. The key constructs of the a-priori conceptual model were derived through a detailed review of prior related literature, and then are summarized and presented alongside each of the hypothetical relationship.

In Chapter 2, we have discussed the literature relating to agility of the firm, customer relationship management systems, smart apps, customer intelligence, technology use by individuals, the key constructs and the underlined theorized relationships between them in expectation confirmation theory. As such, the discussion elaborated on five key constructs – individual’s use of technology, customer expectations, customer’s experience, customer’s evaluation of met expectations and the satisfaction, in detail.

Next, the discussion in this chapter, first introduces the background and context of the study, prior establishing the conceptual discussion of a firm’s customers’ use of smart shopping apps, firm’s potential of customer sensing and the subsequent customer expectations and presenting the preliminary research model comprising customers’ use of smart apps, digital expectations and customer satisfaction constructs. Following discussion then develops the hypothetical propositions that are to be tested empirically later in the study, before concludes with a summary.
THE STUDY CONTEXT

The advent of mobile computing, together with the growth of tech-savvy digital natives (Vodanovich et al., 2010), have facilitated digital business strategies in organizations. When Sambamurthy et al. (2003) first introduced digital options in sensing and responding over a decade ago, they argued that ubiquitous technologies, where mobile IT is the archetype of, present an unparalleled level of digital connectivity between firms and customers, enhancing firm’s sensing and responding capabilities (Chakravarty et al., 2013; Sambamurthy et al., 2003). Thus, contemporary firms especially the consumer retailers aim for heightened customer interactions through the deployment of smart devices and associated smart apps, to sense-and-respond to shifting customer requirements in a timely and tailored manner (Overby et al., 2006; Roberts & Grover, 2012a, 2012b). As literature reports retailers in general have invested heavily in mobile apps to encourage their customers to mimic their daily routines (purchasing, purchase intentions) (Lamarre et al., 2012). As Narayanaswami et al. (2011) noted, smart devices and applications are heavily influencing the customer-retailer landscape, making global shifts towards ‘everywhere – ubiquitous – retailing’, and ‘everywhere - ubiquitous sensing and responding’. This renewed interest of connecting customers through ubiquitous technologies and the emergence of digital natives provides the necessary impetus for this study.

The Australian retail industry provides the context for this research where this study focuses on the deployment of smart shopping apps by the two leading Australian retailers Coles and Woolworths. The two main retailers (Woolworths with 41.1% of market share / $48.56 billion revenue, and Coles with 31% market share / $34.1 billion revenue in 2012) maintain a retail duopoly in Australia. They both have launched mobile apps in 2011 and currently over 3 million customers (~30% of total retail population) has downloaded these apps from Android® and Apple® markets. Both mobile apps provide customers the option of developing shopping lists, connecting to store locations, downloading and contributing to recipes. Furthermore, each mobile app is registered to a ‘loyalty card’ which includes customer details where the customer scans at the point of purchase. Consequently, the use of their mobile apps (linked with a loyalty card) provides Woolworths and Coles the potential
to understand shopping habits, potential shopping items and favoured store locations. As such, in 2013, Woolworths acquired a business intelligence company “Quantium” citing the importance of better analysing the shopping habits of Australians outside its stores (Kohler, 2013).

Whilst this study investigates the deployment of smart shopping apps for improved firm-customer connectivity in the context of consumer retail industry in Australia taking the two leading retailers Coles and Woolworths, we see a significant generalizability potential of the findings. It is not just Coles and Woolworths in Australia but all other retailers in Australia as well as elsewhere globally, in many different industries such as book stores, airlines, fast-food outlets and hotels too are deploying similar apps (e.g. Aldi, Target, Big-W, BWS, Tesco, Homeplus Dominos, Pizza Hut, and Costco). This highlights the significance, timeliness, practicality of the topic and the generalizability potential of the intended findings. Not only smart apps, but the deployment of multitude of digital technologies in customer connectivity and regular interactions is becoming one of the key strategies and priorities of contemporary firms in gaining and sustaining competitive potential (J. Luftman & Derksen, 2012).

CONCEPTUAL MODEL DEVELOPMENT

Customers’ Use of Smart Apps and a Firm’s Customer Agility

Firm’s contemporarily use digital technologies - combinations of information, computing, communication, and connectivity technologies- to transform their business strategies (A. Bharadwaj et al., 2013) with the objective of achieving better customer connectivity anticipating improved firm’s agility towards its customers. As empirical investigations suggest, firm’s gain unfettered information access through effectively leveraging the digital technologies to connect with external environment (Nazir & Pinsonneault, 2012). At the same time, innately techno-savvy new generation of consumers are letting ubiquitous technologies to weave them into the very fabric of everyday life (Vodanovich et al., 2010). They mimic their daily routines in digitized environments allowing organizations to sense their needs better, through
the analysis of their digital thumb prints they create in the digital environment. As such contemporarily the firms have a greater potential to gain a heightened digital interactions with their customers through the customers’ engagements in digital environment further strengthening firm’s sensing and responding. In other words, in the context of the deployment of smart shopping apps in consumer retail the degree of mimicking, extent to which an individual uses a smart mobile app defines the degree to which the firm could sense customer intelligence. Thus, the firm’s potential to sense customer intelligence in the context of smart mobile apps depends on the extent to which the individual uses the smart mobile app.

Therefore, following A. Burton-Jones and Straub (2006) work on technology use by individuals, this work relates a firm’s potential to sense customer based opportunities to the customers’ use of smart apps. A customer using a smart mobile app for shopping related activities, frequently provides more opportunities for the firm to sense his shopping related behaviour. When customers use smart mobile shopping app, they leave information footprints as a by-product (Chi et al., 2010; Zuboff, 1988). They include not only customers’ personal information, but also all the data relating to their unique shopping requirements. Hence, with increased use of smart app, a customer creates more information foot prints, thus creates a better defined digital thumb print thus providing more potential to the firm to sense the customer better. As such, firms now have the potential to derive unique intelligence on each customer’s needs and expectations, which can then be used to provide tailor-made, unique shopping experiences for each customer. However, the amount of sensing that a firm can achieve depends upon the quality and the amount of such high quality digital interactions or the digital connectivity between a customer and a firm, thus in a mobile shopping environment the amount of sensing depends on the extent and the nature / quality of the mobile app use by the customers. Because high quality frequent interactions would create more and better information footprints thus have a greater potential to provide richer customer insights compared to the less frequent inferior interactions. So, a firm’s potential to sense customer insights relates to the extent to which a customer performs shopping related tasks, no of functionalities used, the frequency or the consistency which a customer performs tasks using such
functionalities. As such, the usage construct that we use to denote firm’s sensing potential, goes beyond generic use of such apps by individuals to the frequency and the depth of mobile app use that enables a firm’s customer sensing. The rich use of smart mobile apps by individual customers then provides insights on the needs and requirements that are unique to the individual customers. Thus, firms could then develop individualized strategies to provide more personalized responses that are customer unique thus providing superior customer experiences. In other words smart mobile shopping apps have a greater potential to facilitate both sensing and responding capabilities of firms thus improving the firm’s overall (customer) agility. Phan and Vogel (2010) too have asserted that, firms can employ prediction models that incorporate their customers’ historical buying patterns and GPS data to enact this potential.

Whilst firm’s improves their potential of sensing and responding with the smart devices and associated apps, customers seem to be well aware of firms’ sensing abilities through the inherent smart capabilities of the smart mobile apps (Gao, Sultan, & Rohm, 2010; A. M. Kaplan, 2012; Lamarre et al., 2012; Rohm, Gao, Sultan, & Pagani, 2012; Shankar, Venkatesh, Hofacker, & Naik, 2010). Since, customers are aware of the firm’s sensing potential that is possible through the customers’ use of smart mobile shopping apps, customers then raise their expectations. Hence, the customers anticipate unique and individualized responsiveness from firms, whereby they expect unique and individualized products or services in a timely fashion in exchange of their daily routines being captured through mobile apps.

The pictorial process model below (Figure 10) depicts how a customer’s use of smart shopping apps drives a customer’s expectations, and then how it relates to his/her experiences thus its relation to a firm’s customer agility. As explains in the notion of agility (sense-respond cycle in agility) (Roberts & Grover, 2012a), in the context of this discussion, firms ‘sense’ their customers unique needs through the customers’ use of smart app and ‘respond’ to the requirements that are unique to the individuals based on what they have sensed. Since the quality of a firm’s sensing relies on customers’ use of smart apps, the firm’s ability to respond to them in a
unique way also shaped by the customers’ use of smart apps. As such, when the customers’ use of smart apps raises customers’ expectations at the same time it improves their experience too. The expectation herein forms as a result of a customer’s use of a smart shopping app thus the formation of customer expectations in this scenario (we termed it digital expectations) is fundamentally different from the way customers form their expectations in traditional product service context (Oliver, 1977; Oliver, 1980b; Oliver, Balakrishnan, & Barry, 1994) or in extant IS literature (A. Bhattacherjee, 2001; Susan A. Brown et al., 2012; Susan A Brown et al., 2014; S.A. Brown et al., 2008; B. Szajna & Scamell, 1993).

<table>
<thead>
<tr>
<th>Business Scenario</th>
<th>Consumer using the app</th>
<th>Consumer giving information</th>
<th>The firm Sense</th>
<th>The firm Respond</th>
<th>Positive organizational outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conceptual model</td>
<td>Customers’ use of smart shopping app</td>
<td>When I give information, I form expectations</td>
<td>Experience</td>
<td>Satisfaction</td>
<td></td>
</tr>
</tbody>
</table>

**Figure 10: Process model of customers’ use of smart apps and agility**

By arguing here that the customers’ use of smart apps relates to agility by improving the two main components of agility-sensing and responding, we further strengthen the notion of sense-response alignment view in agility (Atapattu & Sedera, 2014; Roberts & Grover, 2012a). As Overby et al. (2006) affirm, a firm to be truly agile, simply possessing or improving the capabilities-sensing and responding, is not enough and do not warrant agility leading to positive organizational outcome, rather the firm needs to align and orchestrate the two capabilities. In other words, an agile firm do not waste either of their capabilities by sensing opportunities that cannot be seized, or possessing responding capabilities that lie unused. Essentially, the orchestration of the two capabilities; sensing and responding is revealed in what customers actually experience, thus the manifestation of how the firm enact these
capabilities is reflected in the actual customer experience and how customer’s perceive experience. Thus, we propose our conceptual model and the theoretical propositions as below.

As discussed above, we take the example of smart shopping apps in the FMCG retail context to investigate the relationship between customers’ use of smart apps, digital expectations, and its implications on customer experiences and their satisfaction. As discussed earlier in this chapter, the customers’ use of smart shopping apps drives customer expectations thus influences their experiences and subsequent satisfaction. As such to empirically investigate and comprehend how the individual customer’s use of smart shopping apps relates to customer expectations, experiences and satisfaction, the following conceptual model was derived following the lens of Expectation-Confirmation Theory (ECT) (Oliver, 1977; Oliver, 1980b).

![Research model involving customers’ use of smart apps, digital expectations, experience and satisfaction](image)

**Figure 11: Research model involving customers’ use of smart apps, digital expectations, experience and satisfaction**

**Hypothesis Development**

Expectation confirmation theory (Oliver, 1977; Oliver, 1980b; Oliver et al., 1994) has four main constructs: expectations, perceived performance, disconfirmation, and satisfaction. The theory has been widely used in the consumer behavior as well as in service marketing literature to study customer satisfaction, post-purchase behavior (A. Bhattacherjee, 2001; Oliver, 1980b; Patterson, Johnson, & Spreng, 1996). The original conception of ECT (Oliver, 1977; Oliver, 1980b; Oliver
et al., 1994) posits that consumers form expectations and desires concerning a specific product (or service), prior purchasing or consumption of the product (or service). Nevo and Chan (2007) defined user expectation as a belief about the probabilities associated with a future state of affairs. Specifically, expectations predict a future state, where an individual thinks what will happen, or would like to happen. Essentially, the expectations are formed prior to the use or consumption. Usually the priori expectations are formed as a result of word of mouth communication, previous experience, or external information such as marketing / promotion related communications. Traditionally, an individual forms priori expectations regarding a product (or service) and then compare the perceived performance of that product (or actual experience of the service) to form their level of satisfaction. As such it implicitly assumes that consumers acquire cognitive expectations of the most probable level of product (or service) performance (Oliver, 1977) thus, expectations are thought to create a point of reference in order to makes a comparative judgment about the product performance (or the experience) (Oliver, 1980b). Hence, an expectation is a belief about the probabilities associated to the future state of affairs (Geers, Weiland, Kosbab, Landry, & Helfer, 2005) accordingly, according to the initial ECT conception predictive expectations were used as the comparison standard Nevo and Chan (2007). Against this backdrop, we employ the ECT lens to comprehend the formation of expectations in the context of this study as below.

In the context of this study, customers form their expectations based on their use of smart shopping app, knowing that the firm has a potential to access their information footprints resulted due to their use of the app. Thus, customers with greater smart shopping app usage would expect more personalized and unique responsiveness from the firm on the needs that are unique to them as opposed to the customers with lesser amount of smart app use. In other words, customers expect higher levels of experiences (e.g. ideal, normative or desired levels) as the customers increase their smart mobile app use. As such, the customers’ aware that firms have the opportunity for sensing as they divulge their information through their use of smart mobile apps, customers with greater smart app use would expect higher levels of
responsiveness from the firm (as opposed to the customers with lesser amount of smart app use). Thus, we propose our first hypothesis:

**H1:** The degree of smart shopping app use by customers is positively associated with the customer’s expectations, such that customers with higher degree of smart app use expect firms to respond with highly personalized responses their unique needs.

Our second hypothesis relates to the notion of sense-response alignment in agility (Atapattu & Sedera, 2014; Overby et al., 2006; Roberts & Grover, 2012a). Earlier in this discussion we stated that customers’ use of smart shopping apps leave more information footprints on their shopping requirements as a by-product (Chi et al., 2010) allowing firm’s to sense their needs and expectations. Further, we argued that the firm’s sensing potential improves with customer’s use of smart shopping app increases. As such, firms have the opportunity to derive unique intelligence on each customer based on their smart shopping app use to provide tailor-made shopping experiences that are unique to the individual customers, given that the firm aligns its sensing and responding capabilities. Hence, when a firm align its sensing and responding capabilities, greater use of smart shopping app by consumers would lead to better firm responsiveness, yielding superior shopping experiences for customers (as compared to lesser engaged customers). Thus, we propose our second hypothesis:

**H2:** for the aligned firms, the degree of mobile app use by a customer is positively associated with the customer’s experiences, such that customers with higher degree of smart shopping app use will receive highly personalized responses to their unique needs hence the superior experiences.

Assimilation model of the expectation confirmation theory built on the cognitive dissonance theory (see..Susan A Brown et al., 2014; S.A. Brown et al., 2008). As per cognitive dissonance theory (Festinger, 1962), deviations from ones expectations create dissonance, thus the deviation creates an uncomfortable situation.
To reduce dissonance, subsequent outcome evaluations are adjusted in order to be more consistent with expectations. Thus, higher the expectations, higher the evaluations (Sherif & Sherif, 1967), as a priori expectations provide an anchor for outcome evaluations (Susan A Brown et al., 2014). The theory further suggest that the individuals minimize the cognitive difference between expectations and experiences (i.e outcome) by adjusting the evaluations of outcomes to be more consistent with the initial expectations, thus reducing dissonance. Further the original ECT also states that the expectations serve as a reference point upon which the performance of a product (or a service) is evaluated.

Meanwhile the contrast model of ECT theory (see..Susan A Brown et al., 2014) suggest that the outcome evaluations are based upon the direction and the size of the gap between expectations and experiences. The ultimate outcome is then biased in the direction of the experience (J. G. A. Churchill & Surprenant, 1982; Patterson, Cicic, & Shoham, 1997). As such, as mentioned in S.A. Brown et al. (2008), the difference between expectations and experience (subsequent evaluations) determines the ultimate outcome. In other words, the satisfaction (the outcome) is derived based on the level to which the expectations are confirmed (Oliver, 1977; Oliver et al., 1994). When the priori expectations are exceeded (degree to which expectations are exceeded) it is called positive disconfirmation whilst the unmet expectations (the degree to which the experiences are falls behind) called as negative disconfirmation (A. Bhattacherjee, 2001; Susan A Brown et al., 2014; Kopalle & Lehmann, 2001). It explains that the level of satisfaction depends on the initial expectations on which that confirmation was based upon and the direction to which the initial expectation was confirmed (A. Bhattacherjee, 2001; S.A. Brown et al., 2008).

As such, in the case of this discussion, a customer assesses actual shopping experience against the initial expectations to determine the extent to which the initial expectations were met and forms ultimate satisfaction or dissatisfaction. Thus, when customer expectations resulted due to the use of smart app (i.e. digital expectations) provide the basis for experience evaluations, and the direction of digital expectation confirmation is then determines the satisfaction or dissatisfaction. As such, per the
contrast model of ECT, the most favourable outcomes occur when the outcome-expectation gap is maximized and experience exceeds expectations (Susan A Brown et al., 2014).

The generalized negativity model of ECT (Susan A Brown et al., 2014) proposes that the discrepancy / mismatch between expectations and outcome (i.e. experience) is bad, where any difference, regardless of positivity or negativity lowered the ultimate outcome evaluation. As such, there is an ideal point (see..S.A. Brown et al., 2008) where the difference between expectations and experiences are zero, or the point in which experience equates the expectations (i.e. met expectations) gives the highest outcome. This suggests that, expectations that are unique to each individual customer should be matched with experiences that are unique to the individual to achieve superior customer satisfaction. This also supports the notion sense-response alignment in agility literature. In essence, the contrasting models suggest competing views on the relationship between customer expectations, their experiences and customer satisfaction (outcomes).

Earlier in hypothesis one, we argued that as with a customers’ use of smart mobile app, customer expectations also increases. As literature affirms the priori expectations provide an anchor for outcome evaluations. As this new state of raised levels of expectations provide the baseline or the reference level for a consumer to form evaluative judgments about the actual experience of the firm’s responsiveness (A. Bhattacherjee, 2001). As assimilation model of ECT suggests, deviation from the raised levels of expectations creates dissonance, an uncomfortable state. Thus, to keep the customer satisfied firm should meet this heightened level of expectations. Hence, as suggested in generalized negativity model of ECT, a firm should align its customers’ shopping expectations that are unique to each individual, resultant due to their ubiquitous digital mobile engagement with matching, personalized experiences to come to the ideal point (i.e. expectation = experience), in order to achieve higher levels of customer satisfaction. This also suggest that, essentially, firms need to raise the levels of customer experiences in concert with raising customer expectations (that resulted due to the increased levels of smart app use) in order to make their customers
satisfied. Meanwhile, following the contrast model of ECT, it suggests that the direction and the gap between expectation and experience define the ultimate satisfaction. Thus, in other words, a firm should positively disconfirm the customers’ raising digital expectations to achieve higher state of customer satisfaction.

Based on the arguments put forth above, we argue here that, a firm either should align (match) its customers’ raising digital expectations or exceed their digital expectations by providing unique, personalized, customer experiences, based on the degree to which a customer uses the smart shopping app. Thus taking the relationship between customers’ use of smart shopping app-expectation, and the tripartite relationship between expectations-experiences-satisfaction, we propose our third hypothesized relationship;

**H3:** **Alignment between customers’ raising digital expectations and their experiences is positively related to their satisfaction, such that customers become satisfied when the difference between digital expectations and actual experiences is at its lowest or when experience exceeds digital expectations.**

Assimilation contrast model of ECT is a combination of the two competing views, the cognitive dissonance and the expectation confirmation (Susan A Brown et al., 2014). As mentioned in Susan A Brown et al. (2014), the model argues that for slight differences, outcome evaluations would assimilate towards expectations whilst for substantial differences, weighted more heavily due to the magnitude of their contrast. When the differences are slight, they fall within the zone of tolerance (Berry & Parasuraman, 2004; Johnston, 1995), the adjustments would be minimal and the any such adjustments would be assimilated towards expectations as discussed in the cognitive dissonance theory (Festinger, 1962). Thus, the outcomes are consistent with the expectations as long as an experience falls within the zone of tolerance.

However, when the discrepancy between expectations and experiences increases, the experience defines the outcome evaluation. As such, the effect either
would be a surprise – when experience exceeds expectations, or disappointment effect – when experience falls well short of expectations (Coughlan & Connolly, 2001).

Meanwhile, in expectation only model (Susan A Brown et al., 2014; S.A. Brown et al., 2008), expectations directly predicts outcomes. Thus, it represents an assimilation towards one’s a priori beliefs, where outcomes only predicted by experience. Alternatively, the experience only model suggests that the outcomes are solely defined by the experience, rendering the priori expectations are inconsequential to the ultimate outcome (Susan A Brown et al., 2014).

In the context of this discussion, when customers uses a smart shopping app more the customers’ heightens the a priori expectations based on the degree of use. As customers increases the level of a priori expectations, the firm needs to elevate its responsiveness towards individual customer needs to make them happy, as the priori expectations serve as the outcome evaluation standard. As per the assimilation contrast model, when the discrepancy between customer expectations and their experience falls within the range of tolerance, ultimate outcome assimilate towards priori expectations thus, resonates with the expectations. If the experience is far stretched from the initial expectations the customers will either be utterly dissatisfied or extremely satisfied depending on the direction and the magnitude of the discrepancy. As expectation only model explains, customer experience is solely determined by the priory expectations. Thus, as experience falls well short of the priory expectations, the ultimate outcome is solely determined by the expectations where higher degree of usage is associates with higher expectations and lower satisfaction. On the other extreme, when the experience exceeds priori expectations, the experience determines the outcome variable satisfaction, as elaborated in experience only model. Thus, based on the three competing models of ECT we propose the following hypothesized relationships as below.
**H4:** For the customers’ with higher smart app use, they become extremely dissatisfied if the experience-expectations gap is high and the difference is assimilated towards expectations, as such expectations define the satisfaction.

**H5:** For the customers’ with low smart app use, they become extremely satisfied if the experience-expectations gap is high and the difference is assimilated towards experience, as such experience defines the satisfaction.

ECT (Oliver, 1977; Oliver, 1980b; Oliver et al., 1994) affirms the priori expectations provide an anchor for outcome evaluations. As such the theory posits that expectations form the basis which actual experience is evaluated against to form satisfaction or dissatisfaction. In our first hypothesized relationship we proposed that customers who use smart shopping app more to have higher levels of expectations. This might leads to the assumption that customers who uses smart shopping app more will have lower levels of satisfaction considering this new raised levels of expectations provide the baseline or the reference level for a consumer to form evaluative judgments about the actual experience of the firm’s responsiveness (A. Bhattacherjee, 2001). This also suggest that, essentially, firms need to raise the levels of responsiveness to elevate customer’s perceived experiences in concert with raising customer expectations (that resulted due to the increased levels of smart app use) in order to make their customers satisfied.

