Balancing Breadth and Depth in Omnichannel Retailing: Understanding Customer Interaction Complexity and Its Impact on Customer Experience

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Abstract

The omnichannel retail environment has allowed customers to interact with a retailer through myriad combinations of channels and touchpoints. Customer interaction has, therefore, become increasingly complex as customers possess the freedom to design their own customer journey across purchase stages. Many have advocated the role of customer interaction in customer experience creation (e.g., Prahalad and Ramaswamy, 2004; Gentile et al., 2007; Echeverri and Skålén, 2011). However, the optimum levels of customer interaction that could maximise customer experience remain unclear. Previous work has supported the notion that a high variety of channel used could lead to increased customer engagement (e.g., Kumar and Venkatesan, 2005; Sopadjieva et al., 2017), but interacting with a single channel (e.g., offline-only, call centre prone) resulted in higher loyalty (De Keyser et al., 2015). Achieving the right balance of customer interaction is, therefore, critical. In doing so, this present study develops a multi-dimensional concept called customer interaction complexity comprises customer interaction breadth (i.e., the number of retail channels used by customers to interact with a retailer) and customer interaction depth (i.e., the frequency and a range of activities performed by customers via each of those retail channels). Using a cross-sectional customer survey (N = 485) and an experimental study (N = 301), this thesis investigates how customer interaction breadth and customer interaction depth shape the overall customer experience. The results suggest that customer interaction breadth has a U-shaped effect on customer experience, while the relationship between customer interaction depth and customer experience is taking an inverted U-shaped. Channel integration is a significant moderator that flips the effect of customer interaction breadth on customer experience. The effect of customer interaction depth on customer experience differs between offline and online channel: it remains an inverted-U shaped in offline channel but linear and positive in online channel. These effects can be further explained by customer effort and customer enjoyment as significant mediators at some levels of depth (low/moderate/high). Thus, these findings provide managers with guidance to create effective channel design leading to the superior customer experience and enrich the omnichannel literature.

Keywords: *omnichannel, customer interaction, customer experience, channel integration, online channel, offline channel.*

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Chapter 1 Introduction

1.1 Introduction

This chapter establishes the background of the research conducted in this thesis. This thesis begins by first presenting an overview of an omnichannel retail environment and its impact on customers' interaction and retailers. This part brings into focus, and defines, the omnichannel retail environment and the distinction between the definition of what constitutes as a retailer's channel and touchpoint. This is followed by a discussion of prominent literature within the omnichannel research stream, in which gaps are identified and research opportunities are presented. This discussion leads to the formulation of our main research questions and objectives. Next, this thesis pinpoints contributions to the omnichannel literature and to managerial practices. Before this chapter concludes, this thesis's overall structure outlined to illustrate how chapters are organised.

1.2 The outlook of an omnichannel retail environment

This section gives an overview on the impact of omnichannel retailing for customers and retailers. To better understand the omnichannel retail environment we begin by taking a look at the illustration below:

> *On one winter night, a customer watches a YouTube video where a vlogger is cooking a vegetarian pasta dish. It gives her inspiration for a weekend meal, but she still wants to explore more ideas. She chats with her friends and receives a recommendation to search for more inspiration from Instagram using the hashtag #veggiepasta. Upon the search, she comes across a post from @TescoFood. She clicks on the picture and reads the caption describing a dish called parsnip pasta. She follows through a link on the post and watches a step-by-step video.*
>
> *A complete recipe is stated on that page, and with one click, she can either put the listed ingredients on her shopping list or directly on her online shopping*

> *basket. She chooses the latter, and as soon as she logs into her Tesco account, the ingredients are ready to be delivered to her home. She receives her groceries two days after, but unfortunately, one of the ingredients is replaced with something she is allergic to. She checks the closest proximity of Tesco store through the Tesco mobile-app and goes to the store. She tells Tesco's salesperson about her issue and gets a product replacement afterwards.*

The preceding vignette is fictional, but the depiction is by no means untypical. Today's customers face what is called an omnichannel retail landscape, defined as a retail environment where an interaction between a customer and a retailer occurs through multiple and integrated channels and touchpoints, leading to a superior and seamless customer experience throughout the customer journey (Rigby, 2011; Brynjolfsson et al., 2013; Verhoef et al., 2015). Retail channels, in this sense, are generally understood as a pathway that facilitates transactional and informational exchanges between a customer and a retailer (Neslin et al., 2006; Dholakia et al., 2010; Verhoef et al., 2015). The vignette above mentions common retail channels in the form of Tesco's Instagram (social media channel), Tesco's webstore (online channel), and brick-and-mortar store (offline channel). On the other hand, a customer touchpoint refers to an occurrence of an individual direct or indirect contact, either verbal or non-verbal, between a retailer and a customer (Duncan and Moriarty, 2006; Baxendale et al., 2015; Lemon and Verhoef, 2016; De Keyser et al., 2020). Hence, while the Instagram account is Tesco's social media *channel*, the parsnip pasta picture including its caption is a customer touchpoint because the customer is indirectly interacting with Tesco when seeing the post online. So, while a channel is the medium where an interaction occurs, a touchpoint is an episode in which an interaction is taking place or the point of the interaction itself. Every channel hosts numerous touchpoints, for instance, an online channel has multiple touchpoints such as an online chat, a FAQ page, a product page, a payment page, a customer account page, a shopping basket, a historical order record, etc.

The advancement of technology has accelerated the proliferation of channels and touchpoints within the omnichannel retail environment. As such, it has become integrated not only into customers' daily lives but also retailers' strategies. Technology allows retailers to gain the new capabilities such as being able to coordinate resources and information across channels and touchpoints (i.e., IT-enabled channel integration capability) (Oh et al., 2012). Through the use of big data and predictive analytics, it enables retailers to learn customers' preferences, subconscious habits, and behavioural responses to the marketing mix at the individual level (Bradlow et al., 2017). As a result, it allows retailers to provide a new height of personalisation and customisation in the customer journey (Yadav and Pavlou, 2014; Barwitz and Maas, 2018) in terms of individual product or service offerings and recommendations (Bijmolt et al., 2019). Personalisation creates a new sense of closeness or intimacy in a customers' mind and so interacting with big retailers can feel similar to interacting with a local coffee shop. In the sense that a seller remembers a customer's favourite products and the provides a tailored service without the customer even asking for one. This new dynamic suggests that the customer-retailer relationship has shifted into something more personal than ever. As for retailers, these hyper-targeting tactics increase the effectiveness of cross- and up-selling initiatives boosting retailers' revenue (Fong et al., 2015; Bradlow et al., 2017).

Scholars have discussed the benefits of implementing omnichannel strategies, for instance, expanding market base (Gao and Su, 2017), strengthening customer loyalty (Wallace et al., 2004; Herhausen et al., 2019), increasing retailer's financial performance (Cao and Li, 2015), and facilitating marketing agility in the ever-changing retail environment (Kalaignanam et al., 2020). These advantages encourage retailers to transform into omnichannel retailers. In the UK, the big four grocers – Tesco, Asda, Sainsbury's, and Morrisons – have adopted at least three channels: offline, online, and

mobile. Even discounters such as Aldi have increased their online presence by offering a click-and-collect service for limited geographical coverage. In a similar way, John Lewis, a high-end department store, has demonstrated its commitment to capitalise on today's digitally enriched retail environment by utilising multiple social media as official channels (Moth, 2013) and developing a mobile app as an established channel that is not only independently able to serve mobile-prone customers, but also assists offline customers simultaneously through inter-connection via in-store technology-infused touchpoints (Hammet, 2018; John Lewis, 2019).

While the aforementioned retailers expand their breadth of channel choice, some other retailers have decided on a different approach. Instead of focusing on the breadth of channel choice, other retailers fix their attention on facilitating a more elaborate range of customer activities in their existing channel. Primark, the Irish fashion retailer, persists in keeping its brick-and-mortar stores as the only purchase channel, leaving its website to act as an online catalogue. Primark focuses on retaining cost leadership and creating the best customer experience through in-store experience (Kraaijenbrink, 2019; Hanbury, 2020). The retailer added more services in-store, such as a beauty corner, a customised t-shirt printing service, and a coffee shop. In 2019, Lush, a British beauty retailer, opted to shut down its social media (Facebook, Twitter, Instagram) in the UK market (Gunia, 2019; Kleinman, 2019) due to its reluctance to invest in social media channels and its preference to interact with customers exclusively through brand-owned channels and touchpoints (i.e., website, call centre, and email) (Gunia, 2019). Instead of relying on multiple social media channels that offer little control for Lush, they added a wider range of services such as new payment methods (e.g., pay later option, bitpay, and PayPal) and an online chat assistant in its online channel. Adding to its offline channels, Lush put in place a new payment system that can access customer's online

wishlist, a voice-activated assistant called Lush Concierge, and a Lush Lens—a visual search tool using augmented reality (Gilliland, 2018).