On the contrary, as discussed in our second hypothesis above, when customer uses of smart shopping app more, firm has a greater potential to sense the customers shopping needs thus can provide a superior customer experiences thus leading to higher levels of customer satisfaction. Meanwhile, the assimilation model of ECT suggest that the higher order expectations of an individual adjust his/her perceptions about the actual experiences in a positive manner, with the objective of reducing the dissonance, thus creating positive outcome (Susan A Brown et al., 2014). Hence we propose the following hypothesized relationships;
**H6:** Higher levels of customers’ use of smart app leads to higher customer expectations thus leading to lower levels of customer satisfaction, but high expectations leads to high satisfaction in the presence of high experience (i.e. high expectations and high experience work together for high satisfaction).

**H7:** Customers’ experience fully mediates the relationship between customers’ use of smart app and customer satisfaction, such that customer experience defines the level of customer satisfaction.
CHAPTER SUMMARY

This chapter described the (1) background and context of the study, (2) pictorial process model explaining customers’ use of smart shopping app, digital expectations and the notion of agility, (3) conceptual model involving a customer’s use of a smart shopping app, and key constructs of the conceptual model using Expectation-Confirmation Theory lens, including customer’s digital expectations, actual experience, customer’s evaluations and satisfaction, and (4) the hypothetical propositions and relationships between the constructs.

Next in chapter 4, the constructs, sub-constructs and the items relating to each sub-construct is explained in detail. Then, the discussion focuses on the data collection methodology. As this study employs empirical data gathered through a survey to discuss our hypothetical propositions, the chapter next discusses the appropriateness of the survey method for the study purposes. Additionally, the next chapter will elaborate the data collection procedures in detail.
CHAPTER 4: RESEARCH DESIGN AND METHODOLOGY

In the previous chapter we discussed the research model of this study and the development of hypothesized relationships. This chapter discusses the operationalization of the research model and the application of the survey method that we have introduced in earlier in Figure 11 in Chapter 3. Thus, the chapter introduces the constructs, sub-constructs, defines them and introduces the items relating to each sub-construct and are explained them in detail. Then, the discussion focuses on the data collection methodology where, in the discussion deeply discusses the data collection objectives and the appropriateness of the survey methodology to find the answer the research questions stipulated earlier in chapter one in this thesis. Then the sections that are following will present, the survey design process and operationalization procedures in detail. Following which the chapter then discusses the steps taken to minimise the common method variance (CMV) prior discussing the ethical concerns relating to respondent anonymity and confidentiality. Finally, the chapter concludes with a summary.
RESEARCH DESIGN

The primary goal of this study is to understand the firm’s deployment of customer focused smart shopping apps in the contemporary retail and the implications of ubiquitous customer sensing that firms achieve through the customers’ use of such smart apps on customer expectations and subsequent perceptions hence on the firm’s customer agility. In doing so, in this research, we aim to understand

(i) how the customers’ use of smart shopping apps relates to a firm’s customer agility

(ii) the implications of uninterrupted customer sensing that a firm achieved through a customer’s use of smart devices and apps, on customer expectations (i.e. digital expectations)

(iii) the implications digital expectations on customer perceptions and satisfaction, and

(iv) identify the salient benefits of smart app enabled contemporary CRM systems to the firms.

To achieve the aforementioned goals, this study is designed in the following manner. First we develop a conceptual framework involving customers’ use of smart shopping app, customer expectations (digital expectations), customer perceptions and customer satisfaction using the theoretical lens of expectation confirmation theory. Then, the conceptual definitions of the key constructs of the research model were derived following related prior literature in the subject domain. Next, to test the research model and the hypothesized relationships between the constructs the study requires to measure individual constructs. Thus, an appropriate instrument was derived based on conceptual definitions and the prior literature for each construct
prior devising the data collection procedure to empirically test the research model. As such, the survey method was chosen as the data collection approach to test the study model and the hypothesized relationships.

The employment of survey methodology was influenced by the objectives of this research. This research intends to test the relationship between a customer’s use of smart app and the customer’s expectations, experiences and its impact on ultimate customer satisfaction. In other words, the study seeks to discover conceptual relationships between the study constructs and test hypothesized relationships between them. As such, the primary focus of this research is on verification rather than discovery. Thus, this research inclined selecting a qualitative approach as the methodology as opposed considering a qualitative method following a careful review of prior literature.

Extant literature in general has extensively discussed the relative merits of qualitative (e.g. survey) and quantitative (e.g. case study) methods (Cook & Reichardt, 1979; Downey & Ireland, 1983; Glassner & Moreno, 1989; Light & Pillemer, 1982; Merton & Coleman, 1979; Miles, 1979; Neuman, 1991; Ragin, 1987; Van Maanen, 1983a, 1983b, 1983c) whilst the debate of considerable merits has received considerable attention in IS research too (Benbasat, 1984; Benbasat, Goldstein, & Mead, 1987; Boland & Hirschheim, 1987; Cash & Lawrence, 1989; Franz & Robey, 1987; Galliers, 1991; Goldstein, Markus, Rosen, & Swanson, 1986; B. Kaplan & Duchon, 1988; Kraemer, 1991; Kraemer & Dutton, 1991; A. S. Lee, 1989, 1991; McFarlan, 1984; Mumford, 1991; Mumford, Hirschheim, Fitzgerald, & Wood-Harper, 1985; Nissen, Klein, & Hirschheim, 1991b; W.J. Orlikowski & Baroudi, 1991). Lately, some have discussed the advantageous of combining both qualitative and quantitative methods in a single study in the context of information systems (e.g. Gable, 1994; Venkatesh, Bala, & Sykes, 2010; Venkatesh, Brown, & Bala, 2013). In IS as well as in behavioural research in general, the construct definition, measures development and construct and measures validation has been a key focus of quantitative survey method for several years (see..Edwards, 2002; Lim, Saldanha, Malladi, & Melville, 2013; S. B. Mackenzie, Podsakoff, & Podsakoff,
Chapter 4: Research Design and Methodology

2011; Pinsonneault & Kraemer, 1993; D. W. Straub, 1989 for a review). Following such work, herein we summarize the key characteristics and the procedural overview of quantitative / survey method as prescribed in prior literature.

Previous research suggests that the survey method seeks to discover relationships through statistical analysis and allow objectively verifying hypotheses (Bikson, 1991; Danziger & Kraemer, 1991; Gable, 1994; Kling, 1991) thus justifies our selection of quantitative survey method as our research approach. Also Vidich and Shapiro (1955) mentions the survey method has relatively superior 'deducibility' over field (case study) methods thus surveys can accurately document the norm, identify extreme outcomes and delineate associations between variables in a sample (Gable, 1994). In addition the survey research usually serves as a methodology of verification (Gable, 1994). Meanwhile, Attewell and Rule (1991) mentions that survey research has the potential to document the norm accurately by identifying extreme outcomes and by delineating associations between variable in a data set. In addition survey methodology allows a researcher to analyse data at aggregate as well as individual levels thus allowing better explanation of validity of the instrument and the characteristics of a research model. Furthermore, as Benbasat et al. (1987) and Ishman (1998) both lauded survey research has the potential to add to the inventory of validated prior research thus easier to excel in research without re-inventing the entire process hence achieving greater productivity. Many researchers in the field of IS has stressed the importance of construct measurement and instrument validation for outcome validity and reliability (Lim et al., 2013; D. Straub, Boudreau, & Gefen, 2004).

However, some researchers in IS argued that the instrument validation is largely overlooked and inadequately addressed in the field (e.g. D. W. Straub, 1989), thus research should be carried out in more pragmatic, systematic manner employing advanced scientific techniques as instrument design is ‘intimately’ connected to the contextual concerns of a research. As Bagozzi (1980) states, validation of survey instruments allows greater clarity to the research findings and in-depth analysis and thus better explanations to research questions. On the other hand, as Hunter, Schmidt,
and Jackson (1982) pointed out, validated instruments provide greater opportunities for other researchers to conduct follow-up research thus enabling cumulative and progressive understanding of the topic. Thus, deriving of survey instrument is a key component of the research methodology / design phase.

THE PROCESS OF SCALE DEVELOPMENT

Scale development procedure in survey method have been discussed under several key steps in the previous literature. For example, it has been discussed in six broader steps: 1) survey instrument design 2) sample selection for data collection 3) content validation of the survey instrument 4) pilot test of the survey instrument 5) revisions of survey instrument; and 6) full scale survey deployment (see Figure 12). The six steps above explain the design considerations of the survey and the operational procedures of data collection using the survey.

Figure 12: Broader Steps of the survey design
Chapter 4: Research Design and Methodology

The design component above mainly considers two key aspects; 1) *operationalization* of the constructs / dimensions and 2) the design considerations relating to the *format* of the instrument. The operationalization component of the design considerations can be sub divided into the following sub tasks.

1. Identification and definition of each construct and the corresponding measures in the research model
2. Designing of appropriate survey questions / items to measure the each construct
3. Deciding of the number of survey items for each dimension / construct
4. Phrasing the survey items that accurately measure the constructs
5. Re-phrasing the already formulated survey items by adding unique contextual information to strengthen the meaning of the questions to the respondents, and
6. Adding demographic items that are useful and meaningful to the study

Then the ‘format’ related design considerations also can be outlined as below.

1. Maintaining the consistence design throughout the survey
2. Sequencing of the items
3. Employment of the consistent scale throughout the survey instrument, and
4. Decide on mandatory / voluntary nature of the questions

Based on prior work on the subject in IS literature S. B. Mackenzie et al. (2011) presented a detailed ten step procedure for construct measurement and validation integrating new and the previous techniques in management information systems and behavioural research domain as below.
The next sections of this discussion explain the aforementioned modus operandi in detail.

The first step of the scale development and validation procedure – the conceptualization, deemed to be the most important, critical and difficult among all other steps. Nunnally, Bernstein, and Berge (1967) described “construct” as an abstract and latent variable (rather than concrete and observable) that a scientist put together from his/her own imaginations and which does not exist as an observable
dimension of behaviour. Thus, majority of theories concern statements about constructs as opposed to specific, observable variables such that by definition, the constructs are more general than specific (S. B. Mackenzie et al., 2011). As such, identification of what the construct is intend to represent and capture conceptually, and how the construct is differs from other related constructs is an extremely important and critical first step of the process of construct definition phase. Thus, the definition of a construct should clearly and concisely express, the nature and the conceptual theme in unambiguous terms in a manner that is consistent with prior research (G. A. Churchill, 1979; S. B. Mackenzie et al., 2011). Thus, S. B. Mackenzie et al. (2011) elaborates several key steps that are important in construct conceptualization process as below.

1) Examination of the employment of focal construct in prior research / or by practitioners.

As they elaborate, a researcher can first conduct detailed literature review on the prior theoretical and empirical work around the focal construct, meaning of related constructs or inductively conduct research with subject matter experts or practitioners in order to gain a broader understanding of the focal construct.

2) Specifying the nature of the construct that have been discussed in the conceptual domain.

The key focus here in the second step is to identify and understand the type of “property” the construct represents and the “entity” to which it applies.

Examples:

- Job satisfaction:

  Property: Positive feelings about the job,

  Entity: Individual

- Job performance:

  Property: Job outcomes

  Entity: Individual
- Firm performance:

  Property: Organizational outcomes (Profit, market share, customer satisfaction etc.)

  Entity: Firm

3) Specification of the conceptual theme of the construct

The objective here in third step of the process is to briefly describe the necessary and sufficient characteristics / attributes (common attributes and characteristics, unique attributes and characteristics, breadth and inclusiveness), dimensionality (Uni-dimensional or Multi-dimensional), stability (over time, across cases, across situations).

4) Defining the construct in unambiguous terms

Here in the final step of the conceptual definition stage a researcher should,

- Provide a concise yet clear conceptual definition of the construct

- Avoid the possibility of multiple interpretations

- Avoid technical terms with narrow meanings (should not be overly technical)

- Define construct positively (not by the denial of other things / negating one thing to imply the affirmation of something else)

- Avoid tautological, circular or self-referential explanations

Once the construct have been defined the important second step in the definition stage is to check the sub-dimensionality of the focal construct and the relationship of such multiple sub-dimensions and the focal construct. This is important because many constructs are defined having distinct sub-dimensions (S. B. Mackenzie et al., 2011). For example the construct firm performance has been defined as a multidimensional construct involving operational excellence, customer relationships and revenue growth (e.g. Rai, Patnayakuni, & Seth, 2006). When the construct has multi-dimensions, the next important question is whether the sub dimensions are representing or constituting the focal construct. When the sub dimensions are
constituting / viewed as defining characteristics, thus the focal construct is a function of the sub dimensions and changes to one of the sub-dimensions could be associated with a change in the focal construct, the sub-dimensions are viewed as formative indicators of the second-order focal construct (S. B. Mackenzie et al., 2011). In contrast, if the sub dimensions are just manifestations of the focal construct where the focal construct is separately exists at a deeper, embedded level compared to the sub dimensions and changes in focal construct would make changes in all the sub dimensions are viewed as reflective of the second-order focal construct (S. B. Mackenzie et al., 2011). Next, when the construct considered to be formative, it is important to consider how such sub-dimensions combine-additive or multiplicative, to form the focal construct, and the union of sub construct needs to be mentioned clearly in the construct definition stage.

Whilst the terms reflective and formative describes the relationship between latent construct and its indicators, it is important to note that the constructs are not inherently formative or reflective in nature (S. B. Mackenzie et al., 2011). Focal construct and its indicators can be modelled either as reflective or formative based on the researcher’s objectives hence in the conceptualization of the construct.

The second phase of the construct measurement and validation procedure has two steps. In the first step, once the construct has been conceptually defined, the set of items needs to be generated to represent the focal construct. Herein the items could be generated with help of many different sources including extant measures of similar constructs in the literature, reviews of the literature, prior empirical and theoretical discussions of the focal construct, expert commentaries and interviews, focus group discussions and deducting from previous theoretical definitions of the focal construct (see..G. A. Churchill, 1979; S. B. Mackenzie et al., 2011; Nunnally et al., 1967).

As explained in S. B. Mackenzie et al. (2011) the ultimate goal of the measures development is to generate the items that fully captures the all essential aspects of the domain of focal construct, no matter the construct is uni-dimensional or multi-
dimensional. However, the care must be taken to include only the aspects that lies within the domain of the construct by eliminating or minimizing the items tap concepts those falls outside the domain of the focal construct. As such, when the construct is multi-dimensional, the sub-dimensions should comprise of all essential aspects of the definition of the focal construct whilst the set of measurement items should be developed for each sub-dimension of the focal construct regardless if it is formative or reflective.

Further, as explained in S. B. Mackenzie et al. (2011) there are several other considerations that should be taken care of in this phase of measures development. For example, the each item should be worded as simple and as precise as possible. Double-barrelled items should split into two simple single-idea statements or if it deemed impossible should be avoided the inclusion of such items altogether. When the terms are ambiguous or unfamiliar to the respondents clarifications should be presented upfront. Any complicated syntax should be made concise and simplified and the refinements should be made on the items that contain obvious social desirability (Fleenor, McCauley, & Brutus, 1997).

Once the items have been generated for a construct, next the evaluations should be taken to assure their content validity – “the degree to which items in an instrument reflect the content universe to which the instrument will be generalized” (D. Straub et al., 2004, p. 424). As such, the content validity refers to the ‘representativeness’ and the ‘sampling adequacy’ of the content of an item (Kerlinger, 1986). Thus, the test of individual item representativeness of an aspect of the content domain of the construct and whether the items are collectively representative of the entire content domain of the construct is performed is the main focus in this stage of the measures development process. Several techniques can be employed to assess the validity of the content (Aiken, West, & Reno, 1991; Glynn, Hayes, & Shanahan, 1997; Kartas & Goode, 2012), where the use of experts-people who have sufficient intellectual ability, in the subject domain being the most popular.
Once the content valid measurement items being derived for the constructs, the next step in the procedure presented in S. B. Mackenzie et al. (2011) is to formally specify the measurement model that captures the expected relationships between the items and the focal construct and sub-constructs they intend to symbolize. Herein, several items can be combined into a single index – parcels, as indicators. Such parcels can be used in reflective indicator models to enhance the reliability or the distributional properties of the indicators, simplify the measurement model parameter interpretations, and increase the goodness of fit of the measurement model (N. Y. Lee & Kim, 2014). However, there are arguments against the use of parcels / bundles when the study objective is on refinement, scale development or testing (Hayes, 2007).

Once the measurement model has been formally specified, the next step is to collect data from a sample of respondents to test the psychometric properties of the scale, convergent, discriminant and nomological validities of the instrument (S. B. Mackenzie et al., 2011). The recommendations of minimum sample size is ambiguous (Bowen & Blackmon, 2003; Clemente & Roulet, 2014; Neumann, 1993; Noelle-Neumann & Petersen, 2004) but the important point is that for a given study, the adequate sample size is determined by the level of communality of the variables and the level of over-determination of the factors, thus even with small samples could provide a reasonably good recovery of population parameters (Scheufele, 2008). In essence, alternative measures of the same construct is required for convergent validity, whilst the measures of constructs that are nomologically/theoretically related to the focal construct is required for the nomological validity assessment. Similarly, for discriminant validity assessment, measures of similar constructs that are potentially cofounded with the focal construct is required (S. B. Mackenzie et al., 2011).

Next, following the data collection and pre-test, the scale purification and refinements are required to further assess and improve the newly formed scales. Such methods of evaluations have been widely discussed in the existing literature (Bagozzi, 1980; Bollen, 1998; Fornell & Larcker, 1981; Mason & Perreault Jr, 1991; Matthes,
Morrison, & Schemer, 2010). Following which S. B. Mackenzie et al. (2011) discussed the ways to which scale evaluations can be performed for both formative as well as reflective indicators.

As such, the important first step is to evaluate the goodness of fit of the measurement model by testing whether (i) the solution is proper, (ii) each relationship that has been hypothesized are statistically significant, and (iii) the relationships as a group consistent with the data obtained (S. B. Mackenzie et al., 2011). As, further elaborated therein, there are several tests are available to test the goodness of fit of measurement models. Further, the assessments can be performed at different levels other than the measurement model level, such as construct level and the individual indicator level. For example, the validity of the set of indicators can be performed at construct level by calculating the average variance extracted method. Next the reliabilities of the set of indicators can be assessed at the construct level Chronbach’s Alpha method or the Fornell and Larcker’s index (S. B. Mackenzie et al., 2011). Similarly, validity of the individual indicators can be evaluated by testing the significance of the relationship between each indicator and its hypothesized latent construct. Alternatively the reliability can be tested by examining the squared multiple correlation for the indicator (Bollen, 1998). In addition, there are methods to identify the problematic indicators. Indicators deemed problematic when they have low validity, low reliability, strong and significant measurement error covariances, and/or cross-loadings that have non-hypothesized are strong and significant (S. B. Mackenzie et al., 2011). In such situations the problematic indicators should be dropped at the researcher’s discretion.

As the items are added, dropped or reworded in the scale purification process, new sample of data needs to be gathered in the next step to re-estimate the measurement model. Herein the sample could be of similar to the one that is used for sample purification, as the sole objective of this step is to re-validate the instrument. As such, with a new sample, the measurement model would be re-estimated, the goodness of fit is re-examined and the psychometric properties were re-evaluated (S. B. Mackenzie et al., 2011).
Once the psychometric properties of the purified scales deemed acceptable, the next step is to perform the construct validation procedures to check whether the responses to the items behave the way valid indicators of the focal construct would (S. B. Mackenzie et al., 2011). Herein the tests are performed to see, (i) whether the items are accurately representing the underlying construct (ii) whether the items are capturing the multi-dimensional nature of the underlying construct (iii) whether the items (indicators) of a given construct are clearly distinguishable from the items of other constructs – discriminant validity, and (iv) whether the items / indicators of a given construct are related to the measures / items of the other constructs that are nomologically related – nomological validity.

The next step in the scale development process is to perform cross validation of the psychometric properties with new samples (S. B. Mackenzie et al., 2011). There are several techniques that a researcher could follow to perform cross validation of the scales (see..Matthes et al., 2012; McDonald, Glynn, Kim, & Ostman, 2001). Essentially, the tests are performed for testing (i) the equivalence of the covariance matrices, (ii) the configural equivalence of the factor structure, (iii) the metric equivalence of the factor loadings, and (iv) the scalar equivalence of the item intercepts (S. B. Mackenzie et al., 2011).

Upon which the final stage of the scale development process is to develop norms to support the interpretation of scores in the measures (S. B. Mackenzie et al., 2011). This requires administering of the scale to a representative sample of the targeted population (Neuwirth, Frederick, & Mayo, 2007). As Neuwirth et al. (2007) further elaborates, size of the sample (to ensure the results obtained are stable) and specifying the time frame (if the norms changes over time) are another important considerations in the final stage of the scale development process.
APPLICATION OF THE CONSTRUCT MEASUREMENT AND VALIDATION PROCEDURE IN THE CURRENT STUDY

The focus of this study is to understand the customers’ use of smart shopping app and the associated implications on customer expectations thus on their perceptions in the context of the deployment of smart mobile shopping apps in fast moving consumer retail. As such, this study intends to conceptualize customers’ use of smart shopping apps, customer’s (digital) expectations, customers’ perceptions (as in perceived experiences) and the customer satisfaction constructs. Thus, using the lens of Expectation Confirmation Theory (Oliver, 1980b), this study investigates the customers’ “use” of smart shopping apps, customer’s ‘digital expectations’ that resulted due to their use of smart shopping apps, customers’ actual shopping ‘experience’ and the outcome ‘satisfaction’ constructs. As such, the constructs that we are interested herein are closely tied to the existing operationalized measures of system use, expectations, experience and satisfaction constructs. Thus, in this study, the appropriate measures for the construct that have been mentioned above are developed using a systematic literature review on the similar constructs and other complimentary sources such as expert interviews, trade press and literature reviews as mentioned in S. B. Mackenzie et al. (2011). Then, the determination of corresponding measures were derived based on the reference disciplines that are closely related to the each construct. The next sections explain the development of items / survey questions for each construct of our research model that have been discussed earlier in chapter 3.

The Measures of Smart Shopping App Use

We refer back to the process model involving customers’ use of smart shopping app and agility (Figure 10) and the research model involving customers’ use of smart shopping app, expectations, experiences and satisfactions (Figure 11) in Chapter 3 to develop our measures for each of the constructs mentioned above.

Based on our argument, customers’ use of smart shopping app influences customers’ expectations as a result of firm’s potential of sensing the customers
through their use of smart shopping apps, we herein refers to the prior literature on technology/system use (e.g. A. Burton-Jones & Gallivan, 2007; A. Burton-Jones & Grange, 2013; A. Burton-Jones & Straub, 2006; Po-An Hsieh et al., 2011) to develop measures to capture the customers’ ‘use’ of smart shopping app that we are interested herein.

System Use has been one of the most mature research streams in the IS discipline. For example, system use is a construct of IS success (DeLone & McLean, 1992, 2003; Petter & McLean, 2009) and technology acceptance (Susan A. Brown et al., 2012; F.D. Davis et al., 1989; Venkatesh et al., 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh et al., 2012). This has resulted in a rich understanding of the construct, differentiating the types of system use measures (A. Burton-Jones & Gallivan, 2007; A. Burton-Jones & Straub, 2006). For example, new conceptualizations such as extended use (Po-An Hsieh et al., 2011) and effective use (A. Burton-Jones & Grange, 2013) provide insights of individual use patterns.

In their work on re-conceptualizing system use, A. Burton-Jones and Straub (2006) has highlighted that a researcher should define the context of the study in order to capture the most relevant usage content for a specific context. Further, they mentions that not all types of usage constructs are not relevant to every type of research where only some of the usage elements might be relevant to the different types of studies. As they explain, a research should be able to identify the most relevant usage content for a given study following the two staged approach they have presented therein. Thus, following their conceptualization of system use, herein we look at the elements of usage, type of the systems and the method of data collection to define the context of this research and select the measures that are most relevant to the objective of this study.

As our focus in this discussion is to study the influence of customers’ use of smart mobile shopping app on customer expectations due to the firms potential to sense their customers through the customers’ use of smart shopping apps, we first
outline the focus of this discussion using the figure 14 below. The figure outlines the scope of this study based on the type of the system (see APPENDIX B for more details on the types of systems), type of the measures (measurement constructs) and then the measurement approach.

![Figure 14: Scope of the study](image)

The figure above summarizes the types of measures based on the three basic elements of system use, (1) subject using the system (i.e. user) (2) Object being used (i.e. system) and (3) the function being performed (i.e. task) as defined by A. Burton-Jones and Straub (2006). On the vertical axis of the figure 14, we defined the scope of the usage measures that this research is interested in. Then, we highlights the study focus based on the type of the system and the type of evaluation in relation to the prior technology use related studies in IS discipline on the two horizontal axis of the figure 14.
Cubes marked ‘A’ in figure 14, denote where extant studies of system usage in IS success, IS/IT acceptance and use, IS for decision making and IS implementation domains have focussed, which the cubes marked ‘B’ denotes the system usage measures that we consider herein for mobile shopping app use measures in this research. Further, we highlight that the existing system use related research predominantly were on the traditional systems in the organizations (marked ‘A’), compared to the smart shopping app use by the consumers (Marked ‘B’) in this research. Also, similar to the usage measures that have been employed in prior research we too use self-reported data in this investigation as opposed to the panel data or the data collected through observations. Having, developed an overall consensus of the study scope and the context as above, now we aim to develop content valid, contextualized usage measures of mobile shopping apps in the context of this discussion as below.

As graphically represented in the Figure 15, the usage measures herein are nomologically linked to the customers’ digital expectations through a firm’s customer sensing. As such, the smart app use that we are interested herein related to the usage that enact a firm’s customer sensing. Thus the term use herein reflects the extent and the amount of smart app use for the routinely shopping related activities by an
individual customer. In other words, use construct refers to the degree of use (frequency, tasks performed and functionality used) that promotes a firm’s opportunity to sense a customers’ shopping related requirements. Thus, the degree of use increases with the usage frequency, number of shopping tasks performed, and the number of functionalities of a shopping app is used by a customer. Hence, a firm’s sensing potential is proportionate to the degree to which an individual uses a smart shopping app. In other words, there is a strong implicit association between the extent a customer is engaged in repetitive and deep use of a mobile app and the firm’s ability to sense and respond to that customer’s unique requirements.

Hence, the use that we refer here (use that relates to a firm’s customer sensing / customer’s expectations) is going beyond the simple use of a smart shopping app, rather the use that reflects the enablement of the firm’s customer sensing through a customer’s use of a smart app. Thus, the use that relates to the customer expectations associates to the deep structure use of Burton-Jones and Straub (2006). For example, a customer’s use of a smart shopping app for online shopping, browsing products or creating shopping lists could provide rich customer insights for the focal firm, thus providing opportunities for the firm to work toward forming a relationship with a customer. Similarly, the frequent use of functionalities to perform tasks that allow a firm to sense their requirements would provide more opportunities for the firm to sense those customers’ requirements. As such, the usage measures herein captures the functionalities of the app an individual used, tasks performed by an individual, and at what frequency. In other words, the measures we are interested reflect the degree to which a customer is mimicking his/her daily shopping related routines in a firm’s smart shopping app. Hence, in this research we capture the frequency to which an individual’s employment of one or more features of a smart mobile app to perform tasks that supports a firm to acquire meaningful insights about the user.

Therefore, based on A. Burton-Jones and Straub (2006) work, the customers’ use of smart shopping app is going beyond the generic use to the frequency and the depth of mobile app use which facilitate firm’s customer sensing. Moreover, as the degree of sensing that a firm can attain will vary on the extent to which the tasks are performed, functionalities are used and the frequency or the consistency which a
customer performs tasks using such functionalities, the usage measurement component herein includes both frequency and extent of use. The Table: 7 below lists the construct measures of smart app use.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Items</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Smart shopping app use.</strong></td>
<td>DC1: I frequently use this mobile app to find products.</td>
</tr>
<tr>
<td></td>
<td>DC2: I frequently use this mobile app to prepare my regular grocery</td>
</tr>
<tr>
<td></td>
<td>shopping list.</td>
</tr>
<tr>
<td></td>
<td>DC3: I frequently use this mobile app to place orders.</td>
</tr>
<tr>
<td></td>
<td>DC4: I frequently use this mobile app to provide comments and feedback.</td>
</tr>
<tr>
<td></td>
<td>DC5: I frequently use this mobile app to find a store more convenient.</td>
</tr>
</tbody>
</table>

Table 7: Construct measures of smart shopping app use

**Measures of Customer Expectations (Digital Expectations)**

Following the guidelines proposed by Churchill (1979) and S. B. Mackenzie et al. (2011) for developing the construct measures that we have discussed earlier in the chapter, we developed the measures of digital expectations from previous validated measures of similar constructs. Since customers form their expectations based on the understanding that the firm is sensing their needs and eants through their use of smart shopping app that the firm has launched, the expectation construct herein represents ‘the level of responsiveness that customer’s expect from the firm’.

As such, to developed measurement items for customer’s digital expectations / customer expected firms responsiveness (i.e. the requirements unique to each customer / customer expected a firm’s agility towards needs that are unique to him/her), this study next latched on the previous validated measures of firm’s
customer agility (Roberts & Grover, 2012a, 2012b) and the expectations in Expectation Confirmation Theory literature (A. Bhattacharjee, 2001; Susan A. Brown et al., 2012; S.A. Brown et al., 2008). Since, expectations that we are interested herein not exactly the ones we see in extant literature, the existing measures of expectations constructs were adapted to the context of this study (See Table 8). For new measures and those that required significant changes, we followed the standard scale development procedures stipulated in S. B. Mackenzie et al. (2011).

<table>
<thead>
<tr>
<th>Construct</th>
<th>Items</th>
<th>Measure sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer expectations / Digital Expectations (The level of responsiveness that customer’s expect from the firm)</td>
<td>“Customer expected firm’s responsiveness to their unique shopping needs and wants”</td>
<td>S. A. Brown et al. (2011); S.A. Brown et al. (2008); Roberts and Grover (2012a, 2012b).</td>
</tr>
<tr>
<td>CXPT1: I expect [retailer] to provide information about discounts and promotions based on my specific requirements.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CXPT2: I expect [retailer] to be responsive to my changing needs and wants.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CXPT3: I expect [retailer] to provide personalized offers based on products that I purchase regularly.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 8: Construct Measures of Customer Expectations / Digital Expectations

Next, we followed a similar procedure as above to developed measurement items for the other constructs in our research model; customer experiences, customers’ evaluations of expectation confirmation and customer satisfaction. Customer experience in this research is defined as ‘a firm’s responsiveness towards an individual customer’s unique needs and wants as perceived by the customer”. As such, our measures of customer experience are primarily based on the prior literature on similar constructs such as in customer agility (Roberts & Grover, 2012a, 2012b), market orientation (Kohli, Jaworski, & Kumar, 1993), customer responsiveness Jayachandran et al. (2004) and expectation confirmation (A. Bhattacharjee, 2001). Where possible, the existing measures of constructs were adapted to the context of
this study. For new measures and those that required significant changes, we followed the standard scale development procedures stipulated in S. B. Mackenzie et al. (2011).

<table>
<thead>
<tr>
<th>Construct</th>
<th>Items</th>
<th>Measure sources</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Customer experience</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>“a firm’s responsiveness towards an individual customer’s unique needs and want’s as perceived by the customer”</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Jayachandran et al. (2004); Kohli et al. (1993); Roberts and Grover (2012a, 2012b).</td>
</tr>
<tr>
<td>CXPR1: [Retailer] quickly react to the essential basic changes in my product requirements by providing me with relevant personalized information.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CXPR2: After browsing recipes using the mobile app, [retailer] is quick to provide promotional information for the products required to make that recipe</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CXPT3: When I continue to purchase a new product (e.g. Baby nappies) repetitively, [retailer] is quick to respond to it by providing other associated product information (e.g. other baby products)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CXPT4: [Retailer], is fast to provide information about discounts and promotions based on the products I purchase regularly.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CXPT5: [Retailer], is quick to provide information on discounts and promotions for my preferred store based on the products I created in my shopping list in the mobile app.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CXPT6: [Retailer], is able to recognize change in my physical location to prompt discounts and promotions on my usual purchases for the store nearby.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CXPT7: [Retailer] often recommend products that can easily satisfy my</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
changing needs.

CXPT8: [Retailer] can easily satisfy my new and changing needs.

CXPT9: The product displayed in my specials section of the mobile app reflects my specific requirements.

CXPT10: Overall, the promotions I regularly receive from [retailer] are useful and match my unique daily requirements.

Table 9: Construct Measures of Customer Experience (A firm’s responsiveness as perceived by a customer)

<table>
<thead>
<tr>
<th>Construct</th>
<th>Items</th>
<th>Measure sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer evaluations</td>
<td>“A customer’s evaluation of his/her actual shopping experience against his/her shopping related expectations (i.e. shopping needs)”</td>
<td>S. A. Brown et al. (2011); S.A. Brown et al. (2008); Roberts and Grover (2012a, 2012b).</td>
</tr>
<tr>
<td>CEVL1: My shopping experience with [retailer] was better than what I expected.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CEVL2: Responsiveness of [retailer] on my shopping requirements is better than what I anticipated.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CXPT3: Overall, [retailer] was able to</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Similarly, we have defined customer evaluations as ‘how an individual evaluate his/her shopping experiences against his/her shopping related expectations i.e. Needs and wants’). Thus, our measures of customer evaluations are primarily based on the prior literature on similar constructs in the ECT literature (S. A. Brown et al., 2011; S.A. Brown et al., 2008). In doing so, the existing measures of expectation-confirmation constructs were adapted to the context of this study. For new measures and those that required significant changes, we followed the standard scale development procedures stipulated in S. B. Mackenzie et al. (2011). The table 10 below lists the measures of customer evaluations of expectation-confirmation that has been derived through the relevant prior literature.
confirm or exceeded most of my shopping expectations.

Table 10: Construct Measures of Customer Evaluations

Next, following a similar approach, we developed our measures of customer satisfaction construct. In doing so, we have defined the customer satisfaction as ‘the level of satisfaction that a customer derives by confirming his/her shopping related expectations through the experience as perceived by the customer (i.e. the level of satisfaction that a customer achieved through his/her shopping experience)’. The table 11 below reports the customer satisfaction measures used in this study, that have been developed based on previous related literature.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Items</th>
<th>Measure sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer</td>
<td>SF1: I am satisfied with the personalized promotions/offers I receive from the [retailer].</td>
<td>A. Bhattacherjee (2001)</td>
</tr>
<tr>
<td>satisfaction</td>
<td>SF2: I am satisfied with the [retailer’s] responsiveness to my changing needs and wants.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SF3: I am satisfied with my overall shopping experience with [retailer].</td>
<td></td>
</tr>
</tbody>
</table>

Table 11: Construct Measures of Customer Satisfaction

GENERAL ASPECTS OF THE SURVEY DESIGN

Literature suggest that the number of items that measure a construct / dimension should be decides upon the domain of interest and the level of parsimony (Cronbach & Meehl, 1955). Anastas (1988) stated that a survey with too many items induce response bias. Nunnally et al. (1967) argues that the content and construct validity is getting compromised when too few items are used to measure a construct.
Incidentally, Hinkin and Schriesheim (1989) also state that the dimension would under-specify when using a single item per dimension. However, some other researchers (e.g. Bailey & Pearson, 1983) proposed a single item measures upon considering practical and theoretical consideration of the particular study. Following such debate, in this research the number of items that has been used in each construct was selected considering the practical, theoretical and the level of parsimony.

Then the phrasing / wording of individual questions have been carefully done to better reflect the intended measure and to capture the accurate reflection of intended measures that is unique to the each respondent. In doing so, we have conducted a several rounds of reviews with a group of respondents comprising of PhD students and academic staff. This allows the collection of responses from a large number of respondents using the same survey instrument. Also, the contextual information relating to the smart mobile app use, customer expectations, experiences and satisfaction alone with an introduction to each construct dimension also have been included in to the survey items to make sure the respondents understand the questions well, thus, thereby removing / minimizing any response bias.

In addition to the design considerations that are related to construct operationalization that we have discussed above there are four key format related design considerations that are important in making the instrument visually consistent and appealing for the respondents. The survey herein consists of two main sections. The first section of the instrument collects the general demographics relating to the respondents, whilst second section, the main survey collected the data relating to the each construct in our research model discussed in the previous chapter. Both main sections and the sub-sections were provided with the clear instruction for completion where a clear description of the intended measurement construct also have been provided therein to make the survey items more understandable.

In addition to the maintaining consistency, the sequencing of the survey items / questions also have been dealt with extra attention to encourage responding to the
survey less annoying thus more engaging. As such, the survey commenced with general demographic details that are easy-to-complete followed by smart shopping app use, expectations, experiences and satisfaction related items. Prior research too have alluded the importance of question wording, format, sequencing of questions and contextual information especially in the case of self reporting of behaviours and attitudes (Schwarz, 1999).

Similarly, employment of an appropriate scale also has been considered as an important consideration in designing and validation of survey instruments because, this refers to the choices that a respondent has on answering the each item of the survey. In IS research, the most frequently used scale in perception, behaviour gathering survey based methodology are the LIKERT type scales, where the respondent chooses a response on a scale. As such the responses were presented in rank choices where the respondents were asked to indicate their preference in a LIKERT scale indicating their level of agreement on each item of the survey. Usually, the selection of scale or the length of the scale is up to the researcher’s discretion. As prior research elucidate (Cicchetti, Shoinralter, & Tyrer, 1985; Lissitz & Green, 1975) a ‘good’ scale accommodates sufficient variability among respondents thus, reliability of scale increases as the number of choices up to five in a scale, and the variation of reliability levels off beyond. Research in IS field commonly used either the five point or seven point LIKERT scales.

With the objective of reducing the complexity, ease of understanding, ease of completion, clarity of instructions and accommodating sufficient variability among respondents, in this research we have used seven point single scale throughout the survey instrument. The use of seven point LIKERT scale has the potential to provide more accurate reflection of an individual’s attitude, opinions or behaviour, allowing more information for statistical nuance (Flynn, van Schaik, & van Wersch, 2004; Reips & Funke, 2008)\(^3\). The scale is based on how respondents believe, where the

answers display in the scale from negative to positive, left to right, indicates as:

Strongly Disagree, Disagree, Slightly Disagree, Neutral, Slightly Agree, Agree and
Strongly Agree as points 1, 2, 3, 4, 5, 6, and 7 respectively as indicated in Table 12.

<table>
<thead>
<tr>
<th>Strongly Disagree</th>
<th>Disagree</th>
<th>Slightly Disagree</th>
<th>Neutral</th>
<th>Slightly Agree</th>
<th>Agree</th>
<th>Strongly Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
</tbody>
</table>

Table 12: Scale of agreement

In this research not all questions in the survey instruments were made mandatory as some questions are not relevant to all the respondents. The questions that are relevant to every respondent were made mandatory instead.

**CONTENT VALIDATION**

As Sekaran (2000) explicate content validation is an important procedure to ensure that all individual measurement items of the survey instrument match the intended constructs and concepts sufficiently well. Specifically the content validity refers to the extent to which the survey items on each measure assess the same content or how well the content material was sampled in the measure (S. B. Mackenzie et al., 2011). This has been characterized and discussed as face validity (Mosier, 1947) in the literature. Following Schouten, Grol, and Hulscher (2010) and S. B. Mackenzie et al. (2011) for all the items that encompass the constructs in this research have been developed as a result of strong literature review and face validity.

As discussed in measures development section earlier in this chapter, following Schouten et al. (2010) and S. B. Mackenzie et al. (2011) to identify the potential determinants and appropriate measures for each construct we reviewed the key theoretical papers on each construct and their list of references in detail. This procedure ensures the consistency of this study has with the previous conceptual definitions that are closely relevant, related and important in the literature. Pursuing
this procedure is important for the assessment of scale items represent the constructs thoroughly, adequately and appropriately. As elaborated earlier in operationalization of constructs section earlier in this chapter, we derived our measures based on the prior literature, thus ensuring this study was grounded well in existing theoretical notions. As the Tiwana (2001) states more the measure items represent the domain of the construct, higher the scale’s content validity, the questionnaire used in this investigation considered to have a greater content validity as the content which the individual items represent matches an actual circumstance that is being studied.

Literature suggest that investigations that employ should address the issue of common method variance when the data collection involved a survey method, specifically when self-reported questionnaires used measure perceptual measures (Chang, Van Witteloostuijn, & Eden, 2010). Common method variance refers to the “variance that is attributable to the measurement method rather than to the constructs the measures represent” (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). As they elaborate, common method variance creates false internal consistency thus, can create false correlations among variables generated by their common source and creates measurement errors. Common method variance can have a serious confounding influence on empirical results, yielding potentially misleading conclusions (Campbell & Fiske, 1959). As suggested by Chang et al. (2010) to reduce or avoid the influence of any potential common method variance we employed different sources of information when developing the measures and have mixed the order of the questions to reduce the likelihood of theory-in-use bias. Further, we made the survey questions reasonably short, simple and specific to improve the precision and to make them less ambiguous as the clarity could influence the responses (Williams, Edwards, & Vandenberg, 2003).

**PRE-TEST AND PILOT TEST**

We employed the face validation procedures to examine the appropriateness of the questionnaire items for accuracy, language and appearance. Face validation is a concept that is similar to content validation, where the evaluation is done by a subjective judgement of experts (Keszei, Novak, & Streiner, 2010). This procedure
helps a researcher to identify the questions that may perceive irrelevant by respondents thus subsequent removal of such items or make necessary revisions before the deployment of main survey. In other words, face validity verify whether the instrument looks valid to the potential respondents and whether the language is appropriate to ensure all the items confirm the research intension and can be easily understood by respondents. Literature recommends three to ten experts depends on the desired diversity of knowledge (Downe-Wamboldt, 1992; J. S. Grant & Davis, 1997). In this study, we have consulted a group of seven respondents comprising of PhD students, academics and general public all of whom are shoppers (both users and non-users of the smart mobile app) of at least one of the two retailers that this study take as samples. They have provided a constructive feedback on the constructs, measures and individual questions thus provided concrete suggestion for further improving the measures. The feedback offered have improved the wording / meaning, readability, ease of understanding, ease of responding and content validity of the instrument (Schouten et al., 2010). Then, we have pre-tested the instrument with 10 respondents comprising of PhD students, cademics and general public all of whom are shoppers of atleast one of the two retailers.

Following the pre-test, next we have conducted the pilot test with 30 respondents to assess the reliability and validity of the individual measures. Our pilot testing has provided a reasonably good results for both validity and reliability thus has provided reasonable confidence of the individual measures. Subsequent to the pilot test follow-up discussions were made with a subset of ten respondents to further strengthen the validity and reliability of the measures, where the research constructs were revisited, refined and have revalidated. This exercise created a sufficient confidence in the scales to proceed with the full-scale survey administration of the target sample frame.
SURVEY DEPLOYMENT

Following the sufficient confidence gained through the pre-test and pilot testing and a subsequent discussions with subset of respondents, we next administered our main anonymous surveys both online and offline, yet seeking a customer sample of the two main retailers (Coles Supermarkets and Woolworths) in Australia, who have launched smart mobile apps offering on-line shopping, shop locators, recipes, preparation of shopping lists and special offers to their customers. As such the online data collection survey was posted on social media community pages of the two retailers. Alternatively, the paper-based survey was administered at multiple locations (e.g. shopping mall, commercial organizations, etc.) targeting the customers of both retailers. Our data collection yielded a total of 431 respondents from both online and offline. The online survey yielded 174, with a response rate of 41%, from 422 who actually accessed the URL. Correspondingly, the off-line survey yielded 257 responses with a response rate of 39.5%, from 650 questionnaires distributed. Subsequent screening for missing data left us with 427 usable respondents as four of the responses omitted due to missing values.

ANONYMITY AND CONFIDENTIALITY OF THE RESPONDENTS

To guarantee the confidentiality and anonymity no personal data was collected or recorded during the data collection exercise. As such nobody would be able to identify who provided the data. For the purpose of follow-up, when collecting the data from commercial organizations, the study team appointed a questionnaire collector in such organizations when performs off-line procedures. Since the off-line questionnaires were handed out personally by the designated person in such commercial entities, agreement on the completed survey collection schedule was made with the collectors and collections were made based on the convenient return date agreed by the two parties. The online surveys were made anonymous and no personal data or identifiable information was collected to guarantee the confidentiality and anonymity.
CHAPTER SUMMARY

The chapter first introduced the research design and the survey design prior describing the constructs, sub-constructs and the items relating to each sub-constructs explained in detail with reference to the related prior literature. Then, we have discussed the data collection methodology that we have employed in this study following the introduction of data collection objectives and the appropriateness of the survey methodology. Following which the chapter presented the detailed survey design process and the construct operationalization procedures. Subsequently the chapter discussed the steps taken to minimise the common method variance (CMV) and the ethical concerns relating to respondent anonymity and confidentiality.
CHAPTER 5: DATA ANALYSIS, RESULTS AND DISCUSSION

In the previous chapter we discussed the design of this research, construct definitions, operationalization of the constructs, and design aspects of the survey and the survey deployment and data collection procedures in detail. In this chapter, the discussion focusses on the quantitative analysis of the data including a discussion of empirical results and the hypothesis testing.

As suc, the first section of the chapter focuses on the design aspects of the data analysis, data analysis methodologies and the procedures, prior reporting the results relating to testing the hypothesized relationships that we have derived earlier in the Chapter 3 in the second section of the chapter. Then the subsequent section of this chapter reports the key findings that this research has unearthed before concluding the chapter with a chapter summary.
DATA ANALYSIS DESIGN

This section of the chapter further elaborates the analysis and design process that we have briefly discussed in the research design section of the Chapter 1. As such, this section mainly focusses on the process of data preparation, analysis, interpretation and evaluation of the findings, as depicted in Figure 16 below. As depicted therein, the data analysis design is discussed under six main phases:

(i) data preparation,
(ii) data description,
(iii) test of content and construct validity,
(iv) model measurement,
(v) hypothesis testing, and
(vi) discussion of the findings.