The aforementioned examples show contrasting strategies adopted by leading retailers. Some retailers embrace the omnichannel strategy by building on more and more channels, while others enrich their current channels to cater to more shopping-related activities. The various omnichannel strategies employed by retailers may be due to the differences in resource allocation and investment priorities. The addition of a completely new channel cost retailers a significant investment both in building a capable supply chain system, a competent army of employees (e.g., training and recruiting) and integrated marketing strategy (Neslin et al., 2006; Neslin and Shankar, 2009; Zhang et al., 2010; Bijmolt et al., 2019). At the same time, more channels present more responsibilities to control and manage. For retailers, focusing on existing channels means managing the level of control over the distribution of information, initiating interaction, and managing the channel's investment. Ultimately, all strategies mentioned were formulated to achieve a superior customer experience believed to be the key to business sustainability (Grewal and Roggeveen, 2020). Between investment and return, retailers have to decide the extent to which they implement strategies. As such, we follow-up with the question, how can retailers utilise and survive within the omnichannel retail environment?

One avenue to answer the previous question is to understand channel and touchpoint design as well as customers response, especially pertaining to customer experience. A retailer's decision in designing channels and touchpoints affects the amount and the accessibility of interaction. New initiatives can generate interactions that were previously unviable, such as checking available stock in-store through a mobile app, virtual try-on products, product fulfilment through a stand-alone parcel locker, or the

ability to order and pay at a different retail channel. The possibilities are endless and customer interaction becomes increasingly complex.

As a result, customers have more options about *where to shop* but also *what to do*. Yet, despite such developments, there is still a limited understanding of the holistic view of customer interaction. Existing studies heavily focus on the *where* aspect and examine the impact of a variety of channels (i.e., customer interaction breadth) and channel choice (Verhoef et al., 2007; Valentini et al., 2011; Bilgicer et al., 2015; Melis et al., 2015; Polo and Sese, 2016). But even in these studies, the combination of channels and touchpoints studied are restricted to those most common. As new channels and touchpoints emerge, there is a growing need to update the current understanding of customer interaction within the retailer's channel.

The '*what to do'* decision is related to actions taken within a shopping journey which are usually grouped into three purchase stages: search, purchase, and after purchase (Konuş et al., 2008; De Keyser et al., 2015; Sweeney et al., 2015). Within each stage, customers can perform various activities to support their journey, which implies a level of customer participation (i.e., customer interaction depth). Together, decisions about "where to shop" and "what to do" shape the complexity of customer interaction. However, there are fragmented studies examining these questions in isolation and no attempt to address them in a unified fashion. The more channels and activities involved in a customer journey, the more complex the interaction becomes. A greater number of activities completed in a customer journey will increase favourable behavioural intention (Sweeney et al., 2015). Interaction with multiple channels can benefit customers in terms of greater satisfaction and enjoyment (Wallace et al., 2004; Konuş et al., 2008; Sopadjieva et al., 2017). However, some scholars argue that having to interact with fewer channels makes a customer happier and willing to do more business in the future (Dixon et al., 2010; Spenner and Freeman, 2012).

The opposing views prompt us to question how customer interaction complexity contributes positively to customer experience. The existing analysis in the literature may not give a full picture of the relationship. Positive and negative effects of customer interaction complexity on customer experience may depend on a certain contextual condition (e.g., product category). However, beyond a moderator, there is also a potential theoretical explanation for why the effects of customer interaction complexity may sometimes be positive and other times negative—social penetration theory. Social penetration theory dictates the development of a relationship based on the level of interaction that progresses through evaluating cost, benefit, and expected satisfaction (Altman and Taylor, 1973). A complex interaction can be rewarding as it triggers a feeling of enjoyment (Anton et al., 2013), but it comes with a cost of increased effort (Clarke and Belk, 1979; Sweeney et al., 2015). Meanwhile, a simple interaction may be seen as convenient (Berry et al., 2002) but can also be a lacklustre experience (Ratner and Kahn, 2002). Existing analysis of customer interaction complexity is perhaps too simplistic, and its effect on customer experience may actually be curvilinear. The challenge here is to find the optimum level in which customer interaction can maximise customer experience.

1.3 Gaps in the literature and research objectives

The previous section highlights how retailers and customers navigate themselves in an omnichannel retail environment. Past research has suggested multiple benefits of being omnichannel retailers. First, omnichannel retailers gain access to a new market base by acquiring new channel-specific customers who would otherwise be neglected (Zhang et al., 2010; Gao and Su, 2017). Second, the business model fosters retailers' ability to collect, analyse, and interpret customers' data from multiple data points (Zhang et al., 2010; Bradlow et al., 2017). Third, omnichannel retailers are better positioned to achieve marketing efficiency and effectiveness through economies of scale and

economies of scope (Neslin et al., 2006). However, applying the omnichannel strategies is not an easy task. Retailers often face operational difficulties such as managing coordination across channels and ensuring product flow considering assortments' variety across channels (Neslin et al., 2006; Zhang and Bartol, 2010; Bijmolt et al., 2019). There is also an increased cost when retailers add new channels, both on tangible assets such as the lease of new stores and intangible assets such as patented technology or internet domain (Zhang et al., 2010).

After all, the aim is to provide a seamless customer experience sought by customers. Myriad options offered within the omnichannel retail environment allow customer interaction to be as complex as possible (Herhausen et al., 2019). However, whether a complex interaction is what contributes to a better customer experience remains a question. Customer interaction, in general, has been found to influence the duration of the customer-retailer relationship development (Venkatesan et al., 2007). Customers with either very low-levels or very high-levels of interaction's frequency formed the relationship slower and took a longer time to adopt a new second channel (Venkatesan et al., 2007). Other studies discussed the positive effect of customer interaction on relational outcomes such as purchase and retention (Lemke et al., 2011; Sopadjieva et al., 2017). Empirical evidence support this notion suggesting that the variety of channels affects customer loyalty linearly through positive disconfirmation of service expectation (Wallace et al., 2004; Herhausen et al., 2019).

Moreover, retail atmospheric elements within online and offline touchpoints have been found to stimulate customer experience (Bleier et al., 2019; Roggeveen et al., 2020). For instance, the use of a comparison matrix was found to be especially effective in stimulating positive cognitive experience, and product visualisation was shown to trigger favourable sensory experience (Bleier et al., 2019). This knowledge, as mentioned above, sets a basis for examining the relationship between customer

interaction and customer experience. The following sections will further unravel the identified gaps pertaining to customers' response to omnichannel retail environment.

1.3.1 Gap 1: Fragmentation of previous studies on customer interaction

In the context of multichannel or omnichannel retailing, previous studies have discussed different aspects of customer interaction. Customer interaction refers to any direct and indirect contact between a customer and a retailer, including the retailer's people, process, product, and technology (Meyer and Schwager, 2007; Bolton and Saxena-Iyer, 2009). A lot of attention has been given to understanding customer interaction with retailer's channels. In particular, studies have examined the impact of the number of channels used by customers during a customer journey. While Konuş et al. (2008), De Keyser et al. (2015), and Herhausen et al. (2019) have used the number of channels as a foundation to formulate customer segmentation, others have tested it against customer purchases to measure customer lifetime value (Kumar and Venkatesan, 2005; Kushwaha and Shankar, 2013; Cambra-Fierro et al., 2016). Similarly, Helmefalk and Hultén (2017) studied the impact of customer interaction within multisensory offline touchpoints and discovered how the variety of sensory cues could positively influence customer emotion and purchase. Another aspect of customer interaction that has been explored is the frequency of interaction. It has been used to measure channel habit (Cambra-Fierro et al., 2020), to predict channel choice (Venkatesan et al., 2007), and as part of customer interaction to retailer's touchpoints (Baxendale et al., 2015).

Customer interaction was also studied respectively to the channel where it happens. For instance, Bleier et al. (2019) focused on understanding customer interaction across online touchpoints and assessed the impact of online atmospheric elements on customer experience. Other studies have focuses on the quality of online and mobile customer interaction, assessing the positive impact of convenience, ease of use, and interactivity on customer experience (Novak et al., 2000; Rose et al., 2012; McLean et al., 2018).

Research within the offline retail environment has examined the effect of customer interaction with other customers (Grove and Fisk, 1997) and with salespeople (Arnold et al., 2005), such as how incidents involving other customers and salespeople carry over to affect the overall shopping experience.

Individually, these studies contribute to the knowledge of customer interaction and customer experience. However, the results of previous studies are fragmented and not directly comparable because they focus on different aspects of customer interaction (e.g., frequency, number of interaction medium, habit, activities). A unified approach that conceptualises interaction holistically and as a multidimensional construct is missing. Therefore, it would be beneficial to adopt a theoretical perspective that enables a cohesive theoretical model of omnichannel customer interaction. For that reason, this thesis attempts to provide a more nuanced coverage of how interaction influences customer experience by conceptualising customer interaction as a two-dimensional construct of customer interaction complexity that comprises *customer interaction breadth* and *customer interaction depth.*

Customer interaction breadth, the first dimension, encapsulates the variety of channels used by a customer to interact with a retailer. The higher the customer interaction breadth, the more it reflects the tendency of a customer being an omnichannel customer. The second dimension, customer interaction depth, depicts the range of customer activities and the frequency of customer performing the activities across a retailer's channels. Customer interaction depth explores the dynamic of customer activities within three main stages of pre-purchase, purchase, and post-purchase. Prevailing research focus on a broader level of purchase stage while neglecting the range of interaction within the individual phase (Verhoef et al., 2007; Konuş et al., 2008; De Keyser et al., 2015). Within this new conceptualisation, customer interaction depth covers the number of activities involved in each stage. For example, during the pre-purchase phase, a

customer may interact with a retailer in the form of consultations with salespeople, price comparison, conversation with other retailer's customers, or receiving a product/service trial. The more elaborate the activities involved and the more frequent the activities performed, the higher participation or involvement a customer has concerning a particular omnichannel retailer.

1.3.2 Gap 2: The lack of channel-related factors in the investigation of customer interaction complexity – customer experience link

Channel Integration

The second gap focuses on the moderating variable that might change the strength of the relationship between customer interaction complexity and customer experience. Current literature has mainly assessed the role of product-related characteristics (e.g., product category, product risk, product complexity) and the experiential context (e.g., emotional involvement, relationship quality) when it comes to examining the moderating role between customer interaction and its outcome (Lemke et al., 2011; Kushwaha and Shankar, 2013). For instance, findings suggest that high levels of customer interaction breadth lead to higher monetary value when it comes to hedonic product (vs utilitarian) (Kushwaha and Shankar, 2013). At the same time, Lemke et al. (2011) found that customers may form a certain level of emotional involvement in a certain product, which will influence that product's perceived importance (Antil, 1984; Mittal, 1989). The increased level of emotional involvement accentuates the positive relationship between customer interaction and shopping values (Lemke et al., 2011).

Customer interaction is indeed affected by the factors above, but past studies have not considered a factor created by the retailer itself, such as channel integration. Channel integration embodies the essence of omnichannel retailers and has been positioned as a factor that differentiates omnichannel retailers from others (Beck and Rygl, 2015; Picot-Coupey et al., 2016). It has a positive direct impact on service quality (Herhausen et al.,

2015), customer engagement (Shen et al., 2018; Lee et al., 2019), and eventually on retailer's performance (Oh et al., 2012; Cao and Li, 2015). In fact, retailers' strategies, such as click-and-collect, have been implemented to increase integration between channels.

Nevertheless, retailers' effort to integrate channels and touchpoints comes at a high price in terms of monetary investment and know-how (Neslin et al., 2006). As a result, the level of channel integration varies between retailers as even those who claim to be omnichannel retailers do not always have the same level of channel integration. The condition perpetuated by omnichannel retailers creates situational variances in the customer journey. Although the importance of channel integration has increased, there is little attention given to how channel integration influences the omnichannel customer journey. An example of this is a neglect of how channel integration affects the creation of customer experience driven by customer interaction. There is a clear need to incorporate channel integration into the current study to get a more realistic approximation of the linkages between customer interaction complexity and customer experience.

Channel Type

The second channel-related factor identified to alter the customer interaction complexity-customer experience linkages is a channel type. In particular, two prominent channel types, offline and online channel. Offline and online channel, as we have seen in the very beginning of this chapter, are not the only available channels in the omnichannel retail environment. However, the comparison of these two channels is highly relevant in the context of research and management practice, since offline and online channels are the most dominant channels in the current retail landscape. So far, the moderating role of offline versus online channel has been studied in regards to the linkages between customer satisfaction and loyalty, which was found to be stronger in

an online channel (Shankar et al., 2003; Hult et al., 2019). Shankar et al. (2003) argued that online channel expedites effort minimisation for future purchase by bookmarking the page address on customers' browsers, recording favourite products (regularly bought), and saving payment details and delivery details. Harris et al. (2006) suggested that a similar reason is responsible for creating power of control. Customers in the online channel feel greater control in making their interaction worthwhile such that a poor service failure recovery will have a weaker effect on them (Harris et al., 2006). The online channel, however, has limitations in transferring physical and sensorial cues. As a result, online customers prone to make a judgement based on heuristic cues such as brand name (Degeratu et al., 2000; Danaher et al., 2003; Saini and Lynch, 2016) and trustworthiness (Martin and Lueg, 2013; Ortinau et al., 2013), which are more beneficial for big brand name. Other studies have similarly discussed the distinction of the offline and online channel in the context of pricing (Grewal et al., 2010; Chintagunta et al., 2012), price dispersion (Zhuang et al., 2018), post-purchase regret (Park et al., 2015), and search cost-price sensitivity (Chiu et al., 2019).

Previous studies have not explicitly drawn a comparison between offline and online channels in influencing customer experience in omnichannel research. Nevertheless, it is pertinent to assess the impact of different channel types on customer experience creation through customer interaction because these two channel types are the most typical channels involved in customers' channel repertoire and retailers' channel management. Considering the strong linkage between customer experience and satisfaction, previous studies can help this present study reveal the effect of offline versus online channels in predicting customer experience.

1.3.3 Gap 3: The lack of mediating mechanism explaining customer interaction complexity – customer experience link

The third gap highlights the need to understand the underlying assumptions regarding how customer interaction complexity has impacts on customer experience. Past studies have proposed mechanisms to understand how customer interaction results in a certain relational outcome, such as through motivation (Lemke et al., 2011), switching cost (Cambra-Fierro et al., 2020), service benefits (Wallace et al., 2004), or perceived utility as a result form cost-benefit evaluation (Balasubramanian et al., 2005; Konuş et al., 2008; De Keyser et al., 2015; McLean et al., 2018).

These studies gave theoretical direction toward identifying potential mediators but could not directly explain the outcome of customer interaction. First, the notion of cost-benefit analysis as customer's evaluation has offered a very strong foundation, however, some studies conceal these cost-benefit dynamics under customer psychographics (e.g. Konuş et al., 2008; De Keyser et al., 2015). For example, cost-saving was captured by price consciousness (Konuş et al., 2008), or exploration was expressed as customer's innovativeness (De Keyser et al., 2015). Moreover, cost and benefit were not assessed as derivatives of a customer journey but instead attributed to customers' characteristics. Second, other studies have presented only one part of the story by testing either the cost or the benefit of customer interaction (Cambra-Fierro et al., 2020; Wallace et al., 2004), and therefore could not provide an integrative framework to examine the mediating mechanism. Third, the value-in-use (i.e., an outcome in relation to customers' sought-after goal), as Lemke et al. (2011) suggested, is largely affected by predefined motivation prior to the journey and not elicited by the process of customer interaction itself.

There is still a need to re-examine the underlying mechanism of customer experience that both captures cost and benefit, applicable for omnichannel context, and represents

an outcome of a journey. Franke and Schreier's (2010) theory of product personalisation can help develop such a mechanism. Psychological reaction derived by the personalisation process, namely customer effort and customer enjoyment (Franke and Schreier, 2010), can be used to form mediators between customer interaction complexity-customer experience link. Customer effort represents the cost of customer interaction, while customer enjoyment can be seen as the benefit of customer interaction. Taken together, both customer effort and customer enjoyment give more representation to the evaluation of customer interaction.

1.4 Research questions and objectives

Building on three literature gaps identified in the previous section, this thesis sets four research questions to help to navigate the overall empirical research process.

1. How does omnichannel customer interaction complexity contribute to the creation of customer experience?
2. What is the role of channel integration in the linkages between customer interaction breadth and customer experience?
3. What is the role of channel type in the relationship of customer interaction depth and customer experience?
4. What are the underlying mechanisms that drive the moderating effect between channel type and customer interaction depth on customer experience?

By answering the research questions above, this study aims to accomplish the following research objectives:

- To understand customer interaction complexity by applying an integrative framework on interpersonal relationships within a complex retail environment.
- To analyse the role of customer interaction complexity (i.e., customer interaction breadth and customer interaction depth) in the creation of customer experience.

- To examine the role of channel integration and channel type as channel-related factors in the omnichannel retail environment that could potentially strengthen or alleviate customer experience.
- To identify the underlying mechanism (i.e., customer effort and customer enjoyment) leading the interactive effect of channel type and customer interaction depth to customer experience.
- To provide scholars and practitioners with a novel understanding of the comprehensive framework on customer experience creation through customer interaction complexity.

To achieve our objectives, this particular research employs a data triangulation approach using multiple methods to collect and analyse data. It combines a cross-sectional customer survey and an experimental study to better understand the conditions and underlying mechanisms that explain when and why customer interaction complexity affects the customer experience. Two studies are employed to answer all of the research questions; Study 1 is the cross-sectional customer survey and Study 2 is the experimental study. This present thesis runs Study 1 to test the direct effect between customer interaction complexity and customer experience. Moreover, Study 1 tests the moderating effect of channel integration on the relationship between customer interaction breadth and customer experience. Channel type, as a moderator on the relationship between customer interaction depth and customer experience is tested using Study 2. Furthermore, this study explores the underlying mediating mechanism involving customer effort and customer enjoyment on the said moderating mechanism. Collectively, all of the studies in this research intend to advance the theoretical, conceptual, and operational understanding of the current body of omnichannel customer interaction.

1.5 Contribution of the study

First and foremost, this thesis seeks to bridge the identified gaps discussed before and provide a vital contribution to the omnichannel retailing literature stream. By making a novel attempt to conceptualise customer interaction complexity, this thesis specifically enhances our understanding of customer response to an omnichannel retail environment (i.e., Venkatesan et al., 2007; Konuş et al., 2008; Dholakia et al., 2010; De Keyser et al., 2015; Verhoef et al., 2015; Cambra-Fierro et al., 2016; De Keyser et al., 2020). This is done by establishing the new multidimensional concept of customer interaction complexity which comprises customer interaction breadth and customer interaction depth. More precisely, we seek to unfold the curvilinear nature of customer interaction complexity's dimensions when it comes to the creation of customer experience. In doing so, this research is aims to identify the optimal levels of both customer interaction breadth and customer interaction depth that contribute to customer experience maximisation.