In this study the statistical data analysis relating to the descriptives were performed using the Statistical Package for the Social Science (SPSS). The tests of the structural model/s and the construct validities were carried out using partial least square method of structural equation modelling (SEM) using SmartPLS software. Further, the hypothesis testing was done using PLS, SPSS and polynomial modelling and response surface methodology.
As depicted above (in Figure 11), the data were prepared for the analysis in the first phase of the data analysis. First, a data file was created and then, the data was compiled prior performing the data cleaning process in order to make the data in to a manageable form. Following which two separate files were prepared in two file formats, one for SPSS and the other for SmartPLS for the first phase of the analysis. In the first phase of the detailed data analysis, the data analysis was carried out for demographics and descriptive statistics using SPSS. Then further tests were performed for construct validity and item reliability using both SPSS and SmartPLS software programs. Next, the testing of the research model was done using partial least square method of structural equation modelling using SmartPLS software. In the final phase of the analysis, the hypothesis testing was carried out with polynomial modelling and response surface methodology together with SPSS and SmartPLS.
Data Preparation

The number of completed 432 survey questionnaires with overall response rate of 40.02% was considered sufficient for the test of research objectives of this project. As the test of research model and the test of hypothesized relationships were tested using different samples of respondents – comprising the users of smart shopping apps under investigation and the non-users of the shopping apps several data files were prepared from the master data file that has been prepared through the compilation of several sources of data collection. As such, for the creation of master data file, firstly the online survey data were downloaded to Microsoft Excel and then the off-line survey data were compiled with the online data file. Once the master data were created on Excel format, then the file was imported to SPSS for further analysis and screening (e.g. to check whether all the survey questions were answered fully and completed).

Subsequently a careful screening was performed to detect any unusual patterns, non-response bias or outliers. Of the 432 responses, 4 were not completed properly, none of the responses seems biased as none of them were found with extreme answers or marked with excessive neutral answers to the questions. Thus, only 4 respondents were deemed invalid and excluded from the final analysis. Removal of these left 428 usable survey responses for the final analysis.

Then to assess the impact of non-response bias, we employed the wave analysis (Armstrong & Overton, 1977), whereby the respondents were grouped into early and late respondents, online and off-line respondents and comparisons were made according to the respondents’ age and gender. Our analysis revealed no significant differences between early and late respondents or between the other combinations. Based on our findings, non-response bias did not appear to impact on our study. Following which the analysis were focussed on the reliability tests, descriptives, model testing and the hypothesis testing. As such, the following sections present the
detailed analysis of results in four different sections: descriptive statistics, reliability tests, research model testing, and hypothesis testing.

**Descriptive Statistics**

This section describes the basic features of our study sample using descriptive statistics. The analysis, outlines the sample demographic statistics, a classification based on the age group, use and non-use of the mobile shopping apps, and gender. The analysis intend to highlight the following aspects:

1) To demonstrate that the sample is representative and includes all appropriate generation cohorts, gender and use;

2) To show that the sample sufficiently represents the two groups of sample respondents - regular users of the smart shopping apps being studied as well as non-users of the two smart shopping apps that is being studied; and

3) to depict the degree of smart shopping app use in a continuum in order to make comparisons against digital expectations.

The subsequent sections discuss the aforementioned descriptive statistics in further detail.

<table>
<thead>
<tr>
<th>Use/Non use</th>
<th>Frequency/ No of respondents</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regular users</td>
<td>171</td>
<td>40%</td>
</tr>
<tr>
<td>Non users</td>
<td>257</td>
<td>60%</td>
</tr>
</tbody>
</table>

Table 13: Response rate by smart mobile shopping app use and non-use
Table 13 presents the two groups of respondents that we use in the analysis, smart shopping app users and the non-users. Majority of the sample (60%) represents non-users of smart mobile shopping apps of either of the two retailers Woolworths and Coles but 40% of the respondents were regular users of the shopping apps. As the sample comprises of reasonably balanced proportions of users and non-users, the sample deemed adequate and assumed satisfactory for the purpose of this research.

<table>
<thead>
<tr>
<th>Generation</th>
<th>Smart shopping App Use</th>
<th>Gender</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>Non</td>
</tr>
<tr>
<td>1964 and prior</td>
<td>25 (5.9%)</td>
<td>8 (1.9%)</td>
</tr>
<tr>
<td>(Baby boomers)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1965 to 1978 (Gen X)</td>
<td>186 (43.5%)</td>
<td>121 (28.3%)</td>
</tr>
<tr>
<td>1979 to 1989 (Gen Y)</td>
<td>185 (43.3%)</td>
<td>106 (24.8%)</td>
</tr>
<tr>
<td>1990 and after</td>
<td>32 (7.48%)</td>
<td>22 (5.14%)</td>
</tr>
<tr>
<td>(New Millennials)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grand total</td>
<td>428</td>
<td>257 (60%)</td>
</tr>
</tbody>
</table>

Table 14: Descriptive statistics of the sample population

As presented in Table 14 above, we have classified the total population into four distinctive groups based on the generation (P.-J. Chen & Choi, 2008; Hewlett, Sherbin, & Sumberg, 2009; Jorgensen, 2003) they belonged. A majority of the sample population represents two of the youngest generation cohorts - Generations X and Generation Y (Early Millennials). The analysis shows that only 40% of the sample population uses the either of the two smart shopping apps and whilst 60% of them (257 respondents) are not using either of the apps that is under our study considerations. From the 40% of users (171 respondents) only 11% (47 respondents) very active uses of the smart shopping app whilst 29% (124 respondents) are actual users of smart shopping app but are comparatively less active. Meanwhile 53% of the active users (High usage) represent “Generation Y”, whilst 26% of them represent the “Generation X”. The sample of non-users represent the predominantly offline Coles and Woolworths customers, where they represent one end of the smart shopping app
Chapter 5: Data Analysis, Results and Discussion

use continuum, as the other end of the continuum is represented by the heavy users of the app.

<table>
<thead>
<tr>
<th>Strongly disagree to strongly agree (%)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>Mean</th>
<th>STD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Smart shopping app use</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.13</td>
<td>1.567</td>
</tr>
<tr>
<td>Use1</td>
<td>60.05</td>
<td>4.90</td>
<td>4.90</td>
<td>8.18</td>
<td>8.18</td>
<td>8.88</td>
<td>4.91</td>
<td>2.39</td>
<td>2.056</td>
</tr>
<tr>
<td>Use2</td>
<td>62.85</td>
<td>4.44</td>
<td>4.67</td>
<td>7.48</td>
<td>7.24</td>
<td>6.54</td>
<td>6.78</td>
<td>1.82</td>
<td>1.526</td>
</tr>
<tr>
<td>Use3</td>
<td>70.09</td>
<td>8.41</td>
<td>6.78</td>
<td>6.31</td>
<td>2.57</td>
<td>3.97</td>
<td>1.87</td>
<td>1.70</td>
<td>1.363</td>
</tr>
<tr>
<td>Use4</td>
<td>73.83</td>
<td>5.84</td>
<td>6.78</td>
<td>7.01</td>
<td>4.21</td>
<td>1.17</td>
<td>1.17</td>
<td>2.29</td>
<td>1.961</td>
</tr>
<tr>
<td>Use5</td>
<td>63.08</td>
<td>5.61</td>
<td>6.54</td>
<td>6.31</td>
<td>7.01</td>
<td>5.84</td>
<td>5.61</td>
<td>3.62</td>
<td>1.455</td>
</tr>
<tr>
<td><strong>Customer expectations / Digital Expectations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4.49</td>
<td>1.832</td>
</tr>
<tr>
<td>CExpt1</td>
<td>15.89</td>
<td>6.54</td>
<td>5.14</td>
<td>13.79</td>
<td>20.33</td>
<td>19.86</td>
<td>18.46</td>
<td>4.49</td>
<td>2.041</td>
</tr>
<tr>
<td>CExpt2</td>
<td>7.94</td>
<td>12.15</td>
<td>5.84</td>
<td>17.52</td>
<td>23.37</td>
<td>20.09</td>
<td>13.08</td>
<td>4.48</td>
<td>1.801</td>
</tr>
<tr>
<td>CExpt3</td>
<td>4.22</td>
<td>11.45</td>
<td>5.37</td>
<td>15.19</td>
<td>19.16</td>
<td>20.79</td>
<td>16.82</td>
<td>4.49</td>
<td>1.956</td>
</tr>
<tr>
<td><strong>Customer experience</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3.30</td>
<td>1.286</td>
</tr>
<tr>
<td>CExpr1</td>
<td>12.85</td>
<td>6.54</td>
<td>20.09</td>
<td>38.79</td>
<td>11.68</td>
<td>7.71</td>
<td>2.34</td>
<td>3.62</td>
<td>1.455</td>
</tr>
<tr>
<td>CExpr2</td>
<td>60.05</td>
<td>3.97</td>
<td>7.00</td>
<td>14.02</td>
<td>7.71</td>
<td>5.37</td>
<td>1.87</td>
<td>2.29</td>
<td>1.782</td>
</tr>
<tr>
<td>CExpr3</td>
<td>29.21</td>
<td>7.00</td>
<td>9.35</td>
<td>35.28</td>
<td>11.22</td>
<td>6.54</td>
<td>1.40</td>
<td>3.18</td>
<td>1.682</td>
</tr>
<tr>
<td>CExpr5</td>
<td>56.31</td>
<td>2.80</td>
<td>5.61</td>
<td>14.25</td>
<td>10.75</td>
<td>5.84</td>
<td>4.44</td>
<td>2.56</td>
<td>1.975</td>
</tr>
<tr>
<td>CExpr6</td>
<td>32.24</td>
<td>7.24</td>
<td>8.41</td>
<td>31.78</td>
<td>13.08</td>
<td>5.14</td>
<td>2.10</td>
<td>3.10</td>
<td>1.731</td>
</tr>
<tr>
<td>CExpr7</td>
<td>8.18</td>
<td>7.71</td>
<td>17.76</td>
<td>31.54</td>
<td>18.69</td>
<td>10.05</td>
<td>6.07</td>
<td>3.99</td>
<td>1.537</td>
</tr>
<tr>
<td>CExpr8</td>
<td>15.42</td>
<td>5.61</td>
<td>10.05</td>
<td>29.21</td>
<td>23.13</td>
<td>11.45</td>
<td>5.14</td>
<td>3.94</td>
<td>1.693</td>
</tr>
<tr>
<td>CExpr9</td>
<td>56.78</td>
<td>4.21</td>
<td>8.64</td>
<td>14.95</td>
<td>9.35</td>
<td>4.67</td>
<td>1.40</td>
<td>2.35</td>
<td>1.753</td>
</tr>
<tr>
<td>CExpr10</td>
<td>7.00</td>
<td>7.48</td>
<td>17.99</td>
<td>29.67</td>
<td>21.50</td>
<td>11.45</td>
<td>4.91</td>
<td>4.05</td>
<td>1.492</td>
</tr>
<tr>
<td><strong>Customer evaluation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4.34</td>
<td>1.150</td>
</tr>
<tr>
<td>CEv1</td>
<td>1.87</td>
<td>4.67</td>
<td>6.54</td>
<td>46.96</td>
<td>22.43</td>
<td>14.02</td>
<td>3.50</td>
<td>4.39</td>
<td>1.170</td>
</tr>
<tr>
<td>CEv2</td>
<td>1.66</td>
<td>5.14</td>
<td>7.71</td>
<td>46.50</td>
<td>24.53</td>
<td>12.62</td>
<td>1.87</td>
<td>4.32</td>
<td>1.116</td>
</tr>
<tr>
<td>CEv3</td>
<td>1.42</td>
<td>6.08</td>
<td>7.24</td>
<td>48.83</td>
<td>21.03</td>
<td>11.68</td>
<td>3.74</td>
<td>4.32</td>
<td>1.164</td>
</tr>
<tr>
<td><strong>Customer satisfaction</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4.35</td>
<td>1.128</td>
</tr>
<tr>
<td>CSat1</td>
<td>4.44</td>
<td>4.67</td>
<td>8.65</td>
<td>43.69</td>
<td>22.43</td>
<td>12.62</td>
<td>3.50</td>
<td>4.27</td>
<td>1.284</td>
</tr>
<tr>
<td>CSat2</td>
<td>2.57</td>
<td>5.14</td>
<td>6.31</td>
<td>49.77</td>
<td>19.63</td>
<td>14.25</td>
<td>2.34</td>
<td>4.31</td>
<td>1.177</td>
</tr>
<tr>
<td>CSat3</td>
<td>2.34</td>
<td>4.21</td>
<td>6.54</td>
<td>41.82</td>
<td>25.47</td>
<td>15.89</td>
<td>3.74</td>
<td>4.47</td>
<td>1.207</td>
</tr>
</tbody>
</table>

*Table 15: Descriptive statistics of survey items relating to the structural model*

Table 15 provides the descriptive statistics of the individual constructs of our research model and the items of the each construct. The details therein also illustrate that a majority of respondents were non or low users of the smart shopping app. Additionally, the descriptive statistics therein also displays that a majority of customers are having higher levels of expectations regarding the firm’s responsiveness on the needs that are unique to the individuals. However, the
descriptives also reveals that a majority of customer perceives that they don’t really receive the level of experience that they expect from the firm (i.e. to the level of their expectations) but remains at tolerable range such that a majority of customers were neither highly satisfied nor dissatisfied.

Reliability Tests

Following Barclay, Higgins, and Thompson (1995), first we examined the construct reliability of the model by the individual measurement item reliability, internal consistency, and discriminant validity using the partial least square (PLS) technique of structural equation modelling in SmartPLS 2.0 (Ringle, Marc/Wende, & Sven/Will, 2005). Individual item reliability is measured through the loadings of the individual items against a predetermined threshold (M. Igbaria, Zinatelli, Cragg, & Cavaye, 1997). Our examination of individual item reliability confirmed that all of the measurement items were within the ideal tolerance threshold of 0.70 (Barclay et al., 1995; Chin, 1998).

Furthermore, to evaluated the construct validities through the test of discriminant and convergent validities. The objective of discriminant validity test is to measure how different a construct in relations to the other constructs used in a model (Schaper & Pervan, 2007). Alternatively the objective of convergent validity is to determine how well the items of a construct converge to measure a given construct. In other words convergent validity shows how well the items of a construct associate with each other to reflect the construct they are designed to measure (D. Straub et al., 2004). As such, we use the PLS technique of structural equation modelling to check the correlations of the constructs and cross loading of constructs to determine the discriminant and convergence validities that we have described earlier in the discussion. Our analysis of discriminant validly by comparing the loadings of a given construct’s indicators against the loadings of any other, and the same indicator’s load against the intended construct lend support to the discriminant validly (See Table 16). Further as seen in Table 17, our investigation of the composite reliabilities too have
affirmed the overall reliability where the indicator values were greater than the tolerance threshold of 0.70. Also, the test of discriminant and convergent validity through the Average Variance Extracted (AVE) and communalities also have confirmed the reliabilities of the measures as both indicators were higher than the suggested tolerance limit of 0.50. Further, the test of composite reliability and Cronbach’s alpha values for each construct too have confirmed the internal consistency of the constructs where all met the suggested tolerances of >0.70 suggested by Fornell & Larcker (1981).

![Table 16: Loadings and cross-loadings of the items in the structural model](image-url)
Chapter 5: Data Analysis, Results and Discussion

<table>
<thead>
<tr>
<th></th>
<th>AVE</th>
<th>Composite Reliability</th>
<th>R Square</th>
<th>Cronbachs Alpha</th>
<th>Communality</th>
<th>Redundancy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smart shopping app use</td>
<td>0.7573</td>
<td>0.9397</td>
<td>0</td>
<td>0.9294</td>
<td>0.7573</td>
<td>0</td>
</tr>
<tr>
<td>Customer evaluation</td>
<td>0.8448</td>
<td>0.9423</td>
<td>0.3918</td>
<td>0.9081</td>
<td>0.8448</td>
<td>0.1814</td>
</tr>
<tr>
<td>Customer expectations / Digital expectations</td>
<td>0.8987</td>
<td>0.9638</td>
<td>0.0794</td>
<td>0.9437</td>
<td>0.8987</td>
<td>0.0712</td>
</tr>
<tr>
<td>Customer experience</td>
<td>0.5852</td>
<td>0.9337</td>
<td>0.4559</td>
<td>0.9218</td>
<td>0.5852</td>
<td>0.2527</td>
</tr>
<tr>
<td>Customer satisfaction</td>
<td>0.8509</td>
<td>0.9448</td>
<td>0.5777</td>
<td>0.9122</td>
<td>0.8509</td>
<td>0.3841</td>
</tr>
</tbody>
</table>

Table 17: Overview of the structural model

Test of the Structural Model

Next, we tested the structural model for the standardised path coefficients, path significance and variance explained ($R^2$) in order to test the predictive power of the model using the PLS technique of the SmartPLS software. Herein we divide the data set into four different samples, namely, the sample of non users (Figure 17), sample containing users (Figure 18), and the two polarised samples - low users and high users (Figure 19 and 20). Our objective here is to investigate how the different levels of smart shopping app use (i.e. non-use, use, low use and high-use) relates to the other constructs in the research model, namely – customer expectations / digital expectations, customer experiences, and customer satisfaction. Thus, we first look at the structural model for the sample containing non-users of the smart shopping apps as below.

Figure 17: Structural model testing – Sample of non-users
Our examination of structural model for the sample containing non-users showed a non-significant paths between use of smart shopping app and the expectations and the experience. However, it showed results similar to that of traditional ECT research among other variables namely, expectations, experience, evaluation and satisfaction. The explanatory power of the model also inline with the traditional ECT applications (43.7% of the variance/R² of customer satisfaction).

Next, our analysis focuses on the test of research model for the sample containing the users of smart shopping app/s (Figure 18).

![Figure 18: Structural model testing – Sample of users](image)

Our examination of structural model for the sample containing users showed significant paths between the customers’ use of smart shopping app and the customer expectations and the customer experiences variables. Further, the model shows a significant yet a moderate pathcoefficients between the customers’ use of smart shopping app and customer (digital) expectations and customer experience. Whilst the customers’ use of smart shopping apps has the potential to explain over 14% of variance in customers’ digital expectations, it has the potential to explain over 43% of variance in customer experiences. Overall the model explains over 65% of variance in customer satisfaction for the smart shopping app users.
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Further, the comparison of the two models, on containing non-users and the other containing the users of the smart shopping app shows that for the model containing users explains the variances in expectations, experiences and satisfaction much better and significant manner compared the sample containing non-users. Thus, to further investigate the relationship between the use of smart shopping app by customers with customers’ (digital) expectations, and customer satisfaction, we next split the sample of user population (171 respondents) into two distinct groups – low users and the high users. The first group – the low users represents the customer group with smart shopping app use rating 4.5 and below in the 7 point likert, whilst the second group – high users represents the customer group who rate their smart shopping app use above 4.5 in the 7 point likert. Then, we tested the structural model using the two polarised samples mentioned above using Smart PLS software as seen in Figure 19 and 20.

![Figure 19: Structural models - polarised sample of low users](image)

As presented in Figure 19, our examination of the research model with the polarized sample containing low users showed a significant yet a moderate pathcoefficient between the customers’ use of smart shopping app and customer (digital) expectations. Next, we examine our research model with the other polarized sample comprising the high smart shopping app users as shown in Figure 20 below.
As shown in Figure 20, our examination of the research model with a polarized sample of high users indicates a strong support to our hypothesized argument on the relationship between customers’ increased use of smart shopping apps and the customers’ (digital) expectations. The path coefficients therein also signifies a strong correlation similar to what our hypothesized relationship predicts. The three structural models with three different samples comprising non-users, low users and heavy users of the smart shopping app further affirms our hypothesized relationship – customers’ increased use of smart shopping app influences and increases the customers’ expectations. Further, the relationship between customers’ use of smart shopping app and the customers experiences too displays a strong significant relationship providing support to our hypothesized relationship between the two constructs. However, the structural model fails to provide adequate evidences to support our other hypothesized relationships between the constructs in the research model.

As such, eventhough our preliminary analysis of the structural model using four different samples with PLS technique provided a reasonable support for the two hypothesised relationships mentioned above, the analysis neither provided insights into the non-linear relationships between the constructs that the original conception that ECT suggests, nor the structural models is able to explain the different tripartite relationships between customers’ use of smart shopping app, customer expectations, customer experiences and satisfaction work in combination. Thus, staying true to the
non-linearities assumed in the original conception of ECT (Susan A. Brown et al., 2012), we relax the linearity assumptions and used non-linear quadratic postulations and to investigate the aforementioned tripartite relationships. As such in the next sections we employ the statistical software package SPSS together with polynomial regression analysis technique and response surface methodology to test the individual hypothesized relationships further.

Polynomial regression (Edwards & Parry, 1993) and response surface analysis (Box & Draper, 1987; Khuri & Cornell, 1987) are two of the sophisticated analytical techniques that have been extremely popular in analyzing non-linearities between variables in the literature. This technique allows a researcher to examine the extent to which combinations of two predictor variables relate to an outcome variable (Shanock, Baran, Gentry, Pattison, & Heggestad, 2010) thus, has been widely used in multisource feedback research. The polynomial regression (Edwards & Parry, 1993) together with response surface methodology (Box & Draper, 1987; Khuri & Cornell, 1987) provides the basis required for testing and interpreting the features of surfaces corresponding to polynomial quadratic regression equations. The combination provides the sophisticated statistical sophistication required to examine the nuanced views of tripartite relationships by graphing the three variable in a three dimensional space where it provides relationships between combinations of two predictor variables and an outcome variable (Shanock et al., 2010). Next the discussion focuses on testing the individual hypothesized relationships as below.

Testing Hypotheses

Testing Hypothesis 1:

To test our first hypothesised relationship between customers’ use of smart shopping app and their (digital) expectations, we first refer back to the four structural models that we have presented in Figure 18, 19 and 20 earlier in this chapter. All three
models therein affirms that customer expectations escalate as their use of smart shopping app increases. For the total sample of users and the two polarized samples, the correlation between customers’ use of smart shopping app and customers’ (digital) expectations show a notably significant, positive path coefficients (β = 0.202 with p<0.001 for total population, β = 0.309 with p<0.001 for the polarised sample of low users of the smart shopping apps and β = 0.588 with p<0.0001 for polarised sample of high users of the smart shopping apps). Further our polarized sample of higher users of the smart shopping apps evidenced that the customers’ use of smart shopping apps have the potential to explain over 34% ($R^2 = 34.3\%$) changes in customer expectations. In order to find further evidences on the hypothesized relationship between customers use of smart shopping app and customer expectations we next plot the correlation between customers’ use of smart shopping app and customer expectations with both linear and non-linear quadratic postulations using the statistical software SPSS as below (Figure 21).
Customer / (Digital) Expectations

Both the linear and non-linear representations in figure 21 above demonstrates that the customers’ raises their expectations as with the increased use of smart shopping app lending support to our first hypothesised relationship. The line relating to the non-linear assumptions, portrays an upward curvilinear relationship, where the customer expectations stayed low for the customers who do not use the smart shopping app, but the customer expectations shifts upward as the customers’ use of smart shopping app increases. Thus, the customers’ expectations peaks for the customers’ who uses smart shopping app the most. In other words it means that the degree of smart shopping app use is positively related to the customers’ expectations such that the customers who uses the smart shopping app more raises their levels of expectations thus they anticipate more personalized firm’s responsiveness towards
their needs. Thus, our first hypothesized relationship “The degree of smart shopping app use by customers is positively associated with the customer’s expectations, such that customers with higher degree of smart app use expect firms to respond with highly personalized responses their unique needs” holds true.

**Testing Hypothesis 2:**

To test our second hypothesized relationship between customers’ use of smart shopping app and customer experience, we again refer back to the three structural models that we have presented in Figure 18, 19 and 20 earlier in this chapter. All three models therein provide reasonable evidences on the relationship between customers’ use of smart shopping app and customers’ experience, as they suggest customer experiences are positively and significantly correlated to their use of smart shopping apps. For example, for the total sample containing the users the correlation between customers’ use of smart shopping app and customer experience shows a significant, positive path coefficient $\beta = 0.696$ with $p<0.0001$, whilst for the polarized sample of low users the path between customers’ use of smart shopping app and experience shows a significant positive path coefficient of $\beta = 0.620$ and $p<0.0001$ with $R^2$ of 38.5%. Meanwhile the polarized sample of high users of the smart shopping app shows a stronger path coefficient of $\beta = 0.686$ and $p<0.0001$ with $R^2$ of 47.1%.

Whilst the three aforementioned structural models provide support for the second hypothesized relationship above, to further investigate and find further evidences on the hypothesized relationship between customers’ use of smart shopping app and customer experience we next plot the data relating to the total sample population with linear and non linear assumptions using SPSS statistical software as below (Figure 22).
Both linear as well as non-linear postulations in Figure 22, exhibits an identical correlations between customers’ use of smart shopping app and the customers’ experiences. The results indicates that customers’ increased use of smart shopping app is positively associated to the customer experiences. As such, it indicates that the firm’s has the potential to improve customers’ experience by responding to the needs that are unique to the individual customers through the customer sensing achieved through their use of smart shopping app. In otherwords, customers use of smart shopping app is related to customer experience through the firm’s sensing and responding alignment. Such that, customers who uses the smart shopping app more will have a greater potential to receive highly personalised responses from the firm towards the needs that are unique to him/her such that they will receive a superior customer experiences. Thus, the findings lent support to our second hypothesised relationship, “for the aligned firms, the degree of mobile app use by a customer is positively associated with the customer’s experiences, such that customers with
higher degree of smart shopping app use will receive highly personalized responses to their unique needs hence the superior experiences”.

**Testing Hypothesis 3:**

Next we look at our third hypothesized relationship the “Alignment between customers’ raising digital expectations and their experiences is positively related to their satisfaction, such that customers become satisfied when the difference between digital expectations and actual experiences is at its lowest or when experience exceeds digital expectations”. Thus, we look at the tripartite relationship between customers’ (digital) expectations, customer experience and customer satisfaction. So to test the above tripartite relationship, next we employ the polynomial regression analysis together with response surface methodology as follows. Herein we relax the linearity assumptions in order to stay true to the non-linearities assumed in the original ECT conception (Susan A. Brown et al., 2012; Oliver, 1977; Oliver, 1980b). Thus, we employ the following polynomial equation to test the aforementioned tripartite relationship between expectations, experience and satisfaction:

$$ \text{Customer Satisfaction} = f (\text{Customers’ Digital Expectations}^*, \text{Customer Experience}^{**}) - (1) $$

$$ Z = \beta_0 + \beta_1 \text{CExpt}^* + \beta_2 \text{CExpr}^{**} + \beta_3 \text{CExpt}^2 + \beta_4 (\text{CExpt} \times \text{CExpr}) + \beta_5 \text{CExpr}^2 + e $$

Where,

* $\text{CExpt}^* = \text{Customers’ Digital Expectations}$

** $\text{CExpr}^{**} = \text{Customer Experience}$

Then, we followed the procedure outlined by Atwater, Waldman, Ostroff, Robie, and Johnson (2005) to perform polynomial regression analysis to obtain the
coefficients. As such we used the following Syntax in SPSS statistical software to obtain the coefficients.

```
COMPUTE EXPTcntr = Expectation - 4.
COMPUTE EXPRcntr = Experience - 4.
EXECUTE.
COMPUTE xsquared = EXPTcntr*EXPTcntr.
COMPUTE xy = EXPTcntr*EXPRcntr.
COMPUTE ysquared = EXPRcntr*EXPRcntr.
EXECUTE.

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS BCOV R ANOVA
/CRITERIA = PIN(0.05) POUT(0.10)
/NOORIGIN
/DEPENDENT Satisfaction
/METHOD = ENTER EXPTcntr EXPRcntr xy xsquared ysquared
```

However, the higher order polynomial equations that often result from a polynomial model are difficult to interpret (Edwards, 2001). For example, simply inspecting the signs and magnitudes of the coefficients reported in the analysis (output obtained by running the above syntax) reveals very little as to the shape of the surface they represent (see Table 18).
Table 18: Results of polynomial equation--(1), involving customer (digital) expectations, experience and satisfaction

<table>
<thead>
<tr>
<th></th>
<th>Beta coefficient / unstandardized regression coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept / constant</td>
<td>4.693</td>
</tr>
<tr>
<td>Expt = Customer / Digital expectations</td>
<td>0.055*</td>
</tr>
<tr>
<td>Expr = Customer experience</td>
<td>0.533**</td>
</tr>
<tr>
<td>Expt$^2$</td>
<td>-0.033</td>
</tr>
<tr>
<td>Expt$^2$ Expr</td>
<td>0.018</td>
</tr>
<tr>
<td>Expr$^2$</td>
<td>0.046</td>
</tr>
</tbody>
</table>

* p<0.0001, **p<0.05

Table 18: Results of polynomial equation--(1), involving customer (digital) expectations, experience and satisfaction

The response surface methodology presented by Khuri and Cornell (1987) provides the basis required for testing and interpreting the features of surfaces corresponding to polynomial quadratic regression equations, where the response surface is used as a visual aid to get a richer and meaningful deeper understanding of complex polynomial equations. The combination provides the sophisticated statistical nuance required to examine the extent to which the combination of two predictor variables relates to an outcome variable, in particular when the discrepancy (or match) between the two predictor variables is a fundamental consideration (Shanock et al., 2010). (Appendix C provides the details of polynomial regression and response surface methodology).

Thus, to test H3, we first investigated the relationship between customers’ (digital) expectations, experiences and their satisfaction using response surfaces for the polynomial regression equation above. Table 18 above provides the coefficients of the regression analysis. Following which the coefficients were inferred using the response surface methodology where the Table 19 summarises the results of the response surface analysis. Figure 23 below depicts the response surface for the
quadratic polynomial equation for customers’ (digital) expectations, customer experiences and customer satisfaction.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Test stat (t)</th>
<th>p-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>a1: Slope along x=y (as related to Z)</td>
<td>0.59</td>
<td>0.11</td>
<td>5.507</td>
<td>0.000</td>
<td>Significant</td>
</tr>
<tr>
<td>a2: Curvature on x=y (as related to Z)</td>
<td>0.03</td>
<td>0.03</td>
<td>1.186</td>
<td>0.236</td>
<td></td>
</tr>
<tr>
<td>a3: Slope along x= -y (as related to Z)</td>
<td>-0.48</td>
<td>0.03</td>
<td>-14.286</td>
<td>0.000</td>
<td>Significant</td>
</tr>
<tr>
<td>a4: Curvature on x= -y (as related to Z)</td>
<td>0.00</td>
<td>0.04</td>
<td>-0.119</td>
<td>0.905</td>
<td></td>
</tr>
</tbody>
</table>

Table 18: Results of the regression analysis – Testing slopes and curves between the three variables customers’ digital expectations, customer experiences and customer satisfaction

The solid line on the floor of the graph represents the line A to B on the three-dimensional surface of Figure 23, where it depicts the perfect agreement between the
two independent variables of customers’ digital expectations and customer experience (i.e. X=Y). As suggested by H3, the alignment between customers’ digital expectations and their actual experience is positively related to customer satisfaction where the line of alignment has a positive slope through the line from B to A. Thus, the agreement between raising customer expectations which resulted due to the increased levels of smart shopping app use and their ultimate shopping experience matters to the customers’ final satisfaction. The level of customer satisfaction is lowest at the front corner of the graph along the line of agreement where customers’ expectation stays low as the customers use of smart shopping app stays low (i.e. low use of smart shopping app) while customer experience also stays low when their use the smart shopping app stays low. Respectively, the satisfaction becomes increasingly higher towards the back of the graph as customer expectation and experience both reach higher levels, which is also corresponds to the increase levels of smart shopping app use by the customers (as discussed in H1 and H2 previously).

In contrast, the dashed line on the floor of the graph in Figure 23 above depicts the line of incongruence (the X and Y variables are not in agreement, i.e. X=-Y) and it represents the surface along the line C to D. Moving away from the interception of the two lines to either the left or right direction shows the degree of discrepancy between expectation (customers digital expectations) and experience and how they relate to customer satisfaction. In summary, the analysis shows that customers become satisfied when the difference between expectations and actual experiences is at its lowest or when experience exceeds their initial expectations.

In addition, the expectation curve (surface along the line B to D) and experience curve (surface along the line B to C) also suggest the value of aligning customer expectations and experiences in order to achieve superior customer satisfaction. The expectation curve explains how customer expectations relate to customer satisfaction. Alignment between customer expectations and actual experience increases when moving along the dotted line on the floor towards the intersection of the two lines. While the match between expectation and experience reaches the maximum when it reaches the solid line A to B, towards the point C from the A-B solid line illustrates
the experience that exceeds the customer expectations. Further, as the response surface depicts, when customer experience is at its lowest, customer expectation influences customer satisfaction (surface along the X axis, B through D along the surface – expectation curve). However, when customer experience is at its maximum, the influence of expectations on satisfaction is not evident as satisfaction does not change with the increase of expectations (surface along the X axis when customer experience is at its maximum = +4, C through A along the surface). This explains that customer experience intervenes in the relationship between customer expectation and satisfaction, such that a firm should either align or exceed customers’ expectations in order to achieve the desired levels of customer satisfaction (lending support to H3).

**Testing Hypothesis 4:**

The fourth hypothesis, ‘*For the customers’ with higher smart app use, they become extremely dissatisfied if the experience-expectations gap is high and the difference is assimilated towards expectations, as such expectations define the satisfaction*’ is relates to the tripartite relationship between customers’ use of smart shopping app, customers’ experience and customers’ satisfaction. As such we examine our fourth hypothesized relationship using the following polynomial equation involving customers’ use of smart shopping app, customer experience and customer satisfaction:

Customer Satisfaction = $f$ (Customers’ use of smart shopping app***, Customer Experience**) ---- (2)

$$Z = \beta_6 + \beta_7 CSU^{***} + \beta_8 CExpr^{**} + \beta_9 CSU^2 + \beta_{10} (CSU \times CExpr) + \beta_{11} CExpr^2 + e_1$$

Where,

***CSU=Customers’ smart app use
**CExpr=Customer experience.**

We then followed the procedure outlined by Atwater et al. (2005) to perform the polynomial regression analysis to obtain the coefficients using the following Syntax.

Syntax for Customers’ shopping app use and Experience

```plaintext
COMPUTE DCcntr = Customers’ shopping app use - 4.
COMPUTE EXPRcntr = Experience - 4.
EXECUTE.
COMPUTE xsquared = CSUcntr*DCcntr.
COMPUTE xy = CSUcntr*EXPRcntr.
COMPUTE ysquared = EXPRcntr*EXPRcntr.
EXECUTE.
```

```
REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS BCOV R
ANOVA
/CRITERIA = PIN(0.05) POUT(0.10)
/NOORIGIN
/DEPENDENT Satisfaction
/METHOD = ENTER CSUcntr EXPRcntr xy xsquared ysquared
```

Then the respective coefficients of the analysis obtained by running above Syntax on SPSS statistical software are reported in Table 20.
Table 18: Results of polynomial equation—(2), involving customers’ use of smart shopping app, customer experience and customer satisfaction

<table>
<thead>
<tr>
<th></th>
<th>Beta coefficient / unstandardized regression coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept / constant</td>
<td>4.517</td>
</tr>
<tr>
<td>CSU = Customers’ smart shopping app use</td>
<td>0.008</td>
</tr>
<tr>
<td>CExpr = Customer experience</td>
<td>0.677**</td>
</tr>
<tr>
<td>CSU²</td>
<td>0.026</td>
</tr>
<tr>
<td>CSU*CExpr</td>
<td>0.076</td>
</tr>
<tr>
<td>CExpr²</td>
<td>-0.016</td>
</tr>
</tbody>
</table>

* p<0.0001, **p<0.05

Table 19: Results of polynomial equation—(2), involving customers’ shopping app use, customer experience and customer satisfaction

As the values presented in the table 20 above explains very little to the surface they represent. Thus, to test the hypothesis, we used the results of the polynomial equation shown in Table 20 above to create the response surface through response surface methodology for the polynomial equation above. Figure 24 presents the graphical representation between the three variables - customers’ use of smart shopping app, customer experience and customer satisfaction. Further, Table 21 presents the results corresponding to the response surface that represent the polynomial equation above.
In order to test our fourth hypothesized relationship we first refers to the response surfaces depicted in Figure 24. The line that represent from the point Q through to S, use of smart shopping app line (when the experience at its lowest / experience = 1), shows that customer satisfaction decreases as the customers’ use of smart shopping app increases. The customer satisfaction reaches its lowest when the customers’ use of smart shopping app reaches its maximum when the experience is at its lowest (point S). The point also corresponds to the point D of Figure 23, as point D
also corresponds to the point where customers’ use of smart shopping app reaches its maximum. As such, the point S is the point which expectation-experience gap is at its maximum. Also, towards the point S the expectation-experience gap assimilated towards the expectations, where towards point S the customer satisfaction gradually decreases. Thus, the evidences supports our fourth hypothesized relationship, “for the customers’ with higher smart app use, they become extremely dissatisfied if the experience-expectations gap is high and the difference is assimilated towards expectations, as such expectations define the satisfaction”.

**Testing Hypothesis 5:**

We next test our fifth hypothesized relationship, “For the customers’ with low smart app use, they become extremely satisfied if the experience-expectations gap is high and the difference is assimilated towards experience, as such experience define the satisfaction”. we again refers back to the graphical representation of the relationship between customers’ use of smart shopping app and customer experience depicted in Figure 24.

The line that represent from the point Q through to R, customer experience line (when the customers use of smart shopping app at its lowest / use = 1), shows that customer satisfaction increases as their experience getting better, when the customers’ use of smart shopping app at its lowest. The customer satisfaction reaches its highest when the customers use of smart shopping app is at its lowest and the experience is at its highest (point R). The point also corresponds to the point C of Figure 23, as point C also corresponds to the point where customers’ expectations at its minimum. As such, the point R is the point which expectation-experience gap is at its maximum. Also, towards the point R the expectation-experience gap assimilated towards the experience, where towards point R the customer satisfaction gradually increases. Thus, the evidences supports our fifth hypothesized relationship, “for the customers’ with low smart app use, they become extremely satisfied if the experience-
expectations gap is high and the difference is assimilated towards experience, as such experience define the satisfaction’.

**Testing Hypothesis 6:**

Next we test our sixth hypothesized relationship, “*higher levels of customers’ use of smart app leads to higher customer expectations thus leading to lower levels of customer satisfaction, but high expectations leads to high satisfaction in the presence of high experience (i.e. high expectations and high experience work together for high satisfaction)*”. The above hypothesis is related to four variables that we have discussed in the previous five hypothesized relationships namely the customers’ use of smart shopping apps, customers’ (digital) expectations, customer experience and customer satisfaction. Thus, we herein refers to the four different graphical illustrations between four constructs that we have mentioned above in Figures 21, 22, 23 and 24 earlier in this chapter.

The results in Figure 21 and Figure 24 both indicate that the higher levels of customers’ use of smart shopping app increases the customers’ expectations. Alternatively, the Figure 23 suggests that higher customer expectations results lower levels of customer satisfaction in the absence of adequate levels of experience (see line B to D). Meanwhile, Figure 24 illustrates that heightened levels of customers’ smart shopping app use lowers customer satisfaction in the absence of adequate levels of experience (see line Q to S). However, Figure 23 portrayed that customer satisfaction stayed high even as the customer’s expectations reached higher levels in the presence of superior levels of customer experience. Alternatively, the Figure 22 too portrayed that customers’ higher usage of smart shopping app results improved customer experiences. As such, our findings suggests that high expectations could work for higher satisfaction at the presence of higher experiences eventhough higher use of smart shopping app use relates to higher expectations thus predicts lowered customer satisfaction. Thus, the evidences supports our predicted hypothesized relationship, “*higher levels of customers’ use of smart app leads to higher customer expectations thus leading to lower levels of customer satisfaction, but high*
expectations leads to high satisfaction in the presence of high experience (i.e. high expectations and high experience work together for high satisfaction)

Testing Hypothesis 7:

Next we test our seventh and final hypothesised relationship, “Customers’ experience fully mediates the relationship between customers’ use of smart app and customer satisfaction, such that customer experience defines the level of customer satisfaction” as below. To find evidences, first we refer back to the discussion we earlier had in the testing of our 6th hypothesized relationship above.

The discussion therein reflects that despite the higher use of smart shopping app results lower satisfaction (resulting due to the (i) inversely proportional relationship between the customers’ use of smart shopping app and customer satisfaction, and (ii) directly proportional relationship between customers’ use of smart apps and customers’ expectations), higher expectations still works well for higher customer satisfaction in the presence of higher customer experiences. This suggests that experience mediates the relationship between the relationships of customers’ use of smart shopping apps-customers’ (digital) expectations-customer satisfaction. Thus, in order to test the mediation role of customer experience on the relationship between customers’ use of smart shopping app and customer satisfaction, we next tested the mediating effect of customer experience on the customers’ use of smart shopping apps-satisfaction relationship.

As mediation in general entails the intervening effect of an antecedent variable on a dependent variable, in this study we tested the intervening effect of customer experience on the relationship between customers’ use of smart shopping apps and customer satisfaction using two approaches, namely, several regression analyses (Baron & Kenny, 1986) and Sobel’s (1982) product of coefficients method.
In several regression analyses, we tested the effect of the independent variable (customers’ use of smart shopping app) on the dependent variable (customer satisfaction) with and without the mediating variable (customer experience) and compared the significance of the coefficients at each step. The results of the several regressions analysis, as summarised in Table 22, supported the proposition that customer experience mediates the relationship between customers’ use of smart shopping app and their satisfaction.

<table>
<thead>
<tr>
<th>Test</th>
<th>$R^2$</th>
<th>Adjusted $R^2$</th>
<th>Std. Error</th>
<th>Level of Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customers’ use of smart shopping app-Experience</td>
<td>0.4923</td>
<td>0.4916</td>
<td>0.0454</td>
<td>0.000</td>
</tr>
<tr>
<td>Customers’ use of smart shopping app-Satisfaction</td>
<td>0.1470</td>
<td>0.1468</td>
<td>0.0838</td>
<td>0.000</td>
</tr>
<tr>
<td>Experience-Satisfaction</td>
<td>0.3700</td>
<td>0.3768</td>
<td>0.1116</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table 22: Results of several regression analyses

We then performed the Sobel’s (1982) product of coefficients test to examine the role of experience on the relationship between customers’ use of smart shopping app and customer satisfaction. The results also demonstrated that customer experience mediated the relationship between customers’ use of smart shopping apps and customer satisfaction (Sobel test statistic=5.630, p<0.0001). The mediation portrayed was complete mediation as the direct effect between the independent variable (customers’ use of smart shopping app) and the dependent variable (customer satisfaction) decreased from 0.383 to -0.109 with t-statistics less than 1.96 (t=0.880).

Following these two tests, we next examined the type of mediation that experience had on the relationships between customers’ use of smart shopping app - customer satisfaction using the response surfaces presented in Figures 23 and 24. The graphical illustrations too revealed that experience fully mediated the relationship between customers’ use of smart shopping app and customer satisfaction. For example, the two diagrammatic representations demonstrated that the influence of
heightened levels of customers’ (digital) expectations results as a result of increased smart shopping app use on customer satisfaction completely diminished as the customer experiences reached the higher levels (B-D line through to C-A line and Q-S line through to R-P line). Further the comparisons between B-D line against C-A line, reveals that in the absence of experience changes in expectations does influences the customer satisfaction (Moving from point B towards D) whilst in the presence of experience, changes in expectations does not influences the customer satisfaction (Moving from point C towards A). Similarly, the comparison of Q-S line against R-P line, shows that in the absence of experience changes in customers’ use of smart shopping app does influences the customer satisfaction (Moving from point Q towards S) whilst in the presence of experience, changes in customers’ use of smart shopping app does not influences the customer satisfaction (Moving from point R towards P). Thus, the evidences supports our seventh and final hypothesized relationship, “Customers’ experience fully mediates the relationship between customers’ use of smart app and customer satisfaction, such that customer experience defines the level of customer satisfaction”.

DISCUSSION

This study attempted to understand the implications of unparallel levels customer interactions that contemporary firm’s achieved through the pervasive ubiquitous technologies such as smart devices (e.g. smart phones, PDA’s) and associated apps (e.g. smart shopping apps) on customers, in particular on customer expectations, perceived experiences and the ultimate customer satisfaction. As such, we developed our conceptual model involving a deployment of smart shopping apps, customers’ use of the app, user expectations as customers, actual shopping related experiences perceived as customers by the users, their evaluation of experience against pre-formed expectations and their satisfaction.

As such this study was undertaken in the context of firm’s deployment of smart devices and apps for ubiquitous sensing and responding for gaining competitive
advantage. As such the firms are deploying multitude of technologies and associated applications contemporarily for sensing the customers’ needs, wants and expectations through the ubiquitous interactions in these digitized mediums in order to respond to such individuals unique needs, wants and expectations better than the competitors. In other words the firms aim to optimoze their agility towards customers through such ubiquitous digitized engagements. Thus, the firms anticipate their customers to engage more in such interactions in order for them to know about customers’ needs, wants and expectations better.

In this study, we have developed a conceptual model involving customers’ use of smart shopping apps, customers’ (digital) expectations, curtomer experiences, customers’ evaluation of their perceived experiences and customer satisfaction in order to understand the interactions between customers’ use of smart shopping apps, its implications on customers and a firms customer agility. Our results indicated that as customers use the smart shopping apps more the customers expects more from the firm. We also found that the increased use of smart shopping app by the customers positively relates to their perceived experiences. Further, our empirical tests suggests that the firms need to improve their responsiveness towards the needs that are unique to the individual customers’ is critical for the customers who uses the smart shopping app more. Further, we found that for customers who uses the smart shopping app more, the difference between their expectations and experience is critical as in such cases the difference is assimilated towards the expectations hence the customers could get very dissatisfied when the difference is high. We also found that for the customers who uses the smart shopping app less, the difference between their expectations and experience is assimilated towards experience thus, often they become satisfied. We also found that the experience is mediating fully (complete mediation) on the relationship between customers’ use of smart shopping apps and customer satisfaction. Further we found that when higher expectations could lower the satisfaction, higher expectations and higher experiences could work together for higher customer satisfaction. It suggests that when the customers’ use the smart shopping app more, the customers raises their levels of expectations thust could easily get dissatisfied, but if the firm is capable of responding to such customers’ unique
individual requirements in a personalized manner and improve their experience the firm can achieve higher levels of customer satisfaction. Further our comparisons of the conceptual model using four different polarised samples, the non-users of the smart shopping app, users of the smart shopping app, low users of the smart shopping app and the high users of the smart shopping app revealed that the degree of smart shopping app use by the customers has a greater potential to explain the variance in customer expectations, their perceived experiences and customer satisfaction. Thus, the customers’ use of smart shopping apps is becoming a strategic imperative for the contemporary firms.