Secondly, this study brings to light the role of channel integration and thus reiterate the importance of it to be considered in designing omnichannel retail strategies. This present research shows how channel integration changes the strength of the customer interaction-customer experience relationship, thereby deepens our knowledge about the retailer's channel attribute by which the customer experience is affected. While previous studies emphasise the role of channel integration in determining customer engagement (Shen et al., 2018; Lee et al., 2019) and retailer's performance (Oh et al., 2012; Cao and Li, 2015), this present research complements such assertions by showing that channel integration impacts the creation of customer experience.

Thirdly, this research investigates the moderating effect of the channel type (i.e., offline versus online) as a channel-related factor in a customer journey. The offline and online retail environment gives a different impact in influencing customers perception and

evaluation, such as found in satisfaction (Shankar et al., 2003; Hult et al., 2019) and regret (Park et al., 2015). Furthermore, this thesis presents the mediating power of customer effort and customer enjoyment in the relationship between the customer interaction depth and customer experience. By understanding this logical process, this thesis explores the role of cost and benefit analysis that customers engage in when shaping their evaluation of customer experience. More specifically, it unravels the dynamic between customer effort and enjoyment and how this will be able to explain the distinct effect of customer interaction depth and customer experience in offline versus online channel. Consequently, our findings will extend the current knowledge regarding similarities and differences in customers responses to offline versus online retail environment.

Finally, these research findings will offer valuable insights to retail managers for which they can use when designing channels and touchpoints. In the practical context, results related to channel integration give options to retail managers regarding how to develop and allocate resource across channels and touchpoints. Findings regarding the optimal levels of customer interaction breadth can be used as guidance when choosing top priority channels to develop and to concentrate on. Similarly, the optimal levels of customer interaction depth give an indication to managers about designing an effective set of activities within multiple touchpoints. More specifically, by showing the differences in customer effort and customer enjoyment between the offline and online channel, this thesis aims to helps managers deciding on the appropriate level of interaction depth respective to each channel type. For instance, managers can choose to give options for a simpler customer journey by designing shortcuts such as one-click shopping or express checkout at an online channel or, conversely, enable a more elaborate journey by enriching activities that promote enjoyment in the online channel.

1.6 Structure of the thesis

This thesis consists of eight chapters following the research process conducted throughout the research project. The table below sums up the themes and content of each chapter.

Chapter 1 lays out the research background and presents gaps within the literature, research questions, and objectives. Contributions of the study are discussed both in terms of advancing the literature and suggestions for managers.

Chapter 2 presents an overview of the literature review in more details. It discusses the current understanding of what has been studied in omnichannel customer behaviour, customer experience, channel integration, and other constructs such as customer enjoyment and customer effort. It highlights the opportunities to contribute through the presentation of literature gaps.

Chapter 3 thoroughly explains social penetration theory as the overarching theory that assists in developing our conceptual framework. This is followed by the formulation of our hypotheses that individually links constructs suggested in our framework. In particular, discussion in Chapter 3 establishes the non-linear relationship between customer interaction complexity and customer experience as well as the moderating role of channel integration on flipping the shape of the relationship. Moreover, we hypothesise the mediating role of customer enjoyment and customer effort, and present arguments on the boundary condition (moderator) of channel type.

Chapter 4 presents a general research methodology that exhibits the basic philosophy used in this research. It discusses the research design and design of the studies (cross-sectional survey and experimental studies). A sampling design and analytical procedures are explained in this chapter. However, a more detail methodology is presented in the following chapters respective to each study.

Chapter 5 and 6 show the data and analysis for each study conducted in this research project. They are completed with the overview of the methodology, which consists of operationalisation of constructs and questionnaire or scenario development. Chapter 5 focuses on the first study regarding the cross-sectional customer survey, while Chapter 6 focus on the experimental study. Chapter 5 and 6 both include a discussion about the data collection process and preliminary analysis. Hypotheses testing are presented, and a discussion of results is shown at the end of each chapter.

Chapter 7 provides a general discussion of results and integrates findings from the two studies. Subsequently, theoretical contribution and managerial implication are discussed. The chapter concludes by disclosing the limitations of this research and offers suggestions for future research. The summary of the chapters can be seen in Table 1.1.

Table 1.1 Structure of the thesis

Chapter	Themes and content of the chapter
1	Introduction to the background of studies, research gaps, research questions and objection, and value of the research.
2	A literature review consisting of an overview of omnichannel literature, a review of customer behaviour in an omnichannel retail environment, and a review of customer experience literature.
3	A discussion of social penetration theory, a formulation of the conceptual framework, and hypotheses development.
4	An overview of research methodology comprising the philosophical foundation and methodological processes utilised in this research.
5	Discussion of methods, data analyses, and results from Study 1 (customer survey)
6	Discussion of methods, data analyses, and results from Study 2 (experimental study)
7	General discussion of the results, theoretical contribution, managerial implication, research limitation, and recommendation for future research.

1.7 Chapter summary

This chapter begins by laying out the research background, contrasting challenges and opportunities within the retail industry, as well as the changes in the way customers interact within the omnichannel retail environment. Subsequently, research gaps are presented to assist the authors in formulating research questions and objectives. The value of the study, then, discusses the contributions to the literature and managers. Lastly, a structure of the thesis is presented, which brings us to the next chapter which presents a more detail review of the omnichannel research.

Chapter 2 Literature Review

2.1 Introduction

This chapter is used to form the theoretical foundation of the thesis and begins with an exploration of the existing literature around multichannel and omnichannel retailing. This is followed by a discussion of customer interaction in the omnichannel retail environment and customer interaction complexity in conjunction with the social penetration theory. Hence, the first two constructs discussed are customer interaction breadth and customer interaction depth. Then, the discussion moves to the moderating variable namely channel integration. The next construct to be discussed will be the customer experience, which is a multidimensional construct. The dimensions include cognitive, affective, behavioural, sensorial, and social; these are individually addressed in a separate subsection. Following this is a section focusing on the mediating constructs, customer enjoyment and customer effort. Finally, an elaborated research gaps are presented followed by a brief summary of the literature review.

2.2 The omnichannel retailing

2.2.1 The evolution of the retail environment

The retail environment is largely affected by micro and macro marketing environment factors (Armstrong et al., 2019). Macro environmental factors, particularly technological advancement and socio-cultural trends, contribute significantly to determining how retailers operate (Berman and Evans, 2013) while the dynamics from customer behavioural changes and the competitors' strategies shape the landscape in the retail industry. In sum, the retail environment is very susceptive to change due to its elasticity against the aforementioned factors.

As a result, retailers continuously explore alternative methods to reach out to customers other than utilising physical stores. The idea is to give customers the flexibility to

interact with retailers at their most convenient time. The non-physical store alternatives offer some benefits that physical stores may not provide. The benefits mostly revolve around convenience, which can be translated into several perspectives such as flexibility of the perceived opening hours, time and effort saving since customers could interact from their home or office (Eastlick and Feinberg, 1999), and the large geographical scope due to deliveries relying on postal or courier service which is mostly available across regions. The latter is probably why the alternative methods are more popular in rural and suburban areas (Lumpkin et al., 1986).

Catalogue shopping and home television shopping are the pioneer of alternative shopping methods to acquire products or services. Catalogue shopping, in particular, enables customers to indirectly interact with a retailer through a careful inspection of the available merchandise assortment at any given time they want and has been described as "an analogue version of the internet" (Cocozza, 2013). Television shopping, similarly, also creates an indirect interaction but, more specifically, a parasocial interaction between customers and the host, which is profoundly within the older customer segment (Lim and Kim, 2011). The advent of commercial consumer access to the World Wide Web started during the 1990s (O'Luanaigh, 2014) and impacted the retailing industry. New retailers were born that operate through online channel only as seen when Amazon and eBay launched their first business in 1995 (Ellis-Chadwick, 2019). As a result, the competition rose between the pure online retailer and pure brick-and-mortar (offline) retailer.

In the 2000s, retailers adopted more than one distribution channel to connect with various segments of their customers, beginning an era called multichannel retailing. It is no longer online retailers versus offline retailers, but instead, single-channel retailers versus multichannel retailers. Neslin et al. (2006, p.96) defined multichannel customer management as "the design, deployment, coordination, and evaluation of channels to

enhance customer value through effective customer acquisition, retention, and development". In the beginning, multichannel retailers tend to adopt a silo approach to manage their channels (Picot-Coupey et al., 2016) as it is perceived to be the most appropriate strategy when retailers serve different types of customers. Each set of channels is dedicated to a distinct group of customers, and therefore, each channel typically has different offerings, service outputs, and marketing mix. Retailers focus on maximising the outcome of each channel as a separate entity. At a very extreme point, there could be fierce competition between channels because channel performance is measured individually.

However, retailers soon realised the importance of integrating their distribution channels to generate a better service to their customers (Zhang et al., 2010; Cao and Li, 2015), which marks the age of cross-channel retailing. The most common combination is perhaps the combination of the offline and online channel. Retailers implement cross-channel strategies to take advantages of offline and online channel combination. One of the strategies is a buy-online-pick-up-store (BOPIS) initiative. Researchers have empirically shown that BOPIS initiative can increase retailers' sales (Bell et al., 2014; Gao and Su, 2017). Another cross-channel strategy is how online retailers such as Made.com build an offline showroom to showcase their online catalogue and finalise the purchasing process through their online shop. This strategy aims to reduce the risks created during online shopping by introducing the touch-and-feel experience to what was previously only virtual.