As our findings suggest, the more the firms are connected to their customers (ubiquitous customer connectivity), more opportunities it creates for the firms for sensing their customers changing needs, wants and expectations, while on the other hand the increased firm-customer connectivity could influence what customers’ expect from the firms. Herein we see a pattern evolving from customers’ use of smart shopping apps towards firm-customer connectedness as a result of the firm-customer connectivity achieved through smart shopping app. Thus, we argue here that firm’s deployment of digitized channels for ubiquitous customer connectivity could leads to a firm-customer digital connectedness (an emotional, psychological bonding, a feeling of belongingness or dependency) in the longer run. We see a notion similar to connectedness construct have been discussed in other fiefs emerging.

Hence, in order to understand the digital connectedness construct, we suggest investigating the general notions of connectedness have been discussed in different fields and in different contexts as reported in prior research (e.g...Jung, 2008; Jung, Qiu, & Kim, 2001; Cristel Antonio Russell, Andrew T. Norman, & Susan E. Heckler, 2004; Cristel A Russell, Andrew T Norman, & Susan E Heckler, 2004). For example in extant literature, the term connectedness discussed in a broader sense, to signify the quality of a relationship, the connection between two things or how much two things being in touch (Townsend & McWhirter, 2005). Meanwhile some others, such as Pavlovich and Krahne (2012) conceptually refers connectedness as a positive collective association between two different things, where it reflects ‘how-well’ two
things interact or the amount of interaction that supports a coalition or connection between two things. Similarly, the term connectedness has been used differently to discuss different types of connections between two or more variable in various different contexts in various different fields.

For example, in the studies of student-school connectedness, the term connectedness used to discuss the student-school relationship in many different dimensions. In some studies student-school connectedness means the feeling connected to or being part of the school (McNeely, Nonnemaker, & Blum, 2002), whilst in other discussions connectedness refers to the the school engagement, school attachment, or emotional bonding to the school (Libbey, 2004). Similarly, connectedness discussions in family environments (Cooper, Grotevant, & Condon, 1983), the term connectedness refers to the individuals openness to the family and the amount of ideas expressed within the family environment. Further the studies involved in human’s connectedness the term connectedness refers to the nature of the relationship, where they describe the term connectedness as feeling of emotionally connected (Mayer & Frantz, 2004). In essence, some have defined connectedness as the interdependence (Stoll, Edwards, & Foot, 2012), whilst for others connectedness indicates the quality of the relationship, cohesiveness, the connection between (Dutton & Heaphy, 2003), or the degree of immersion in an affiliation. Similarly, the studies that refers to the term connectedness in the context of technology discusses it temrs of internet connectedness (Jiang, 2014), or connectedness to television (Cristel Antonia Russell et al., 2004; Cristel A Russell et al., 2004), thus have been explained as the level of access, degree of interactions/usage or the degree to which a person is connected/attached to a particular technology. In similar line, M. DeSanctis (2013) has used the term digital connectedness to imply how much a person glued or attached to a [digital] technology.

Thus, given the context of mobile apps, we argue here that the two different terms digital connectivity and digital connectedness that we introduce herein can be viewed in two different yet a related way. The term digital connectivity (rather the degree of digital connectivity) can be treated as a continuum of digital medium
(mobile app) use, following the system use conceptions in IS literature (A. Burton-Jones & Gallivan, 2007; A. Burton-Jones & Grange, 2013; A. Burton-Jones & Straub, 2006). This also falls in line with the discussion of M. DeSanctis (2013) on digital connectedness, as therein the digital connectedness implies ‘how-much’ a person utilizing the attached technology. As such the notion digital connectivity (firm-customer connectivity via a digital medium) refers to the degree (how-well) as well as the amount (how-much) of engagement that a person (customer) maintains over a period of time in a digitized environment. When applies this notion to the context of this study (focussing on smart shopping apps) the digital connectivity, refers to the extent to which a customer is repetitively uses a smart shopping app to interact/engage with a firm, where the customers’ use of smart shopping app enables initiation or continuance of firm-customer relationship (i.e. digital connectivity is leading to digital connectedness). Thus, the firm-customer digital connectedness through smart (shopping) apps is not a simple reflection of a customer’s ‘use’ of a firm’s customer focused smart (shopping) app, rather a customer’s use of a digital technology that allows a deeper, closer and intimate relationship between the customer and the firm in a longer run. As such when customers digitally engage with a firm in a more meaningful way as discussed above (digital connectivity), the firm is able to get rich insights about such individual customer’s preferences as such activities leave wealth of digital information footprints (Chi et al. 2010), thus leading towards firm-customer digital connectedness. The more the customers are get digitally connected (degree of digital connectivity), the more opportunities are created for firms to learn about individual customers (firm’s customer sensing possibility) and provide firm’s with greater possibility of achieving customer connectedness. Whilst, customers also are well aware that the firms have the potential to know about their activities on the smart apps through the smart features of smart apps, such interactions potentially influences customers’ connectedness to a firm thus such innate relationships are influencing the customers’ expectations and the perceptions. Hence, we suggest future research to focus on such innate connectedness concepts to better understand the implications of ubiquitous sensing and responding on customer perceptions and firms agility.
CHAPTER SUMMARY

This chapter elaborated the data collection, analysis and interpretation that have been concisely described earlier in the research design section in the introduction chapter. As such, first we discussed the data preparation, data description, test of content and construct validity, model measurement, hypothesis testing and discussion of findings in detail. The analysis of data was performed using SPSS and SmartPLS statistical software packages. In particular the descriptive statistics were derived through SPSS software, whilst the structural model testing and the construct validities were performed through discriminant and convergent validities through partial least square method of structural equation modelling using SmartPLS software. Finally the hypothesis tests were carried out using polynomial regression analysis and response surface methodology. Next, in Chapter 6, we touch upon the concluding remarks, implications and limitations of the research.
CHAPTER 6: CONCLUSIONS, IMPLICATIONS AND LIMITATIONS

This study sought to conceptualize, operationalize and apply the notion of customers’ use of smart shopping apps in contemporary business environment to study the implications of customers’ use of smart shopping apps, the customer sensing that the firm’s achieved as a result of customers’ use of the smart shopping apps and the related implications of such sensing on customer expectations, customers’ perceptions and firms agility in the context of consumer retail. Our discussion on the conceptual framework highlighted the impact of customers’ use of smart shopping apps on agility and the need to revisit the implications of the customers’ use of smart shopping apps on customer expectations, experiences and satisfaction. Most past studies on customer expectations, experience and satisfaction were focused on customer expectations formulated on products or services prior consuming them. However, in the context of this study the customer expectations are continuously getting influenced and gets elevated by the firms’ ability to sense customer needs through firm-customer digital interactions as in customers’ use of smart shopping apps. Thus, the heightened customer expectations resulted due to the increased use of smart shopping apps by the customers, their demand for unique shopping experiences and ultimate customer satisfaction highlight the need to conceptualize the notion smart shopping app use, and investigate the implications of intensified ubiquitous interactions firms achieved through customers’ use of smart shopping apps on customer expectations, customer perceptions and firm’s agility. As such our conceptualization and measurement are driven to fill this gap.

Thus, we conceptualized the customers’ use of smart shopping apps in the context of contemporary consumer retail firm’s deployment of smart mobile shopping apps for virtual shopping in relations to the system use construct in prior IS research. As such we differentiated the customers’ use of smart shopping apps from the prior conceptualizations of system use in IS research. Most past studies of system/technology use has focused on the use of simple functional applications such
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as word processing, spreadsheets (known as functional IT) or enterprise IS/IT such as enterprise resource planning solutions or decision support systems mainly focusing on the traditional IS/IT use by individuals for professional use in office environments. Whilst, the discussions of connectivity and connectedness has been discussed deeply in IS/IT as well as in other fields, the notion connectedness in IT/IS predominantly discussed the digital divide and one’s dependency to a technology (e.g. connectedness to internet, TV, mobile phones etc.). Meantime, the literature in IT / IS also discussed on the ubiquity of technology, rise of digital natives, their engagement with technology and innovative deployments of ubiquity of technology such as in smart shopping apps for ubiquitous customer connectivity (through the customers’ use of smart shopping apps) for sensing and responding highlighting the need to re-conceptualize IT/system use in light of ubiquitous digital connectivity and its implications to both research and practice.

Essentially, digital connectivity in this discussion refers to the customers’ use of smart shopping apps where we argue here that the customer connectivity that firms achieved through smart apps could leads to firm-customer digital connectedness in the longer run. We conceived the notion smart shopping app use by customers as a formative construct whilst its respective measures derived from prior system/technology use studies, as reflective. We followed a structured, theoretical two stepped approach suggested by A. Burton-Jones and Straub (2006) to deconstruct the notion system use and re-construct the construct customers’ use of smart shopping app to ensure the development of complete, content valid and contextualized measures for smart shopping app use construct that fits our study objectives, theory as well as the methods. Conceived primarily through the deployment of ‘smart mobile shopping apps in consumer retail’, this study presented a conceptual framework involving customers’ use of smart shopping apps, and the implications of customers’ use of smart shopping apps on customers (digital) expectations, customers’ perceived experiences and customer satisfaction. In doing so we discuss its implications to both research and practice, and we then tested the model with quantitative empirical data obtained through a field study.
First, we tested the relationship between customers’ use of smart shopping apps and customer expectations empirically with both linearity as well as non-linearity assumptions. Our analysis revealed that, with linear assumptions, the model predicted a continuous upward trend in expectations as the customers use of smart shopping app increased. With the non-linear assumptions, the model demonstrated an upward curvilinear relationship, where the levels of expectation were low when the customers were not using the smart shopping apps, but moved upwards slowly when they start using the smart shopping apps; the momentum then increased as the use of smart shopping app increased and peaked as use reached higher levels. We then tested the customers use of smart shopping apps against customer experiences, again with both the linear and non-linear postulations. Our analysis showed a positive relationship between the degree of smart shopping app use by customers and the customers’ experience, thus leading to customer satisfaction for the linear and non-linear assumptions.

Next, taking the matching perspective of alignment, we analysed the tripartite relationships between customers’ digital expectations, customers’ experiences and customer satisfaction through the lens of ECT and employing polynomial regression technique together with the response surface methodology in the analysis. Our investigation of the relationship between customer expectation, experience and satisfaction revealed that: (1) the alignment between digital expectations and customers’ experience is positively related to customer satisfaction, such that the customer expectations resulted due to the increased use of smart shopping app needs careful management by the firms in order to make customers satisfied, and (2) firms at least need to manage their customers’ rising digital expectations by providing matching experiences or, ideally, by exceeding their customers’ digital expectations in order to make them satisfied. Next, our investigation of the relationship between customers’ use of smart shopping apps, customers’ experiences and customer satisfaction indicated that the congruence between customers’ use of smart shopping app and customer experiences is an important determinant of customer satisfaction, while the increase in smart shopping app use gives the firm more opportunities to know their customers’ unique needs better, to provide unique customer experiences.
and hence to achieve higher levels of customer satisfaction. Further, our investigations on the direction of incongruence between customers’ use of smart shopping app and their experience revealed that (1) for the customers with higher smart shopping app use, the incongruence is assimilated towards expectations when the difference between expectations and experience is high thus expectations defines the customer dissatisfaction (disappointment), whilst (2) for the customers who uses the smart shopping app less, the incongruence is assimilated towards experience when the difference between expectations and experience is high thus experience defines the customer satisfaction (excitement). Further, our investigation of the intervening effect of customer experience on the relationships between customers’ use of smart shopping app, customer expectation and customer satisfaction revealed that the impact of increased use of smart shopping apps and heightened customer expectation on customer satisfaction was only prominent when the customer experience was inadequate or mediocre.

Following these steps, we investigated the role of experience and its mediating or intervening effect on the relationship between customer expectation-customer satisfaction and customers’ use of smart shopping apps-customer satisfaction. The results revealed that the higher expectations resulting from the increased levels of smart shopping app use by the customers influences the customer satisfaction negatively in the absence of adequate levels (or in the presence of inferior levels) of experience, whereas high expectations and experience worked together for high satisfaction. Thus, we further investigated the nature of mediation using the two response surfaces and two traditional approaches, namely, (1) several regression analyses (Baron & Kenny, 1986) and (2) Sobel’s (1982) product of coefficients method. All three methods endorsed the idea of the mediating role of customer experience, with the test results affirming that the mediation of customer experience on the said relationships was complete mediation.

This suggest that a firm’s digital business strategy should not only focus on the deployment of combinations of information, computing, communication and connectivity technologies for ubiquitous customer connectedness but also needs to be
aligned with their customers’ changing needs and expectations in order to deliver unique customer experiences and hence superior customer satisfaction. Therefore, firms need to put more emphasis on customer experience management in digital engagements as it is tedious and tricky for firms to strike a balance between customer sensing and customer expectations management in such environments.

**Implications, limitations and follow-on research**

This study provides several contributions to both research and practice. First, this research provides a logical, systematic framework for conceptualising the ‘use’ of smart shopping app which is relevant to firm’s sensing thus relates to customer expectations taking the example of smart phone enabled ubiquitous firm-customer digital engagements in the fast moving consumer goods retail sector. Next, we developed new measures from existing system usage measures to operationalise customers’ use of smart shopping apps using the two-step approach suggested by A. Burton-Jones and Straub (2006), with careful attention to the characteristics of usage that matter for firm’s sensing and customers’ digital expectations. As such, this discussion also contributes to the cumulative progress of measuring system and technology usage, as the method used herein to conceptualise usage and develop measures clarifies the subset of usage being measured, and theoretically justifies the measures employed for customers’ use of smart shopping app that promote firm-customer connectivity. We employed our conceptualisation of ‘use of smart shopping app’ in a real world example to investigate the implications of ubiquitous firm-customer customer connectivity achieved through smart shopping apps. Thus, we empirically tested a conceptual model involving customers’ use of smart shopping apps, customer expectations, customer experiences and customer satisfaction using polynomial regression and response surface methodology. Further, using two traditional methods of analysis (several regression analyses and Sobel’s test) and the response surfaces, we highlighted the mediation role of customer experience on customer satisfaction and showed the importance of aligning the heightened customer expectations that result from increased use of smart shopping apps by the customers with better managed customer experiences in order to achieve desired levels of
customer satisfaction. Our use of non-linear assumptions and application of polynomial regression and response surface methodology in this study also contribute to the research methodology as few studies in IS have employed these two techniques before. Table 23 presents a summary of the key points in the study.

### Key findings of the study

- Firms’ deployment of ubiquitous digital technologies such as mobile apps for customer sensing and responding influences the customers’ expectations.

- The formation of customer expectations in such digital engagements (i.e. digital expectations) is fundamentally different to how they are formed in traditional product/service scenarios used in the original ECT conception.

- Firm-customer ubiquitous connectivity achieved through smart apps influences and heightens the customers’ expectations; thus, it could have a negative influence on customer satisfaction in the absence of adequate levels of experience.

- Whilst high customer expectations negatively influence customer satisfaction, high customer expectations and high levels of experiences work together for high customer satisfaction.

- The degree of smart app use by customers should be matched with adequate or superior customer experiences corresponding to different degrees of digital interactions in order to make the customers satisfied and maintain their levels of satisfaction.

- The customers use of smart shopping app could work negatively for the firm and thus could work against customer satisfaction in the absence of adequate levels of customer experience due to the heightened levels of expectations. However, superior levels of customer experience completely nullify such effects to create greater levels of customer satisfaction.

- As it is tedious and impractical for a firm to manage individual customer expectations in digital environments, and considering that experience completely mediates the expectation-experience relationship, firms should focus more on managing customer experience.

Table 21: Summary of key points of the study

As summarised in Table 8 above, this study has several implications for both research and practice. Regarding the implications for research, we relaxed the traditional linearity assumptions and demonstrated that in doing so it is possible to
uncover complex interactions between the constructs in a research model. We recommend that future researchers relax the linearity assumptions and use new analytical methods, such as the three-dimensional modelling techniques of polynomial regression and response surface methodology, especially when they use theoretical viewpoints that suggest non-linear relationships.

While we discussed the implications of a firm’s customer-focused digital mobile strategy in the case of firm-customer ubiquitous digital connectivity achieved through smart shopping apps, we suggest that future researchers look at business-IT alignment in a new light, namely, the alignment between the digital business strategy (IT and business strategy as one) and customers. In particular, we suggest studying the alignment between the digital business strategy and customer expectations to provide unique customer experiences and customer satisfaction by understanding the customers’ perspective on IT alignment.

In addition, since our non-linear assumption revealed that customers’ expectations rise initially, accelerates as the digital interaction (as in smart shopping app use by the customers) increases and peak when the engagement reach higher levels, we suggest that future research investigates this oscillation deeply, as it is important for both research and practice to understand the underlying phenomenon behind this pattern. This understanding has the potential to provide novel insights into how a firm should manage digital connectivity and customer expectations as well as the way a firm should be responding to unique customer needs and individual expectations. This pattern also suggests that customers anticipate greater responsiveness and agility from the firm as their digital connectedness with the firm increases, highlighting the importance of a firm’s ability to respond to unique individual needs/requirements in an agile and unique manner in order to make customers satisfied. We therefore suggest that future research looks at how firms use the customer intelligence generated through such digital interactions and the factors that inhibit or promote such mechanisms. Further, we see a pattern emerging from customers’ use of smart shopping apps towards firms-customer digital connectedness as a result of the ubiquitous digital connectivity created by the smart devices and
associated apps. Thus, we urge future research to look at the notion ‘digital connectedness’ construct closely, deeply and carefully with the emergence of digital natives, ubiquitous technologies and the increasing availability and popularity of multitude of smart devices and associated apps.

As we envisage here that firm’s deployment of digitized channels such as smart shopping apps for ubiquitous customer connectivity goes beyond the simple connectivity and is leading to a firm-customer digital connectedness which is an emotional, psychological bonding, with a feeling of belongingness or dependency in the longer run, we see here a notion similar to connectedness construct have been discussed in other fields emerging. Thus, in order to understand the digital connectedness construct fully, we suggest further research investigating the general notions of connectedness have been discussed in different fields and in different contexts as reported in prior research (e.g., Jung, 2008; Jung et al., 2001; Cristel Antonia Russell et al., 2004; Cristel A Russell et al., 2004). We also suggest future research look at the process which digital connectedness is formed in relation to the cognitive aspects of connectedness discussed in prior research. Further, we therefore propose that future studies should consider other contexts of digital engagements (other than the smart shopping apps) and the psychological aspects of the notion connectedness to confirm our findings and to develop more rigorous measures for firm-customer digital connectivity and /or digital connectedness incorporating the constant advancements of digital technologies, the nature of digitised applications and interactivity and their use in the organisational context. Also, as we see a link between the notion digital connectedness, influence of digital connectedness on customer cognitions to the firm’s digital business strategy, we suggest future research to look at new form of alignment: digital business strategy and customer cognitions.

In addition this research contributes to the ECT (Oliver, 1977; Oliver, 1980b) literature by introducing digital expectations and delineating digital expectation construct from the expectations construct that have been used in prior product service context. Whilst expectation remains the fundamental construct in Expectation Confirmation Theory (ECT) (Oliver, 1977; Oliver, 1980b; Oliver et al., 1994), the
theoretical conception of ECT presumes that satisfaction is a function of prior expectations and a posteriori dis-confirmation (Oliver, 1980a; Susarla et al., 2003). As Oliver (1980a) elaborated on the process which consumers go through in forming re-consumption or repurchase intentions, first, consumers form initial expectations of a specific service (or a product) prior to consume (Use), before they agree and consume (use) that service (product) and form perceptions of performance based on the consumption experience. Once consumed (used), they evaluate its perceived performance against their original expectations and determine the extent to which their expectation is confirmed. Upon confirmation, they form satisfaction or affection (revulsion if dissatisfied) based on the level of confirmation. Then, the consumers form a repurchase (discontinue) intention based on the level of satisfaction (or dissatisfaction).

Further, Parasuraman et al. (1985) mentions that the level of expectations a customer forms could be diverse depending on a customer’s subjective predictions. Thus, in the literature expectations have been seen at several levels such as a minimum tolerable emotional state (Zeithaml et al., 1993), highest ideal standard (Tse & Wilton, 1988), desired level (Swan & Trawick, 1980), experience based norms (Woodruff et al., 1983), realistic level of evaluation (Spreng et al., 1996) or subjective belief (Olson & Dover, 1979). Alternatively, Santos and Boote (2003) have summarised nine different levels of expectations that a customer could form in the form of a hierarchy from highest to the lowest as follows. The ‘ideal’- is the highest level of expectations that a customer has, followed by the ‘should’ - what the customer feel ought to happen, the ‘desired’ – what the customer wants to happen, the ‘predicted’ – what the customer thinks will happen, the ‘deserved’, the ‘adequate’, the ‘minimum tolerable’, the ‘intolerable’, and the least being the ‘worst imaginable’. As posited in the original conception of ECT (Oliver, 1977; Oliver, 1980b; Oliver et al., 1994), consumers form expectations and desires concerning a specific product (or service), prior purchasing or consumption of the product (or service). Nevo and Chan (2007) defined user expectation as a belief about the probabilities associated with a future state of affairs. Specifically, expectations predict a future state, where an individual thinks what will happen, or would like to happen. Essentially, the
expectations are formed prior to the use or consumption. Usually the priori expectations are formed as a result of word of mouth communication, previous experience, or external information such as marketing / promotion related communications. As elaborated in Oliver (1980a), traditionally, an individual forms priori expectations regarding a product (or service) and then compare the perceived performance of that product (or actual experience of the service) to form their level of satisfaction. As such it implicitly assumes that consumers acquire cognitive expectations of the most probable level of product (or service) performance (Oliver, 1977) thus, expectations are thought to create a point of reference in order to makes a comparative judgment about the product performance (or the experience) prior to the actual consumption (Oliver, 1980b). However, this research delineates the fundamental difference in the way the digital expectations are formed compared to the traditional product service context.

Contrary to the original conception, instead of forming expectations prior to the consumption, this research has argued that the digital expectations are formed post-consumption. We conceived that the digital expectations forms as a result of subsequent sensing of customer information achieved by firms through the customers’ use of digitally enabled connections rather than the word of mouth communication, previous experience, or external information such as marketing / promotion related communications. This conception of digital expectations is extremely important and significant for today’s environment as ubiquitous commerce is becoming popular with the availability of ubiquitous of technologies, smart mobile devices and smart apps (Lyytinen et al., 2004; Sheng, Nah, & Siau, 2008). Because, firms now have more opportunities to sense customer intelligence through the unparalleled level of ubiquitous connectivity, where smart devices such as mobile phones act as a universal device that allows individuals and firms to stay connected with each other as well as with their associated networks all the time regardless of time or their locations (Sheng et al., 2008). Intelligent and interactive features of these smart devices and apps allow firms not only to connect but have made it technically possible to sense user identities, preferences, and geographical locations and deliver personalized products or services to the users with a reasonable precision (Junglas & Watson, 2006). On the
other hand the ownership and use of smart apps and devices such as mobile phones and associated apps, electronic cards such as loyalty cards are meant to be personal. Thus, the users can be uniquely identifiable making user specific information accrual is theoretically feasible (Junglas & Watson, 2003; Sheng et al., 2008; D. Zhang, 2003). When the individuals being continuously plugged in with the firms customer focused digitally enabled connections over a period of time, confluence of multiple technology induced interactions can create the users digital thumbprints based on information foot-prints they leave as a by-product (Chi et al., 2010).