At the stage of cross-channel retailing, retailers' channel scope is limited to their owned channels such as an offline store, online channel, catalogues, or interactive home shopping. As retailers adopt omnichannel retailing, their channel scope grows broader, integrating customer touchpoints into their channel management (Verhoef et al., 2015). Customer touchpoint refers to an episode where a customer interacts with an aspect of a

retailer (Baxendale et al., 2015), which may include two-way or one-way communication channels (e.g. TV, radio, print media).

The term omnichannel was first introduced in the context of the retailing industry by Rigby (2011) in his HBR article “The Future of Shopping”. It refers to a retail business model in which numerous channels and touchpoints are integrated and managed synergistically to create a seamless customer experience (Rigby, 2011; Brynjolfsson et al., 2013; Verhoef et al., 2015; Bijmolt et al., 2019). It differs from multichannel retailing in several ways. First, the multichannel model adopts a siloed approach where each channel is managed as an individual entity (Picot-Coupey et al., 2016). An omnichannel model focus on integrating all channels and touchpoints, and creating synergies between physical and virtual channels (Rigby, 2011). Second, multichannel performance is measured based on individual channel performance, while omnichannel retailers aim to achieve aggregate performance across channels (Verhoef et al., 2015). The last distinction between multichannel and omnichannel retailing is on the overall firm’s objective. While multichannel retailers pursue singular channel experience, omnichannel retailers aim at delivering customer expectation while crafting a consistent and seamless customer experience across channels (Verhoef et al., 2015). It becomes pertinent for retailers to survive, adapt, and compete in an omnichannel retail environment because it can extend the business sustainability in the future (Rigby, 2011).

2.2.2 Omnichannel retailing literature overview

The evolution of multichannel retailing to omnichannel retailing has also been reflected in the literature. A large volume of published studies have investigated the effect of multichannel strategies on retailers’ performance and customers’ behaviour (see Neslin et al., 2006; Neslin and Shankar, 2009; Dholakia et al., 2010). These multichannel research have acted as the groundwork for omnichannel literature that are published

later on (see Verhoef et al., 2015; Bijmolt et al., 2019). Therefore, it makes sense to include multichannel literature into the overview of omnichannel literature. We limit our literature search to 4* and 3* journals within the Academic Journal Guide (formerly known as ABS List) with additional of retail-focused journal in the lower rank such as Journal of Retailing and Consumer Services. For the database search, we first constructed a search string using five main keywords linked by the Boolean operator *AND*: marketing, retailing, omnichannel, cross-channel, multichannel. Based on the preliminary result, we added two more keywords channel integration and offline-online in order to capture more articles in the area of interests. In the next step, we consider the relevancy of the publications based on whether the articles (1) consider one or more variables related to our research, (2) suggest fundamental and general knowledge of a specific type of retail business model, and (3) within the customer-firm relationship scope. In this way, several areas of research are excluded such as message framing in marketing communication, information and technology system, and inventory and supply chain management system. Appendix A lists all of the relevant literature that contributed to the growing area of omnichannel research. Four major research streams emerge from the list: (1) typology and categorisation of omnichannel retailers (2) omnichannel retail strategy, which include cross-channel strategy and retail mix, (3) examination of channel integration and (4) consumer research in omnichannel retailing.

Marketing scholars have attempted to differentiate what constitutes omnichannel retailers and what differentiates them from others. Using retailers' capability to integrate channels and to initiate interaction with customers, retailers are divided into three categories: no integration (i.e., multichannel), partial integration (i.e., cross-channel), and full integration (i.e., omnichannel) (Picot-Coupey et al., 2016). Saghiri et al. (2017) also use the concept of integration but not limited to channel types; instead, they added two more dimensions which are channel stages (i.e., information, payment, product

delivery, and product return channel) and channel agents (i.e., manufacturer, physical retailer, digital retailer, and third parties). Collectively, Saghiri et al.'s framework is useful for identify critical aspects of the omnichannel system based on the channel types in every stage of the customer journey and the responsible party of said channels.

Within the second domain, researchers have studied initiatives commonly applied at omnichannel retailers such as BOPIS, showrooming, and cross-channel promotion. In general, the optimum utilisation of omnichannel strategies considers two aspects, customer preferences and channel attributes (Hosseini et al., 2018). For instance, the implementation of BOPIS is useful in eliminating customers' uncertainty about price and product availability, and hence reduce potential problems during the search stage (Bell et al., 2014). However, the success of BOPIS initiative depends on the congruity between product and channel (Gao and Su, 2017). Products that sell best offline should not be made available for BOPS in order to keep the offline-traffic high (Gao and Su, 2017). This is also why it is financially better for retailers to promote online customers to shop offline, but not the other way around because impulse buying happens more frequently in the offline channel (Zeng et al., 2016). However, if retailers want to take advantage of customers' showrooming behaviour (i.e., search offline, buy online), they need to list a related-but-not-identical product or niche products exclusively on the online channel (Brynjolfsson et al., 2013; Gu and Tayi, 2017). This strategy increases purchase incidents and offers additional variety at the purchase channel while minimising product handling cost in the search channel.

In the third domain, researchers have explored the importance of adopting channel integration. Marketing scholars have examined channel integration as an antecedent to retailers' performance (Payne and Frow, 2004) through increased customer trust (Cao and Li, 2015) and retailers' competence (Oh et al., 2012). Past studies have demystified concern over channel conflicts (e.g., channel cannibalism, negative spillover effect)

when considering appropriate channel integration strategies. Herhausen et al. (2015) studied a multichannel retailer and found that the increased service quality in online channel bear no negative effect on customers' perception towards the offline channel. Channel harmony can be further extended by applying profit sharing between channels (Yan et al., 2010). Researchers have also assessed the impact of channel integration on customer engagement, noting its positive influence through customer perceived control (Zhang et al., 2018), service quality (Sousa and Voss, 2006; Herhausen et al., 2015; Shen et al., 2018; Lee et al., 2019), and shopping benefits (Emrich et al., 2015).

In the end, the core interest of this thesis is the last research stream focusing on how customers respond to the omnichannel retail experience. Customer responses to the omnichannel retail environment can be characterised by four major research topics: (1) customer value, (2) customer segmentation, (3) channel choice, and (4) customer interaction. This topic is further discussed in the analysis in the section below.

2.2.3 Customer-related research in omnichannel literature

A considerable amount of literature has been published on the examination of customer value based on channel usage (Kumar and Venkatesan, 2005; Kushwaha and Shankar, 2013; Cambra-Fierro et al., 2016; Sopadjieva et al., 2017). Omnichannel customers are generally perceived as the best segment for retailers. They tend to use more retailer's touchpoints and are associated with bigger shopping basket value and future purchase intention (Sopadjieva et al., 2017). As a result, they are seen to be more valuable for retailers. This is partially true if product and retailer characteristics are considered (Kushwaha and Shankar, 2013). Omnichannel customers are profitable for mass merchandisers and specialty stores, especially for hedonic products (Kushwaha and Shankar, 2013). On the other hand, for the banking industry, omnichannel customers are proven to be too expensive to serve and, therefore, less profitable than single-channel or two-channel customers (Cambra-Fierro et al., 2016).

Past research also investigates the emergence and characterisations of multichannel customer segmentation. Several studies have used channel usage in different purchase stage to categorise customers into different groups (Konuş et al., 2008; De Keyser et al., 2015; Herhausen et al., 2019). Furthermore, Konuş et al. (2008) and De Keyser et al. (2015) have analysed the psychographic characteristics for each group to differentiate them. Single-channel customers, such as offline-focused or call-prone segments, have been identified as the most loyal segments. Meanwhile, multichannel customers have consistently reported the highest level of shopping enjoyment (Konuş et al., 2008). Thomas and Sullivan (2005) investigated the presence of different segments within multichannel retailers and suggested a framework to formulate channel migration and marketing communication strategy. Interestingly, they did not recommend retailers to pursue all segments to be multichannel customers. Some segments were profitable if they stayed as single-channel customers (e.g., offline-focused segment).

Much of the past literature on omnichannel retailing pays particular attention to motivations and consequences regarding channel choice (Wallace et al., 2004; Balasubramanian et al., 2005; Venkatesan et al., 2007). Customers have a different motivations when engaging with an omnichannel retailer, which affects their channel choice (Balasubramanian et al., 2005). They also use different cues to adopt new channels: frequency of interaction when adopting a second channel and purchase-related attribute when adopting the third channel (Venkatesan et al., 2007). Once they become part of multichannel segments, they report a higher satisfaction level, which eventually leads to loyalty to retailers (Wallace et al., 2004). The mechanism behind the customer multichannel interaction and satisfaction is due to customers experience multiple service outputs from interacting with multiple channels (Wallace et al., 2004).