Whilst, firm-customer digital interactions through smart devices facilitates customer intelligence generation through the smart functionalities of smart devices and associated apps, customers also aware that current generations of mobile phones in general has a much higher potential to capture user specific information with GPS, mobile based apps and other smarter features (Hutchinson, 2011) making the device potentially a portable, personal spy (Clifford, 2009). They also aware that the advancements in mobile technology, mobile devices, apps and data synchronization capabilities make it possible for firms to identify individuals based on who they are, where they are, what they like and what they would more likely to purchase at anytime anywhere in order to respond to the individuals unique requirements real-time (Sheng et al., 2008). As customers are aware of the technology capabilities to carry out such surveillance, storage, retrieval, and make use of personal information (Culnan, 1993), and they are accessible and traceable continuously for capturing transactional (Luo, 2002) and personal information (Günther & Spiekermann, 2005; Ohkubo, Suzuki, & Kinoshita, 2005) when they are connected digitally with firms, hence the possibility of providing personalized benefits such as product/service recommendations, offers, promotions, and discounts based on his/her previous exchanges (Sheng et al., 2008), they form expectations regarding firms responsiveness towards their shopping related needs. Thus, the digital expectations, the expectations derived as a consequence of having near-constant digital interactions with one another, and the subsequent sensing of customer information, is distinctively different from the traditional forms of expectations as digital connectedness is a critical precursor for digital expectations.
Chapter 6: Conclusions, Implications and Limitations

Regarding the implications for practice, this study provides a meaningful way of understanding firm-customer digital connectivity achieved through smart devices and associated apps (e.g. shopping apps) and its practical implications. As our empirical investigation suggests, if a firm is to be successful in its digital strategy, it should align its customers’ expectations with personalised experiences in order to match or exceed the customers’ expectations, and in this way achieve business benefits and sustained competitive advantage through superior customer satisfaction. We therefore suggest that firms put equal (or more) emphasis on nurturing the capabilities that support the localised improvisation and responsiveness required to provide superior customer experiences. As increased digital connectivity (achieved through the customers’ use of smart shopping apps) and heightened customer expectations (digital expectations) go hand in hand, we suggest that firms should find the ideal level of digital interactivity to set customer expectations at manageable levels. This is because neither very high, unrealistic levels nor very low, mediocre levels of expectations are healthy for a firm, as they are more likely to produce relatively unhappy customers (as evident in our analysis).

When firms start interacting with their customers through ubiquitous mediums as in smart mobile apps the firms, we suggest firms to put more emphasis on the responding side of firms customer agility and start using the customer intelligence generated through such interactions to understand individual customers better and respond such customers in unique ways. In other words, in line with digital customer interactions firms need to strategize how they are going to utilize such interactivity to generate superior customer experiences. Thus, such firms need to think about complementing technologies such as business analytics in order for them to generate rich insights from the customer generated data through such digital interactions. Also, firms required to assess their interactions closely and should manage such interactions in order to manage adequate levels of responsiveness to such customers and to maintain only manageable levels of customer expectations. The process that might helpful for firm’s to achieve this objective may be to make the decision makers aware of the intelligence generated through the ubiquitous digital customer interactions. Alternatively, there needs to be a mechanism to let managers aware of the associated
vulnerabilities such as lowered customer satisfaction and heightened customer expectations that are associated with constant digital customer interactions through market research. In addition, the firms need to have a mechanism to keep managerial decision makers motivated in order to take timely and effective responsive actions and to continuously develop capabilities that are mandatory to take such customer focussed competitive actions.

Further, as there is a possibility of losing customer interest in continuing digital engagement with a firm due to a lack of uniqueness in their experience, customers may decide to opt out from the digital interactions / use of smart shopping apps. Whilst the customers’ continued use of smart shopping apps is important for firms seeking to sense shifting customer needs, firms need to find a better balance (alignment) between the customers’ digital interactions and the firm’s responsiveness to those customers in order to promote further adoption and continuation. It is also important to note that a firm’s deployment of apps to connect with customers and/or business partners could possibly reveal its strategic posture/direction to its competitors in the long run, and therefore introduces the risk of eroding its competitive position unless managed properly (See....Grover & Kohli, 2013). Hence, a firm’s digital initiatives have implications for both the short-term and long-term. We therefore propose that it would be beneficial for future research to study the implications of a firm’s digital connectivity and the connectedness achieved through such connectivity with multiple stakeholder groups in the short-term and long-term.

The guidelines proposed by G. A. Churchill (1979) and A. Burton-Jones and Straub (2006) were followed in developing the measures in this study and the rigorous research approach suggested by K. D. Mackenzie and House (1979) and S. B. Mackenzie et al. (2011) was employed. The validity and reliability were demonstrated in the results. However, we recognise several limitations requiring attention beyond the scope of this study and the discussion.
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First, our use of smart shopping apps in consumer retail as the sole context of this study, and model validation through the data collected from customers of two Australian organizations in the fast moving consumer goods retail sector as the sole context, limited our ability to fully understand the notion of firm-customer digital connectivity achieved through smart app and the associated implications. In addition, these limitations raise questions about the completeness and representativeness of the smart shopping app use construct and measures, as well as the generalisability of the final measures to other contexts. The study context (customer focussed smart shopping apps in consumer retail) also limited our ability to explain how customer expectations behave in other forms of firm-customer digital interactions (e.g. customers’ digital/online involvement in product/service innovation and service delivery as in automated banking and the airline industry) and potentially limited the appropriateness of the measures we used to study firm-customer digital connectivity and its implications. We therefore propose that future studies should consider other contexts of digital engagements and the psychological aspects of the notion connectedness to confirm our findings and to develop more rigorous measures for firm-customer digital connectivity and /or digital connectedness taking into account the constant advancements of digital technologies, the nature of digitised applications and interactivity and their use in the organisational context.

Even though this study captured different combinations of firm-customer digital interactions through smart shopping apps and corresponding levels of customer expectations from customers at different stages of the adoption life-cycle, our ability to fully explain the changes in expectations as customers increased their use of smart shopping apps was hindered as our survey only provided a snapshot view of the use of smart shopping apps-customer expectation relationship. We suggest that future research should include longitudinal studies that employ a mix of different methods (interviews, experiments, longitudinal survey, etc.) in order to better explore and explain this relationship. Whilst our investigation provided insights into how individual customers change their expectations as their use of smart shopping app changes, it is not adequate enough to explain the implications of digital connectivity between the partners and their expectations on each other in B2B (i.e. firm to firm)
scenarios. We therefore recommend that future research considers the digital connectivity / connectedness, expectations, responsiveness and satisfaction relationship in B2B settings.

In conclusion, an extensively validated and widely-adopted model of smart shopping app use by customers, customer expectations, customer perceptions and customer satisfaction including meticulously developed measurement items derived from system usage related constructs would facilitate cumulative research, and has the potential to provide a benchmark for organisations to track their customer-focused digital strategic initiatives. Further we believe that this study provides the basis to understand the wider implications of digital connectivity achieved through smart functionalities of smart devices and associated smart apps as a par of firm’s digital strategies on multiple stakeholder groups. We believe that this study offers a significant step in this direction.
APPENDICES

Appendix A – Competing models, direct measurements, nonlinearity and methodological advancements in prior ECT research

Based on met expectation research (Irving and Meyer, 1994, 1995, 1999) (L. W. Porter & Steers, 1973), S.A. Brown et al. (2008) introduced three models to study satisfaction, namely, the disconfirmation, ideal point, and experience only models in the context of a new information systems implementation in an organization. All three models view satisfaction as a function of expectations and experiences. S.A. Brown et al. (2008) analyzed the three competing models through three different graphical and analytical representations.

The disconfirmation model (Figure 1.A) was developed based on the disconfirmation and contrast theories (Churchill and Suprenant, 1982; Sherif and Hovland, 1961) where the model suggests that satisfaction is influenced by the degree to which the expectations are unmet or the level of disconfirmation. In that model, disconfirmation suggests that either the experiences fall short of expectations (it reduces satisfaction due to the effect of disappointment) or the experiences exceed the expectations (it influences satisfaction through the positive surprise effect) (S.A. Brown et al., 2008). Staying true to the hypothesis put forth in notions of met expectations research, this model argues that satisfaction is a function of the difference between experience and expectations (Porter and Steers, 1973; Wanous, 1992), wherein the degree to which expectations are exceeded leads to greater satisfaction while the degree to which expectations are falling short leads to lower satisfaction (S.A. Brown et al., 2008; L. W. Porter & Steers, 1973). This suggests that the expectations should be understated in order to increase the degree to which the experiences exceed expectations (by maximizing the expectation-experience gap in the positive direction) (S.A. Brown et al., 2008). Some of the earlier studies (e.g.

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4 The stream of research that focuses the understanding of the relationship between a priori expectations, a posteriori evaluations, and subsequent satisfaction is referred as met expectations (S.A. Brown et al., 2008)
Kotter, 1973) also suggest that unrealistically high expectations can result in low satisfaction whilst low expectations are more easily met and exceeded, hence the higher satisfaction (Premack and Wanous, 1985). On another note it was empirically found that the individuals were more satisfied with a positive outcome when a negative outcome was expected and vice versa (Mellers et al., 1997).

The ideal point model (Figure 1.B) was developed on the idea of congruence where it proposes that any difference between expectations and experiences will result in a lowered evaluation and hence result in a lowered satisfaction regardless of the direction of incongruence (Oliver, 1976; Olson and Dover, 1979). Contrasting to the disconfirmation model, this model anticipates negative outcomes for both unmet expectations and exceeding expectations (Brown et al. 2008) where the expectations serve as an anchor or an ideal point of experience in which the incongruence is at its minimum. Oliver (1976) argued that the reduced satisfaction due to exceeded expectations were more likely to occur when the expectation object is particularly important for an individual. Additionally the psychology literature suggests that the expectations are formed based on perceived promises (Robinson, 1996) where the violations (experiences that are exceeding or falling short) have a negative impact on satisfaction (Brown et al., 2008; Lambert et al., 2003; Sutton and Griffin 2004; Turnley and Feldman, 2000) possibly due to the fact that excess levels could interfere with need fulfilment (Lambert et al., 2003). In an information systems context Ginzberg (1981) argued that people will be more satisfied when they have more realistic-neither too high nor too low expectations, suggesting that meeting high expectations or minimizing the difference between expectations and experiences will create the most satisfaction.
The experience only model (Figure 1.C) suggests that the outcome (satisfaction) depends solely on the actual experience, rendering expectations inconsequential to the satisfaction outcome (S.A. Brown et al., 2008). This notion has been supported by previous empirical investigations (Hom et al., 1999; Irving and Meyer, 1994). Tversky & Kahneman (1974) argued that the recency effect causes the experiences to be most salient hence most influential in determining the level of satisfaction. In the subsequent empirical tests, Brown et al., (2008) suggested that the equal role of expectations and experiences posited in the disconfirmation and ideal point models was not evident; that is, the influence of experience on satisfaction was comparatively stronger as depicted in the experience only model (S.A. Brown et al., 2008). However, a strong role of expectation in determining satisfaction is evident in previous research (Ginzberg, 1981; B. Szajna & Scamell, 1993), thus the overall influence of expectation appears to be less prominent in more current work (S.A. Brown et al., 2008). S.A. Brown et al. (2008), for example, cautioned that flawed empirical techniques such as the use of linear models and the limitations associated with different scores may have led to the overemphasizing role of expectations where, in reality, it only had a marginal influence on satisfaction.

Recently researchers in the IS context raised several limitations associated with prior ECT applications (Susan A. Brown et al., 2012; S.A. Brown et al., 2008; Venkatesh et al., 2008; Venkatesh & Goyal, 2010). The first group of limitations were related to the predominant use of linear models and associated analytical techniques in ECT studies (J. G. A. Churchill & Surprenant, 1982; B. Szajna & Scamell, 1993) when the fundamental theoretical propositions of both ECT (Susan A. Brown et al., 2012; S.A. Brown et al., 2008; Venkatesh & Goyal, 2010) and satisfaction (E. W. Anderson & Sullivan, 1993; Cheung & Lee, 2009) predict nonlinear effects. For example, E. W. Anderson and Sullivan (1993) reported that negative disconfirmation affects consumer satisfaction more than positive disconfirmation, and this nonlinearity has been well documented and empirically demonstrated in consumer-behavior research (Cheung & Lee, 2009) (See Figure 2). The linearity in general implies similar effects of expectations and experiences on an outcome (Figure 1a), whereas
some prior research hints that the assumption of linearity possibly masks the true relationship among the variables (Edwards & Rothbard, 1999; D. S. Staples et al., 2002). As Edwards (2001) argues, higher-order terms in curvilinear representations have the potential to explain substantial variance over and above linear representations.

Figure 2: Linear and non-linear relationships of satisfaction (a) A symmetric and linear relationship; (b) a negative asymmetric and nonlinear relationship; (c) a positive asymmetric and nonlinear relationship (Adopted from Cheung and Lee 2009).

The second group of limitations highlighted in the extant ECT studies includes the use of difference scores in analysis. As Brown et al. (2008) elaborate the difference scores have been used in a variety of studies in the past (e.g. Ilgen, 1971; Patterson, 1993; Staples et al., 2002; Venkatraman & Prescott; Weaver & Brickman, 1974). As Browns et al., (2008) reports, previous studies suggest that the difference scores carry significant statistical flaws (Edwards, 1994, 2002; Edwards & Harrison, 1993; Peter et al., 1993; Pitt et al, 1997; Prakash, 1984). For example, the use of difference scores in expectation research suggests that expectations and experiences possess equal and opposite effects on the outcome variable (i.e. satisfaction), but it does not always hold true and is likely to impose constraints in some representations of ECT models (S.A. Brown et al., 2008; Hom, Griffeth, Palich, & Bracker, 1999). While this is consistent with the disconfirmation model discussed earlier, it does not comply with the other two models: ideal point or experience only. Hom et al., (1999) also have shown that the use of difference scores overstates the mediating role of met
expectations. So, the aforementioned studies suggest that the use of difference scores imposes constraints where it is likely to support only the disconfirmation model (Brown et al., 2008).

The third measurement issue is associated with the use of direct measures of disconfirmation (Anol Bhattacherjee, 2001; Bhattacherjee & Premkumar, 2004; S.A. Brown et al., 2008; Oliver, 1977; Venkatesh & Goyal, 2010) instead of using the measures of expectations and experiences separately. In this approach, a researcher is essentially measuring the degree to which a participant’s expectations were met, but it does not support the understanding of the relative impact of expectations and experiences on satisfaction (S.A. Brown et al., 2008; P.G. Irving & Meyer, 1995). As P.G. Irving and Meyer (1995) reported, responses on met expectations questions are likely to be excessively influenced by current experiences. In addition the cognitive dissonance theory (Festinger, 1962) also suggests that the individuals underreport differences in order to remain cognitively consistent as they attempt to limit the dissonance between expectations and experiences (Brown et al., 2008). As a result it would be difficult to assess whether the individual’s evaluation of the experience is consistent and reflects the actual post hoc experiences or whether it is assimilated towards expectations. More recent work on ECT suggests polynomial regression analysis and response surface methodology (Edwards, 2001) as an alternative approach to counter these limitations of prior research (S.A. Brown et al., 2008; Venkatesh & Goyal, 2010).
Appendices

**Appendix B – Classification of Systems**

We employed McAfee (2006) classification to demonstrate the differences between the types of systems as the Table below. The table compares three types of systems that we have used to define the context of our study.

<table>
<thead>
<tr>
<th>Group</th>
<th>Functional IT</th>
<th>Network IT</th>
<th>Enterprise IT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Definition</td>
<td>Assists the execution of discrete tasks</td>
<td>Facilitates interactions without specifying their parameters</td>
<td>IT that specifies business processes</td>
</tr>
<tr>
<td>Characteristics</td>
<td>Can be adopted without complements. Impact increases when complements are in place</td>
<td>Does not impose complements, but lets them merge over time Does not specify tasks or sequences Accepts data in many formats Use not mandated</td>
<td>Imposes complements throughout the organization. Defines tasks and sequences Mandates data formats. Use is mandatory</td>
</tr>
<tr>
<td>Examples</td>
<td>Spreadsheets, computer aided design, statistical software</td>
<td>Emails, instant messaging, wikis, blogs and mash-ups</td>
<td>ERP, CRM and SCM</td>
</tr>
<tr>
<td>Automation</td>
<td>Some degree of automation (e.g. Spell check)</td>
<td>Very low level of automation</td>
<td>High level of automation</td>
</tr>
<tr>
<td>Key-User-Groups</td>
<td>More likely to have a single Key-User-Group</td>
<td>More likely to have a single Key-User-Group</td>
<td>Multiple Key-User-Group using the same system very differently</td>
</tr>
</tbody>
</table>

Key distinctive differences between Network IT, Enterprise IT and Functional IT are apparent in the table above, yet the ubiquitous IT does not fit into any of the three groups have mentioned therein whilst some of the functions are overlapping between the groups. Thus we have created a separate group for ubiquitous IT.
Appendix C – Regression and Response Surface Methodology

In statistics, polynomial regression is a form of linear regression analysis technique (a special case of multiple linear regression) that models the relationship between independent variable/s (X/X and Y) and a dependent variable (Z) as the nth degree polynomial, and has been used to describe the non-linear relationships between independent and dependent variables. Thus, polynomial regression [Edwards and Parry, 1993] and response surface analysis [Box and Draper, 1987; Khuri and Cornell, 1987] are two sophisticated analytical techniques that have been extremely popular in analysing non-linearities between variables in the micro and macro organisational literature that investigates congruence and/or discrepancies. This technique allows a researcher to examine the extent to which the combinations of two predictor (independent) variables relate to an outcome (dependent) variable [Shanock, et al., 2010] and has been widely used in multisource feedback research. The polynomial regression [Edwards and Parry, 1993], together with the response surface methodology [Box & Draper, 1987; Khuri & Cornell, 1987], provides the basis for testing and interpreting the features of surfaces corresponding to polynomial quadratic regression equations. The combination provides the statistical sophistication required to examine the nuanced views of tripartite relationships by graphing the three variables in a three-dimensional space where it provides the relationships between combinations of two predictor variables and an outcome variable [Shanock, et al., 2010].
Basic Assumptions of Polynomial Regression

Generally, the polynomial regression and response surface methodology can be used for any circumstance in which the research questions involve an investigation of how combinations of two predictor variables relate to an outcome. However, as Edwards [2002] points out, a few assumptions must be met in order to apply this analytical technique:

- First, as Edwards [2002] explains, the two predictor variables must be commensurate and thus should represent the same conceptual domain. Thus, the relationship between the predictor variables can be interpreted in a meaningful way in relation to the dependent variable. For example, if a researcher is trying to predict a customer’s satisfaction with a hotel service-related activity, it is more meaningful to look at customer satisfaction in relation to the discrepancy or agreement between the customer’s expectations and the actual customer experience.

- Second, as mentioned by Edwards [2002], the predictor variables must be measured on the same numeric scale; or, when the scales are different, the scales should be transformed to a standardised scale so that the degree of correspondence between the variables can be determined in a more accurate manner. For example, both variables are required to be measured on a 5-point or 7-point Likert scale (e.g. “strongly disagree” to “strongly agree” / “not at all” to “very frequently”) but not one variable on a 5-point Likert scale and the other on a 7-point Likert scale or vice versa. In case the two scales are different (e.g. 7-point Likert and 5-point Likert scale), the scales need to be
standardised to a single scale in order to place both the variables on a common metric (see Harris, Ansaal, and Lievens [2008]).

- Third, as with any regression technique, all the standard assumptions relating to the multiple regression technique as explained by Tabachnick and Fidell [2007] need to be met in order to apply this technique. Moreover, polynomial regression could be used in the place of moderated regression to study the relationships between combinations of variables since the polynomial regression has more explanatory power compared to the traditional moderated regression. Polynomial regression has the potential to provide nuanced views on the relationships between different combinations of predictor variables and a dependent variable.

- Finally, the polynomial regression and response surface methodology can be used when the underlying theoretical assumptions suggest non-linearity between the independent and dependent variables. For example, the original theoretical assumptions of the ECT suggest non-linearities in the relationships between expectations, experience and satisfaction [Oliver, 1977, 1980]; thus, studies that use ECT as the underlying theoretical lens could employ polynomial regression together with response surfaces to establish nuanced views of the relationships between the three variables of expectation, experience and satisfaction [S. A. Brown, Venkatesh, and Goyal, 2012; Susan A Brown, Venkatesh, and Goyal, 2014; S.A. Brown, venkatesh, Kuruzovich, and Massey, 2008].
Conducting the Polynomial Regression Analysis and Creating the Response Surface

In order to create a response surface for two predictor variables and a dependent variable, the polynomial regression is conducted as the first step. As such, the polynomial equation for two dependent variables X (Predictor Variable 1) and Y (Predictor Variable 2) and a dependent variable Z is developed as follows. First, the polynomial equation is developed based on the understanding that the dependent variable is a function of the two predictor variables X and Y. It is denoted as per the following equation:

\[ Z = f(X,Y) \]

Then the outcome variable Z is regressed on each of the predictor variables (X and Y), the interaction of the two predictor variables (XY) and the squared terms for each of the two predictors X and Y (\(X^2\) and \(Y^2\)) in order to develop the general form of the polynomial equation as follows:

\[ Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e \]

If the primary concern of the study is the effect of disagreement or discrepancy on an outcome variable, it is advisable to inspect the respondents with discrepancies between the two predictor variables prior to running the polynomial regression. To evaluate the discrepancies between two predictor variables, the scores of the two predictor variables need to be standardised if the scales are different [see Fleenor, McCauley, & Brutus, 1997 for procedural instructions]. To be considered to have discrepant values, the standardised value of one predictor variable needs to be half a standard deviation above or below the standardised score of the other predictor.
variable for any respondent. Then, a comparison of the percentages of the discrepant values on each other in either direction (i.e., % of Predictor Variable 1 more than Predictor Variable 2, and % of Predictor Variable 1 less than Predictor Variable 2) against the % of agreement can be used to evaluate the practical sense of proceeding with polynomial regression analysis. Once the existence of discrepant values in the data is confirmed, the next step is to proceed with the polynomial regression analysis.