In recent years, there has been an increasing amount of literature focusing on omnichannel customer interaction (e.g., Dholakia et al., 2010; Yadav and Pavlou, 2014;

Barwitz and Maas, 2018; Cambra-Fierro et al., 2020). Customer interaction within the omnichannel retail environment is influenced by various aspects from within customers themselves, the process, and the actions (Dholakia et al., 2010). Customers bring in a certain expected value-in-use (Lemke et al., 2011; Barwitz and Maas, 2018) and goals (Balasubramanian et al., 2005) that might define interaction outcomes such as channel choice or certain psychological responses. For instance, an expected utilitarian value will drive more information seeking and knowledge generation behaviour (Barwitz and Maas, 2018). Consequently, there is a tendency to use an online channel in the pre-purchase stage due to its ability to discover and compare vast information (Balasubramanian et al., 2005). These values include utilitarian, hedonic, economic, or relational motivation (Balasubramanian et al., 2005; Lemke et al., 2011; Barwitz and Maas, 2018). Depending on the type of value-in-use that customers seek from their interaction, a different pattern emerges consisting of different interaction attributes and consequences (Barwitz and Maas, 2018). Customers may decide to move between channels, and understandably so within an omnichannel retail environment. They may choose to pursue another channel based on an expected gain, as seen in research shopping behaviour (Verhoef et al., 2007). Customers may also move to a different channel that offers less channel interactivity, as seen during the after-purchase stage (Barwitz and Maas, 2018). In this case, customers look for a more straight-forward interaction to perform administrative task.

This expected gain comprises the benefits derived from the process and from the channel itself. The channel benefits such as convenience, variety of assortment, and efficient waiting time drive customer satisfaction through the increased positive disconfirmation of expectation (Wallace et al., 2004). For example, while the online channel may excel in providing enormous assortments, it has the drawback of delayed product fulfilment. Hence, making each channel’s benefit unique. Nambisan and Baron

(2007) delineated four customer interaction benefits based on the purchasing process. These benefits were drawn using the uses and gratification perspective and consist of learning, social integrative, personal integrative, and hedonic benefit (Nambisan and Baron, 2007). These benefits positively influence customer engagement and especially stronger in the high-involvement product category (Nambisan and Baron, 2007).

If customers choose to stick to a particular channel, a higher frequency of interaction creates a channel habit that evidently affects service usage (Cambra-Fierro et al., 2020) and relationship quality with a service provider (Hudson et al., 2016). The content of interactions also influences service quality, more specifically, informational interaction is useful for reaching a positive outcome while a very high frequency of social interaction tends to be counter-productive in resolving customers' inquiries, and hence negatively influences quality (Köhler et al., 2011). Moreover, each channel type encourages a different outcome. While an offline channel habit promotes loyalty, a virtual channel habit (e.g. online and self-service kiosk) negatively affects service usage due to lower switching cost (Cambra-Fierro et al., 2020).

Past studies have included a facet of customer interaction as a contributor to predict relational or behavioural outcomes. Some established theories such as theory of use and gratification (Nambisan and Baron, 2007), social exchange theory (Venkatesan et al., 2007), media dependence theory (Rippé et al., 2017), contagion theory (Rapp et al., 2013), and theory of planned behaviour (Konuş et al., 2008) have been used to analyse the role of customer interaction within a retail environment. There have been some relational outcomes linked as consequences of customer interaction, such as customer engagement and trust (Nambisan and Baron, 2007; Lemke et al., 2011; Hudson et al., 2016; Sopadjieva et al., 2017). The overview of each study from customer-related research in omnichannel literature can be seen in Table 2.1. This present thesis will

further examine customer interaction from the perspective of the customer-retailer relationship, using social penetration theory.

Table 2.1 Key literature of customer-related research in omnichannel literature

Authors (Year)	Area of interest	Type of data	Number of channels	Number of activities	Frequency	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Kumar and Venkatesan (2005)	Customer value	Customer database	✓	-	✓	Customer- & supplier-related factors	None	None	Multichannel shopping	Customer lifetime	B2B multichannel customers provide higher revenues, higher s-o-w, higher likelihood of being active, and a higher tendency to use another touchpoint.
Kushwaha and Shankar (2013)	Customer value	Customer transaction data and profiles	✓	-	-	Channel usage	Product type	None	Monetary value	Role of a product category	Multichannel customers are profitable for large mass-merchandise retailers and specialty retailers (hedonic products). Traditional channel customers are more lucrative for utilitarian ones (esp. low-risk products).
Cambra-Fierro et al. (2016)	Customer value	Customer transaction panel data	✓	-	-	Channel usage	None	None	Gross margin	Multichannel retailer customers value	Gross margin is highest when customer interaction was concentrated on some single channels of a combination of two channels.
Thomas and Sullivan (2005)	Customer segmentation	Customer transaction data	✓	Partial	-	Customer purchase characteristic	None	Channel choice and marketing expenditure	Marketing communi-cation channel	Customer relationship management	Two major segments emerged consisted of catalogue-prone and offline-focused customers. Depending on the first channel choice, segments were encouraged to migrate, stay, or use a dual-channel.
Konus et al. (2008)	Customer segmentation	Customer survey panel data	✓	Partial	-	Psycho-graphic	None	Perceived benefit and cost	Channel choice	Customer journey and perceived utility	Three segments emerged with two stages of purchase: uninvolved shoppers, multichannel enthusiasts, and offline-prone customers. Multichannel enthusiasts are more innovative and have higher shopping

Authors (Year)	Area of interest	Type of data	Number of channels	Number of activities	Frequency	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
											enjoyment, but offline-prone customers are more loyal than other segments.
De Keyser et al. (2015)	Customer segmentation	Customer survey	✓	Partial	-	Psycho-graphic	None	Perceived benefit and cost	Channel choice	Customer journey and perceived utility	Six segments emerged using three purchase stages: online-prone, offline prone, call centre prone, and research shoppers (after-sales channel: offline/ online/ call centre). Call centre-prone and offline-prone customers are more loyal than others.
Herhausen et al. (2019)	Customer segmentation	Customer survey	✓	Partial	-	Satisfaction	Segment	None	Loyalty	Anticipated utility theory	Five segments emerged: offline-focused, pragmatic online, extensive online, multichannel shopper, & online-offline shopper.
Wallace et al. (2004)	Channel choice	Customer interview and survey	✓	✓	-	Channel usage	None	Satisfaction	Loyalty	None	The use of multiple channels by customers increased their exposure to higher service outputs and increased satisfaction which led to loyalty.
Balasubramanian et al. (2005)	Channel choice	Customer interview	-	-	-	Shopping goals	None	Utility	Channel choice	Purchase process	Customers choose a specific channel at a specific phase of their journey based on shopping motivation, which is identified as economic, self-affirmation, symbolic, social influence, and invocation of a schema.
Venkatesan et al. (2007)	Channel choice	Customer transaction data	Partial	-	✓	Customer interaction characteristic	None	None	New channel adoption duration	Social exchange theory	Second channel adoption is influenced by frequency-related interaction. Third channel adoption was mainly driven by purchase-related interaction.

Authors (Year)	Area of interest	Type of data	Number of channels	Number of activities	Frequency	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Polo and Sese (2016)	Channel choice	Longitudinal data of customer interaction	-	Partial	-	Channel preference, prior customer attitude	Nature of interaction (high-risk vs low-risk)	None	Channel choice	Perceived risk	The effect of attitude is more pronounced when choosing a purchase channel (high-risk), while the personal touch is stronger when it comes to the communication channel (low-risk).
Rodríguez-Torrico et al. (2017)	Channel choice	Customer survey	Partial	-	✓	Personality traits	None	None	Channel usage	Impulse and contemplative behaviour	Impulsive shoppers use mobile devices more often, whereas individuals with a high need for touch are more likely to use online devices in their omnichannel process.
Rapp et al. (2013)	Specific channel strategy	Three-level dataset.	-	-	✓	Social media usage	Interaction freq, service ambidex-terity, reputation.	None	Loyalty and performance	Contagion theory	Social media usage by a supplier, retailer, and customer influence customer loyalty, brand-, and retail performance. All moderators except customer interaction have found to enhance the use of social media.
Rippé et al. (2017)	Specific channel strategy	Scenario methodology	Partial	-	-	Mobile channel usage	Adaptive selling	Perceived control	Purchase intention	Media dependence theory	A salesperson can use adaptive selling technique to influence purchase intention and promote positive interaction with customers.
Kohler et al. (2011)	Virtual employee interaction	Dyadic agent and customer survey	-	Partial	-	Interaction style and content	Interaction style	Newcomer adjustment	Employees' performance	Buyer-seller interaction	Virtual employees' interaction style and content significantly influence the newcomer adjustment and influence their performance. Specifically, there is an inverted U-shaped effect between social content interaction on newcomer adjustment.

Authors (Year)	Area of interest	Type of data	Number of channels	Number of activities	Frequency	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Sopadjieva et al. (2017)	Customer interaction	Customer panel data and survey	✓	-	-	Channel usage	None	None	Customer purchase	None	There are positive correlational results between omnichannel behaviour and loyalty, customer purchase, and positive word-of-mouth.
Nambisan and Baron (2007)	Customer interaction	Customer survey	-	-	-	Interaction benefits and affective evaluation	Product involvement, community identification	Customer attitude	Customer engagement	Uses and gratification perspective	Customer virtual interaction benefits influence their engagement. Customer attitude is shaped by customers' affective response and affect customer participation positively. The effect is higher within the high-involvement product and high-identity relation.
Dholakia et al. (2010)	Customer interaction	Conceptual	Partial	Partial	-	None	None	None	None	Customer-focused framework	Three areas that define customer behaviour in the multichannel and multimedia environment are (1) what they bring, (2) what they encounter, and (3) what they strive for and do.
Yadav and Pavlou (2014)	Customer interaction	Conceptual	-	Partial	-	None	None	None	None	IT-mediated environment	Two areas related to this thesis are (1) Firm-customer interaction and (2) customer-firm interaction. There is a need to develop a typology based on customer-firm interaction and a structured version of shopping funnels.
Hudson et al. (2016)	Customer interaction	Experimental studies	-	-	✓	Customer interaction in social media	Anthropo-morphism perception & uncertainty avoidance	None	Brand relationship quality, WOM, brand loyalty	Consumer-brand relationship	Customer interaction on social media is highly related to brand relationship quality. Moreover, the effect is stronger with high anthropomorphism perception. The effect also different across culture.

Authors (Year)	Area of interest	Type of data	Number of channels	Number of activities	Frequency	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Barwitz and Maas (2018)	Customer interaction	Expert interview and focus group	Partial	Partial	-	Value-in-use	None	None	Interaction choice	Channel choice, journey choice, and segmentation	Customer interaction choice is defined by the value they are looking for, and the inter-connection of customer attributes in one's journey. It unravels the inertia and customer journey patterns within omnichannel interaction.
Cambra-Fierro et al. (2020)	Customer interaction	Customer transaction data and survey	Partial	-	-	Customer interaction - channel habit	None	Switching cost and loyalty	Cross buy and service usage	Theory of planned behaviour	Offline channel habit increases perceived switching cost and contributes positively to attitudinal loyalty. Online and self-service kiosk habits negatively impact service usage.
This research	**Customer interaction**	**Customer survey and experiment**	✓	✓	✓	**Customer interaction complexities**	**Channel integration**	**Customer enjoyment and effort**	**Customer experience**	**Social penetration theory**	**The nonlinear relationships exist between dimensions of customer interaction complexity and customer experience, in which the effect is flipped considering the level of channel integration (for interaction breadth). Customer effort and customer enjoyment mediate the relationship between customer interaction depth (and not on interaction breadth), differently between online and offline channel.**

2.3 Customer interaction in the omnichannel retail environment

As was pointed out in the previous section, customer interaction is an important part of the customer journey and contributes to customer experience. Nonetheless, the definition of customer interaction is yet to be discussed. This section aims to thoroughly explain customer interaction and its related component used in this research.

Customer interaction enables the co-creation process that shapes individual customer experience (Prahalad and Ramaswamy, 2004). It precedes customer experience, hence being positioned as the antecedent of customer experience, echoed by Gentile et al. (2007) and Lemke et al. (2011). Customer interaction, in this sense, is generally understood as any direct or indirect contact between a customer and a retailer that occurs along the way throughout the customer journey (Meyer and Schwager, 2007). Its scope is beyond a conversation but rather an encounter, and aligns with what was suggested by Voorhees et al. (2017, p.270) who said that "service encounter is any discrete interaction between the customer and the service provider relevant to a core service offering". It is broad in a perspective that customer interaction can include one-way interaction, but also narrow because it is discrete, or isolated, and not a continuous event.

Customer interaction involves any interaction with processes, people, and physical elements (Bolton and Saxena-Iyer, 2009). A customer interacts with the process through activities that enable communication and exchange (Yadav and Pavlou, 2014). The object of exchange ranging from information, financial instruments, products, or services that create value for customers. These exchanges are facilitated by people, which can easily be translated into employees of retailers (e.g., salespeople, delivery man, cashier, customer service assistant) or other customers in the same shared premises. This is the basis of how the discussion of customer interaction is commonly divided into customer-firm interaction and customer-customer interaction. Retailer's

employees and other customers are both crucial in shaping the outcomes for any interaction. Past studies offer empirical evidence on how customer interaction with a firm can enhance new product development success (Gruner and Homburg, 2000; Foss et al., 2011). Lastly, the physical element can be perceived as any tangible object that facilitates interaction. Think about the signage, the self-service checkout machine, and the context of omnichannel retailing; physical element refers to retailer's channels and touchpoints. Existing literature discusses customer interaction based on the environment where the interaction takes place, virtually and physically. The striking differences lie in whether the environment facilitates direct/face-to-face interaction (physical environment) or indirect/computer-mediated interaction (virtual environment).

Differences between offline and online channels impact how customer interaction is executed and subsequently evaluated. For instance, Saini and Lynch (2016), who replicated a study by (Degeratu et al., 2000), suggested that customers use more sensorial cues during offline interaction and form a subsequent judgment. The offline channel allows customers to be physically involved by facilitating more of their senses (taste, smell, hear, sight, touch). The online channel might be lacking in olfaction and touch, but brands have attempted to bridge this gap by sending product samples to their customers (Roggeveen et al., 2020). One caveat is the lack of instant gratification caused by delayed fulfilment from online inquiries. However, the online channel excels in providing information to customers (Shankar et al., 2003). Customers are able to see multiple types of information on one page of a website (e.g., product specification, reviews, price), cutting the search cost to the minimum (Roggeveen et al., 2020).

The online channel, however, possesses a greater risk when it comes to purchasing. Financial risk, product risk, and privacy risks are among interaction risks influenced by online interaction (Dai et al., 2014). These risks are negatively related to online purchase intention but can be mitigated by increased online interaction experience (Dai

et al., 2014). Offline interaction may reduce the inflation of these risks and trim down uncertainty. The tempering uncertainty in offline channel enhances the effect of customer expectation on the evaluation of satisfaction (Hult et al., 2019). One motivation of being an omnichannel customer is to extract multiple benefits offered by various channels (Wallace et al., 2004). By combining the positive features of multiple channels, customers are expected to get the best out of omnichannel retailers.

All of the retail elements discussed above (i.e., people, process, physical elements) serve as service clues which can be categorised into functional clues, mechanical clues, and humanistic clues (Haeckel et al., 2003). Functional clues concern the reliability of the service, while the mechanic clues refer to the tangibles that support the sensory presentation of the service (Berry et al., 2006). Humanic clues originate from the behaviour and appearance of service providers (Berry et al., 2006). People, process, and product can serve as any number of clues depending on which clues are being delivered. For instance, the presentation/communication style of salespeople can be categorised as a humanistic clue, but the content of information given by the salespeople would be perceived as a functional clue, while the uniform worn serves as a mechanic clue. However, there should be active participation from both customers and retailers to enable the interaction and allow the transference of these clues. Access and transparency should be granted to customers as a means of obtaining and receiving information (Prahalad and Ramaswamy, 2004). By providing access and transparency, retailers create an equal partnership with customers in which meaningful dialogue occurs (Prahalad and Ramaswamy, 2004). Altogether, meaningful dialogue facilitates customers to analyse the cost and benefit of every interaction (Prahalad and Ramaswamy, 2004), which helps customers evaluate and shape perception towards cognitive and affective experience (Berry et al., 2006). Although Prahalad and Ramaswamy (2004) identified dialogue as a two-way interaction, or conversation, in

their study, access and transparency are relevant for any customer interaction. The creation of experience is not limited to two-way interaction but includes indirect interaction (Helkkula et al., 2012).

The proliferation of channels and touchpoints within the omnichannel retail environment has increased customers access to information. This information is not only limited to firm-generated information (e.g., product features and claims) but also customer-generated information (e.g., social media post, review, blog). The increased access supports the establishment of service transparency (Liu et al., 2015) which is critical in helping retailers to win the omnichannel competition (Brynjolfsson et al., 2013). However, Liu et al. (2015) have emphasised that access itself does not guarantee transparency; customers need to be able to access information that reflects the factual quality of service. In this case, customer-generated information is perceived to have greater objectivity than firm-generated information.

In the context of omnichannel retailers, service transparency indicates the extent to which customers understand the available channels and all services provided by retailers (Sousa and Voss, 2006; Liu et al., 2015; Quach et al., 2020). It reduces uncertainty (Liu et al., 2015) and privacy risk (Quach et al., 2020) on customer-retailer interaction. Simultaneously, understanding the range of activities that customers can perform at the available channels is useful in pursuing journey personalisation. Personalisation allows customers to exercise their freedom to choose channels and retailer's offerings, and is motivated by the pursuit of authenticity (Fisher and Smith, 2011). Throughout the process, customers take more and more control over their journey, given that the retail environment becomes more interactive and interconnected (Fisher and Smith, 2011). While service transparency influences cognitive experience positively (Quach et al., 2020), interactivity inspires social experience (Fisher and Smith, 2011).

The above discussion displays how customer interaction links to the creation of certain customer experience dimension. Echeverri and Skålén (2011) have suggested that customer interaction could also contribute to the destruction of customer experience. The creation or destruction of customer experience arises when there is either a congruity or incongruity between the delivery (from retailers or service providers) and the reception (from customers) pertaining to the elements of activities (Echeverri and Skålén, 2011). The elements of activities consist of procedures, understanding and engagement. For instance, an incongruity can be seen at an overly complicated return process (procedure), a salesperson with poor product knowledge (understanding), and a negative temporal emotion from customers (engagement); all of these can damage customer experience. Incongruity potentially inflates psychological cost (e.g., time, effort, emotional distress) during an interaction, which can then be detrimental to customer experience (Sohn et al., 2017). Though the psychological cost may not directly affect the monetary cost, it is very much included in customers' analysis of cost and benefit when evaluating their interaction and subsequently the whole relationship to a retailer.