Prior to performing the polynomial regression analysis, scale centering on the two predictor variables needs to be done in order to reduce or eliminate the potential multi-collinearity issues. As Aiken, West, and Reno [1991] note, a researcher could centre the scales of the variables around the mean or the midpoint of the scale based on the questions under investigation and/or the interpretation objectives. Edwards [1994] recommends the scale centering to be done around the midpoint of the scale by subtracting the midpoint of the respective scale on each predictor variable for polynomial regression analysis. For example, if the two variables are measured on a 7-point Likert scale, four (4) should be subtracted from each score (similarly, if the variables are measured on a 5-point Likert scale, three (3) need to be subtracted from each score). The scale centering not only helps reduce the possible multi-collinearity issues but also aids interpretations [Aiken, West, and Reno, 1991]. Once the scale centering of the two predictor variables is completed, the next step is to create the square of the two centred predictor variables (i.e. $X^2$ and $Y^2$) and the cross-product of the two centred predictor variables (i.e. $XY$). The final step of the analysis is to run the polynomial regression analysis by regressing the outcome variable on the two centred variables ($X$ and $Y$), the product of the two centred predictor variables ($XY$) and the centred squared terms of the two predictor variables ($X^2$ and $Y^2$) into the regression equation. All these procedural steps can be performed through the syntax
illustrated in Figure 3 (for predictor variable items measured on a 7-point Likert scale).

```
COMPUTE PV1cntr = Predictor variable1 - 4.
COMPUTE PV2cntr = Predictor variable2 - 4.
EXECUTE.
COMPUTE Xsquared = PV1cntr*PV2cntr.
COMPUTE XY = PV1cntr*PV2cntr.
COMPUTE Ysquared = PV2cntr*PV2cntr.
EXECUTE.
REGRESSION /MISSING LISTWISE
/STATISTICS COEFF OUTS BCOV R ANOVA
/CRITERIA = PIN(0.05) POUT(0.10)
/NOORIGIN
/DEPENDENT DV
/METHOD = ENTER PV1cntr PV2cntr XY Xsquared Ysquared
```

**Figure 3. Syntax for Polynomial Regression**

The higher order polynomial outputs that often result from a polynomial model are difficult to interpret [Edwards, 2001]. Simply inspecting the directions and magnitudes of the coefficients reported in the analysis (the output obtained by running the above syntax) reveals very little as to the shape of the surface they represent. For example, the magnitude and direction of the intercept, coefficients of \( X, Y, X^2, XY \) and \( Y^2 \), do not convey anything meaningful on their own. The response surface methodology presented by Khuri and Cornell [1987] provides the basis for testing and interpreting the features of surfaces corresponding to polynomial quadratic regression equations, where the response surface is used as a visual aid to get a richer, more meaningful and deeper understanding of complex polynomial equations. The combination provides the sophisticated statistical nuance required to examine the extent to which the combination of two predictor variables relates to an outcome variable Shanock [2010]. Thus, the results of the polynomial equation (the results of the regression) are evaluated in relation to the surface they represent, as opposed to
the variance in the outcome variable explained by the regression equation – $R^2$ (as in common regression analysis).

The three-dimensional response surface can be generated through the graphing function in Excel or the data visualisation function in MATLAB software. The corresponding points relating to the dependent variable Z on the surface for different combinations of predictor variables X and Y are calculated by solving the polynomial equation put forth earlier in this discussion (replacing beta coefficients $b_1$ through to $b_5$ and the X and Y coordinates). The Excel worksheet at the end of this section (adopted from Shanock [2010]) provides the detailed step-by-step guideline to creating the response surface from the polynomial regression outputs. The result of the response surface is evaluated based on four surface test values ($a_1$, $a_2$, $a_3$ and $a_4$) as follows:

- The test value $a_1$ corresponds to the line of perfect agreement between two predictor variables ($PV_1 = PV_2$ or $X=Y$) as related to the dependent variable Z and is given by $a_1 = (b_1 + b_2)$, where $b_1$ and $b_2$ are the unstandardised beta coefficients for the scale-centred $PV_1$ and $PV_2$, respectively.

- The test value $a_2$ corresponds to the curvature along the line of perfect agreement between two predictor variables ($PV_1 = PV_2$ or $X=Y$) as related to the dependent variable Z and is given by $a_2 = (b_3 + b_4 + b_5)$, where $b_3$, $b_4$ and $b_5$ are the unstandardised beta coefficients for the scale-centred $DV_1$ squared ($X^2$), cross-product ($DV_1 \times DV_2$ or $XY$) and $DV_2$ squared ($Y^2$), respectively.

- The test value $a_3$ corresponds to the line of incongruence between two predictor variables ($PV_1 = -PV_2$ or $X=-Y$) as related to the dependent variable Z and is given by $a_3 = (b_1 - b_2)$, where $b_1$ and $b_2$ are the unstandardised beta
coefficients for the scale-centred PV\(_1\) and PV\(_2\), respectively. This line explains the changes in DV (Z) as related to the direction and magnitude of the discrepancy between two predictor variables (IV\(_1\) is higher than / lower than IV\(_2\)).

- The test value a\(_4\) corresponds to the curvature along the line of disagreement between two predictor variables (PV\(_1\) = - PV\(_2\) or X= -Y) as related to the dependent variable Z and is given by a\(_4\) = (b\(_3\)-b\(_4\)+b\(_5\)), where b\(_3\), b\(_4\) and b\(_5\) are the unstandardised beta coefficients for the scale-centred DV\(_1\) squared (X\(^2\)), cross-product (DV\(_1\) * DV\(_2\) or XY) and DV\(_2\) squared (Y\(^2\)), respectively.

**Interpretation of the Response Surface**

A number of different research questions can be answered through the resultant response surface and the calculated surface values. For example, using a response surface, a researcher can examine: (i) the agreement or alignment between two predictor variables on an outcome variable, (ii) the discrepancy between two predictor variables on an outcome variable, (iii) the direction and magnitude of the discrepancy between two predictor variables on an outcome variable, (iv) the nature of the synergy between two predictor variables (+ve or –ve) and outcome variable, and (v) the mediation effect of one predictor variable on the other predictor variable (complete or partial) on an outcome variable. The following section elaborates these five research questions in detail using a hypothetical response surface in Figure 4.
Agreement between Two Predictor Variables as Related to an Outcome Variable:

Response surface analysis allows researchers to study how the agreement between two predictor variables relates to an outcome variable. The ABCD surface along the black solid line on the floor of the graph in Figure 2 (Point A through to Point B) depicts the perfect agreement or alignment between the two predictor variables (X=Y). Whilst the surface property $a_1$ explains the slope of the surface along A to B (i.e. the agreement line), $a_2$ explains the curvature or the non-linearity of the surface along the A-B line. If the test value $a_1$ is positive (negative), the outcome variable increases (decreases) as the two predictor variables increase. Whilst the significant value of $a_2$ indicates a non-linear (curvilinear) slope along the agreement axis, a significant positive $a_2$ value suggests an upward convex curvature for the surface along the A-B line, whilst a significant negative $a_2$ value suggests a downward concave curvature for the surface along the A-B line. If the agreement between two predictor variables shows a linear additive relationship to the outcome variable $a_1$, the slope is positive but if it shows a linear additive relationship to the outcome variable, thus $a_2$, the curvature of the surface along the line of agreement would not be significant.

Moving along the solid line from the front of the graph in Figure 2 (Point B) to the back (Point A), the line of perfect agreement of two predictor variables as related to outcome variable (Z) has a positive slope. Further, the lowest level of the outcome variable is at the front corner of the graph on the A-B line (Point B) where both predictor variables are low, and increasingly higher towards the back corner of the graph on the A-B line (Point A) where both predictor variables are high.
Disagreement between Two Predictor Variables as Related to an Outcome Variable

Disagreement, or incongruence, explains how the discrepancy between two predictor variables relates to an outcome variable. The line perpendicular to the line of perfect agreement (the A-B line on the ABCD response surface) represents the line of incongruence. The dotted line on the floor of the graph in Figure 4 depicts this line of incongruence (X=-Y), that is, when the two predictor variables are not in agreement. As the surface property $a_4$ explains the curvature along the line X=-Y, a significant negative curvature depicts that the dependent variable drops as the difference between the two predictor variables widens (i.e. increasingly discrepant as moving away from the line of agreement). Whilst a significant negative $a_4$ indicates a concave surface, a

Figure 4. Hypothetical Response Surface for Two Predictor Variables (X and Y) and an Outcome Variable (Z)
significant positive $a_3$ indicates a convex surface. The concave surface explains that the value of the outcome variable decreases more sharply as the degree of discrepancy between the two predictor variables increases; whilst the concave surface explains vice versa. The surface along the line of disagreement of the graph in Figure 4 displays a concave surface and shows a sharp decrease in the outcome variable as the discrepancy between the predictor variables widens.

**Direction and Magnitude of the Discrepancy between Two Predictor Variables as Related to an Outcome Variable**

The slope along the line of incongruence between the two predictor variables ($X = -Y$) as related to the dependent variable explains the extent to which the direction of the discrepancy matters to the outcome variable. As the surface property $a_3$ relates to the slope of the line of incongruence as it relates to the outcome variable, a significant value for $a_3$ shows that the direction of discrepancy indeed matters to the changes in the outcome variable. A significant positive $a_3$ indicates that the outcome variable decreases when Predictor Variable 1 ($X$) is less than Predictor Variable 2 ($Y$) and vice versa.

The graph in Figure 4 shows that towards the left (towards Point C) and right (towards Point D) of the ABCD response surface on the graph, where the two predictor variables become more and more discrepant (i.e. move away from the agreement between the two predictor variables), the outcome variable decreases. Thus, the slope along the line of disagreement explains the extent to which the dependent variable is influenced by the discrepancy between the two predictor variables. Towards Point C in the graph from the line of agreement ($X=Y$) along the dotted line on the floor of the graph, Predictor Variable 2 ($Y$) increases as Predictor
Variable 1 (X) decreases and the outcome variable Z decreases rapidly. Similarly, towards Point D in the graph from the line of agreement (X=Y) along the dotted line on the floor of the graph, Predictor Variable 1 (X) increases as Predictor Variable 2 (Y) decreases significantly, yet the slope is less significant. This explains that the discrepancy between the two predictor variables assimilate towards Predictor Variable 2 (Y) matters more for the changes in outcome variable Z than the discrepancy between the two predictor variables assimilate towards Predictor Variable 1 (X).

**Synergy between Two Predictor Variables as Related to an Outcome Variable**

Synergy has been described as the combined effect of two factors, where the combined effect could either create a negative synergy (making the combined effect of the two factors less than the sum of each factor’s separate effect) or a positive energy (making the combined effect of the two factors greater than the sum of each factor’s separate effect) [Titah & Barki, 2009]. Positive synergy explains the complementarity of two variables, whereby it explains that the increase in either factor increases the impact of the other [Titah and Barki, 2009]. Similarly, negative synergy explains the substitutability of two variables, whereby it explains that the increase in one factor decreases the impact of the other.

The A-C and B-D lines of the ABCD response surface of the graph in Figure 4 provide an example of positive synergy. The B-D line represents the relationship between Predictor Variable 1 and the outcome variable when Predictor Variable 2 is at its lowest. The A-C line represents the relationship between Predictor Variable 1 and the outcome variable when Predictor Variable 2 is at its highest. Both lines show that the outcome variable increases with the increase of Predictor Variable 1 (Points C
to A and B to D). However, the rate of increase (i.e. slope of the curve) is higher in the C-A curve compared to the C-D curve. The in-between line on the response surface that runs parallel to the two A-C and B-D curves also shows that the slope of the curve increases when moving from the B-D line towards the A-C line. This shows that, as Predictor Variable 1 increases, it positively influences the relationship between Predictor Variable 1 and the outcome variable Z, suggesting a positive synergy between the two predictor variables.

The A-C and E-C lines of the ECBD response surface of the graph in Figure 4 provide an example of negative synergy. The B-D line represents the relationship between Predictor Variable 1 and the outcome variable when Predictor Variable 2 is at its lowest. The E-C line represents a hypothetical relationship between Predictor Variable 1 and the outcome variable when Predictor Variable 2 is at its highest. Both lines show that the outcome variable increases with the increase of Predictor Variable 1 (Points C to E and B to D). However, the rate of increase (i.e. the slope of the curve) is less in the C-E curve compared to the C-D curve. Similar to the earlier example, if hypothetical lines were drawn on the hypothetical ECBD response surface, hypothetical lines that runs parallel to the E-C and B-D curves (lines), it would show that the slope of the curve decreases moving from the B-D line towards the E-C line. This shows that, as Predictor Variable 1 increases, it negatively influences the relationship between Predictor Variable 1 and the outcome variable Z, and suggests a negative synergy between the two predictor variables.

Test of Mediation

Mediation in general entails the intervening effect of an antecedent variable on a dependent variable. Thus, mediation refers to the intervening effect of one of the
predictor variables on the relationship between the other predictor variable and the outcome variable. The discussion herein focuses on the mediation of Predictor Variable 2 (Y) on the relationship between Predictor Variable 1 (X) and the outcome variable Z. Two types of mediation, namely, partial mediation and complete mediation, are discussed in the literature [see Roberts & Grover, 2012]. To discuss the two types of mediation, this section uses the two response surfaces – ABCD and ABDF – of the graph in Figure 4.

We take the ABCD response surface of the graph to discuss partial mediation. Both the AC and BD lines (or curves) of the graph explain the relationship between Predictor Variable 1 and the outcome variable Z. The B-D line of the graph explains the relationship between Predictor Variable 1 and the outcome variable Z when Predictor Variable 1 is absent or at its lowest, whilst the A-C line explains the relationship between Predictor Variable 1 and the outcome variable Z when Predictor Variable 1 is at its highest. Both the AC and BD lines in the graph show that as Predictor Variable 1 (X) increases, the outcome variable also increases as a consequence. When moving from the BD line towards the AC line on the response surface, it shows that as Predictor Variable 2 increases its magnitude the relationship between Predictor Variable 1 and the outcome variable (i.e. the slope or curvature between Predictor Variable 1 and the outcome variable) is slightly disturbed but overall keeps its original relationship intact. It means that Predictor Variable 2 mediates the relationship between Predictor Variable 1 and the outcome variable, but the impact of the predictor variable is partial.

Next, we take the ABDF response surface of the graph to discuss complete mediation. Similar to the above discussion, both the AF and BD lines (or curves) of
the graph explain the relationship between Predictor Variable 1 and the outcome variable Z. Whilst the B-D line of the graph explains the relationship between Predictor Variable 1 and the outcome variable Z when Predictor Variable 2 is absent or at its lowest, the F-A line explains the relationship between Predictor Variable 1 and the outcome variable Z when Predictor Variable 2 reaches its highest. Whilst the BD line shows that, as Predictor Variable 1 (X) increases, the outcome variable also increases as a consequence, the FA line shows no change to the outcome variable as Predictor Variable 1 (X) increases when Predictor Variable 2 is at its highest. When moving from the BD line towards the FA line on the response surface, it shows that as Predictor Variable 2 increases its magnitude the relationship between Predictor Variable 1 and the outcome variable (the slope or the curvature between Predictor Variable 1 and the outcome variable) is extremely disturbed, altering its original relationship completely. This explains that Predictor Variable 2 completely mediates the relationship between Predictor Variable 1 and the outcome variable as the impact of Predictor Variable 2 on the relationship is complete.
Appendices

Instructions for using the Graphing worksheet for calculating and plotting response surfaces

1. Enter the unstandardized regression coefficients and their associated standard errors reported from the polynomial regression run in SPSS (through the syntax) into the ‘Data Entry Area’ at the top left hand corner of the spreadsheet. Also enter the sample size of your data set in the space provided (i.e. n).

2. Enter the covariances for regression coefficients in the right hand column of the ‘Data Entry Area’. These values are obtained from the SPSS output resulted from the polynomial regression run through the use of the ‘beov’ subcommand in SPSS in the syntax (that generates the covariance matrix of regression coefficients).

3. The ‘Testing Slopes and Curves’ box to the right of the spreadsheet calculates the surface values α₁ through α₄ and assesses their significance. These calculations will occur automatically once the corresponding data is entered into the ‘Data Entry Area’.

4. The ‘Points to Plot’ box shows the predicted values of the outcome variable (affective commitment dependent variable-DV) for each combination of the two predictor variables based on the polynomial regression equation and associated unstandardized beta weights. The values -2 to 2 in the gray area represent the points along the X and Y axes and are based on centered-scores of a 5-point Likert-type scale ranging from 1 to 5 (these values can be changed to fit the parameters as per the scale of the measures, keeping within the 5-point framework. If the scale is 7-point Likert type, the points to plot could be used as -4, -2, 0, 2, and 4 as the values). Values are dependent upon the original metric of the scale. DV1 values are across the top, DV2 values are down the left-hand side.

   The polynomial regression formula would be as follows with some hypothetical values for b₀, b₁, b₂, b₃, b₄ and b₅:

   \[ DV = (1.10) + .5(\text{PV}_1) + .5(\text{PV}_2) + .04(\text{PV}_1^2) + 29(\text{PV}_1*\text{PV}_2) + .14(\text{PV}_2^2) \]

   The Excel sheet calculates the predicted values of A.C in the ‘Points to Plot’ box automatically, but as an example, to create the predicted value for the cell -1 PV₁ and 4 PV₂ plug -1 and 4 into the polynomial regression formula as follows:

   \[ DV = 1.10 + .5(-1) + .5(4) + .04(-1)^2 + 29(-1*4) + .14(4^2) \]

5. The Excel spreadsheet automatically creates the graph. Alternatively to create a graph providing corresponding points a table like ‘Points to Plot’ table can be created as above. Once the table is created highlight the table including the -4 to 4 values on both sides, choose “insert chart,” then choose “surface chart.” If using the table setup as shown above, choose “series in columns” and continue with the chart wizard. The minimum and maximum on the Z-axis (the axis for the outcome variable, DV) should span the minimum and maximum values of the scale of the original outcome variable (in our case, 1 is the minimum and 5 is the maximum for 5-point Likert, 1 and 7 if the scale is 7-point Likert). Values on the diagonal represent the line of perfect agreement. Values below the diagonal represents when PV₁ > PV₂. Values above the diagonal represents when PV₁ < PV₂.
## Appendices

### Data Entry Area

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Error</th>
<th>Tolerance</th>
<th>Covariance</th>
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</thead>
<tbody>
<tr>
<td>Constant</td>
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<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>X (16)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Y (16)</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>X^2 (16)</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>X*Y</td>
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<td>0</td>
<td>0</td>
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</tr>
<tr>
<td>Y^2</td>
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### Testing Slopes and Curves

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<th>Method</th>
<th>Standard Error</th>
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<th>Covariance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope: x - y (related to Z)</td>
<td>0.00</td>
<td>0.10</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Curvature: x - y (related to Z)</td>
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<td>0.10</td>
<td>1.00</td>
<td>0.00</td>
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</table>

### Points to Plot

<table>
<thead>
<tr>
<th>X</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>-4</td>
<td>0.00</td>
</tr>
<tr>
<td>-3</td>
<td>0.00</td>
</tr>
<tr>
<td>-2</td>
<td>0.00</td>
</tr>
<tr>
<td>-1</td>
<td>0.00</td>
</tr>
<tr>
<td>0</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>0.00</td>
</tr>
</tbody>
</table>

*Note: Shown is a box of covariance (x = y). Select the desired X; Above the desired Y.*

---

<table>
<thead>
<tr>
<th>Instructions</th>
<th>Graphing</th>
</tr>
</thead>
</table>

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Appendix D – Syntax for polynomial output

a) Syntax for expectations, experience and satisfaction

COMPUTE EXPTcntr = Expectation - 4.
COMPUTE EXPRcntr = Experience - 4.
EXECUTE.
COMPUTE xsquared = EXPTcntr*EXPTcntr.
COMPUTE xy = EXPTcntr*EXPRcntr.
COMPUTE ysquared = EXPRcntr*EXPRcntr.
EXECUTE.

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS BCOV R
ANOVA
/CRITERIA = PIN(0.05) POUT(0.10)
/NOORIGIN
/DEPENDENT Satisfaction
/METHOD = ENTER EXPTcntr EXPRcntr xy xsquared ysquared
(b) Syntax for Customers’ shopping app use and Experience

COMPUTE DCcntr = Customers’ shopping app use - 4.
COMPUTE EXPRcntr = Experience - 4.
EXECUTE.
COMPUTE xsquared = CSUcntr*DCcntr.
COMPUTE xy = CSUcntr*EXPRcntr.
COMPUTE ysquared = EXPRcntr*EXPRcntr.
EXECUTE.

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS BCOV R
ANOVA
/CRITERIA = PIN(0.05) POUT(0.10)
/NOORIGIN
/DEPENDENT Satisfaction
/METHOD = ENTER CSUcntr EXPRcntr xy xsquared ysquared
Appendices

Appendix E – Survey Instrument

DIGITAL CONNECTEDNESS [SMART MOBILE SHOPPING APP USE]

DC1: I frequently use this mobile app to find products
DC2: I frequently use this mobile app to prepare my regular grocery shopping list
DC3: I frequently place orders using the mobile app
DC4: I frequently provide comments and feedback using mobile app
DC5: I frequently use this mobile app to find a store more convenient

EXPECTATIONS [EXPECTED RESPONSIVENESS]

EXPT1: I expect retailer [Woolworths/Coles] to provide information about discounts and promotions based on my specific requirements.
EXPT2: I expect retailer [Woolworths/Coles] to be responsive to my changing needs and wants.
EXPT3: I expect retailer [Woolworths/Coles] to provide personalized offers based on products that I purchase regularly.

EXPERIENCE [PERCEIVED RESPONSIVENESS]

EXPR1: Retailer [Woolworths/Coles] quickly react to the essential basic changes in my product requirements by providing me with relevant personalized information.
EXPR2: After browsing recipes using the mobile app, retailer [Woolworths/Coles] is quick to provide promotional information for the products required to make that recipe.
EXPR3: When I continue to purchase a new product (e.g. Baby nappies) repetitively, Retailer [Woolworths/Coles] quick to respond to it by providing other associated product information (e.g. other baby products).
EXPR4: Retailer [Woolworths/Coles], is fast to provide information about discounts and promotions based on the products I purchase regularly.
EXPR5: Retailer [Woolworths/Coles], is quick to provide information on discounts and promotions for my preferred store based on the products I created in my shopping list in the mobile app.
EXPR6: Retailer [Woolworths/Coles], is able to recognize change in my physical location to prompt discounts and promotions on my usual purchases for the store nearby.
EXPR7: Retailer [Woolworths/Coles] often recommends products that can easily satisfy my changing needs.
EXPR8: Retailer [Woolworths/Coles] can easily satisfy my new and changing needs.
EXPR9: The product displayed in my specials section of the mobile app reflects my specific requirements.
EXPR10: Overall, the promotions I regularly receive from retailer [Woolworths/Coles] are useful and match my unique daily requirements.
EVALUATION  [EVALUATION OF THE PERCEIVED RESPONSIVENESS]

EV1: My shopping experience with the retailer [Woolworths/Coles] was better than what I expected.
EV2: Responsiveness of the retailer [Woolworths/Coles] on my shopping requirements is better than what I anticipated.
EV3: Overall, the retailer [Woolworths/Coles] was able to confirmed or exceeded most of my shopping expectations.

SATISFACTION

SAT1: I am satisfied with the personalized promotions/offers I receive from the retailer [Woolworths/Coles].
SAT2: I am satisfied with the retailer’s [Coles / Woolworths] responsiveness to my changing needs and wants.
SAT3: I am satisfied with my overall shopping experience with the retailer [Woolworths/Coles].
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