Interacting with an omnichannel retailer may involve multiple processes, multiple people, and multiple physical elements, depending on customer preferences and needs. Omnichannel customer interaction is not a one-dimensional interaction in a particular sphere (physical vs virtual), but rather it is a combination of both spheres. Customer interaction with an omnichannel retailer also occurs across multiple stages within a customer journey. Previous examples highlight the pre-purchase stage where customers search for purchase-related information, however, the purchase stage and post-purchase stage that come into play when completing the customer journey. These stages can be iterative, dynamic, and even nonlinear (Lemon and Verhoef, 2016; Grewal and Roggeveen, 2020). Considering the nature of these stages and the multiplicity of

retailers' elements, customer interaction has its own complexity. Thereby, to better understand it, we must examine it from a multidimensional perspective.

2.3.1 Customer interaction complexity and social penetration theory

Customer interaction with an omnichannel retailer has become more complex as customers interact with different channels and touchpoints with different level of involvement within each channel. Once the complexity is acknowledged, the next question is, how to analyse a complex object? According to Wang and Von Tunzelmann (2000), complexity can be, and is, commonly examined by analysing *breadth* and *depth*. They explored how researchers used the term *complexity,* which they found to be represented by either breadth or depth, or both. This aligns with the social penetration theory dimensions, which are indicated as breadth and depth of penetration. In marketing, the term breadth and depth have also been used to analysed various topics: distribution network (Jindal et al., 2007; Bucklin et al., 2008; Käuferle and Reinartz, 2015; Ailawadi and Farris, 2017), customer relationship (Ruth et al., 2004; Ackermann and von Wangenheim, 2014), and online interaction (Huang et al., 2009; Hudson et al., 2016).

The follow-up question is then, how to conceptualise customer interaction breadth and depth? Two theories can be combined to offer strong conceptualisations. First, social penetration theory suggests that an interpersonal relationship is thought to proceed along two dimensions: breadth of penetration and depth of penetration. Penetration breadth signifies the amount of interaction in terms of variety of discussion topics and the degree of intimacy (Altman and Taylor, 1973). Individuals engage in a varying level of discussion for every topic of discussion. A discussion related to an international business course may go deeper than a conversation about a weekend plan, showing that an academic topic's penetration depth is greater than personal life. From this brief

illustration, social penetration explains how a pair of individuals have relationships that vary in level of breadth and depth.

Second, as a means of narrowing down the application to customer interaction in an omnichannel retail environment, we draw inspiration from a study about the organisational search of knowledge. Laursen and Salter (2006) used the term breadth and depth in assessing the complexity of the organisational external search of knowledge. There is some degree of similarity when it comes to organisational behaviour in the search for knowledge and customer behaviour in acquiring a product. First, both utilise channels to collect information and form expertise for a particular purpose - innovation (for organisations) and purchase decision (for customers). Second, they both use channels as a pathway to attain certain output - knowledge (for organisations) and product (for customers). Third, they both must sacrifice cost, such as investment (for organisations) or time and effort (for customers) when interacting with the channels. Fourth, eventually, both expect a return as a result of their interaction in the form of knowledge and information to aid their objective - innovative performance (for organisations) and satisfactory consumption (for customers). The summary of this is shown in Table 2.2.

Table 2.2 Comparison between organisational and customer behaviour in using channels and touchpoints (external search of knowledge vs omnichannel interaction)

	Organisation	**Customers**
Aim	Innovation	Purchase decision
Object of interest	Knowledge	Product or services
Cost	Investment	Time and effort
Reward	Innovative performance	Satisfactory consumption

By combining social penetration theory and theory behind organisational search for knowledge, this study argues that customer interaction complexity is best portrayed by two dimensions: *customer interaction breadth* and *customer interaction depth*.

Customer interaction breadth refers to the range of channels used to facilitate customer interaction. Meanwhile, customer interaction depth represents the level of closeness between a customer and a retailer resulting from customer interaction. Further discussion related to these two dimensions is presented in separate sections later in this thesis. Nonetheless, the importance of customer interaction breadth and depth is linked to the progression of the customer-retailer relationship.

The establishment of customer interaction breadth and depth presents the need to understand their implications to the relationship between a customer and a retailer. In other words, how does the customer interaction complexity fit within the development of customer -retailer relationship. To do so, this study revisits the social penetration theory which discusses the development of an interpersonal relationship. An interpersonal view is a good way to approach how a relationship between a customer and a retailer emerges. This is because in the current retailing practice, personalisation is perceived to be an integral part of a retailer's strategy, making a relationship between a customer and a retailer more personal (Cao and Li, 2015).

According to this theory, an interpersonal relationship grows as individuals exchange more information, more expressions, and share mutual activities (Taylor et al., 1969; Altman and Taylor, 1973). This results from reciprocal behaviour within social interaction that is overt and includes verbal, nonverbal, and environmentally oriented interaction (Altman and Taylor, 1973). Verbal behaviours are represented by the exchange of information related to attitude, value, demographic and personal data. Nonverbal behaviours involve the exchange of expression, which includes body language such as gesture, position, head movement, and facial expression. A combination of closedness between individuals and the topic of discussion can determine the type of nonverbal behaviour involved in an interaction (Keiser and Altman, 1976). Environmentally oriented behaviours include spatial and personal

distance among individuals and the use of physical objects. Werner et al. (1992) found that individuals utilise physical environment, while considering social environment simultaneously, as a way of nurturing strong ties and enhancing the feasibility of their relationships. These environmentally oriented behaviours are led, accompanied, and followed by an internal subjective process, which contributes to developing another individual's image, the feeling towards them, and the projection of their behaviour.

A relationship grows as individuals interact more by expanding their breadth of penetration and depth of penetration (Altman and Taylor, 1973). Mangus et al. (2020) offered empirical evidence that B2B partners who share both personal- and business-related information with each other form a greater relationship empathy that, in turn, has a positive impact on trust. Three factors may influence the acceleration of the relationship growth: personal characteristics, the outcome of the exchange, and situational context (Altman and Taylor, 1973). Personal characteristics influence how individuals manage their relationships; some individuals are more extroverted and easily engage in conversation with strangers at a party, but others may be more reluctant to enter the relationship. Obviously, this depends on the situational context, such as the institution, the time, or the place in which the relationship may develop. At the end of an exchange, individuals project the outcome of a relationship and behave accordingly. The progress of a relationship can be achieved through the assessment of reward and cost as well as the expected level of satisfaction. A favourable future encourages progressive movement, while an unfavourable one discourages progress. According to this theory, increasing or decreasing the level of interaction and the subjective feeling towards the counterpart can either be an initiation or dissolution of a relationship, respectively.

This theory relates to our study in two ways. First, it suggests customer interaction as the basis of interpersonal relationships, which can be applied to relationships between a

customer and a retailer. Interaction, based on this theory, is a fundamental entity that plays a role in two instances - it is a vehicle to exchange topic of discussion (i.e., penetration breadth) and facilitate an expression of intimacy (i.e., penetration depth). Second, this theory suggests that such interactions will lead to satisfaction before eventually transforming into a relationship. This is a useful background to consider how interaction may lead to customer experience since past studies have established a link between satisfaction and customer experience (Rose et al., 2012; Pansari and Kumar, 2017), or even used satisfaction as an element of customer experience (McLean et al., 2018).

2.3.2 The conceptualisation of customer interaction breadth

In a broader term, breadth represents a degree of heterogeneity (Wang and Von Tunzelmann, 2000). Hence, many scholars have used the term breadth to represent the variety and diversity of a subject. As we recall the study from Laursen and Salter (2006), breadth relates to the variety of search-channels used by an organisation to pursue innovation. Using their study as a benchmark, we posit that customer interaction breadth refers to the variety of channels which customers rely upon in their customer journey.

In the omnichannel retail environment, channels are a prominent element that facilitates the interaction between customers and retailers. Customers can choose to only interact with a particular channel or decided to engage with more than one channel. In an ideal omnichannel world, there are no boundaries from which channel customers should initiate contact. In other words, retailers enable customers to complete their purchase from whichever channel available. The number of available channels within a retailer can influence customers perception regarding the retailer’s service quality (Sousa and Voss, 2006). However, even when there are multiple channels, customers do not

necessarily use all available channels. Customer interaction breadth is affected by customers preference and expected value-in-use (Barwitz and Maas, 2018).

Past studies have revealed the impact of customer interaction breadth within the discussion regarding multichannel customer segmentation. Moreover, customer interaction breadth has been linked to customer purchase (Kumar and Venkatesan, 2005) and retailers' profit (Kushwaha and Shankar, 2013; Cambra-Fierro et al., 2016). Customer spending increases as customer interaction breadth expands (Kumar and Venkatesan, 2005) due to a greater degree of trust and lower perceive risk when interacting (Kumar and Venkatesan, 2005). One caveat is that the finding was extracted from a B2B setting which employs rational decision-making. In a B2C setting, customers with high interaction breadth were also found to be profitable but only for hedonic products (Kushwaha and Shankar, 2013). In contrast, the same effect was not found in the banking industry where the highest profit was contributed from a single- or two-channel customer segment (Cambra-Fierro et al., 2016). Single-channel customers were consistently found to be the most loyal segment compared to the multichannel segment, particularly offline channel and telephone channel segments (Konuş et al., 2008; De Keyser et al., 2015).

Customer interaction breadth has also been linked to some psychographic characteristics. Customer innovativeness has been found to be stronger in segments with high interaction breadth (Konuş et al., 2008). These customers are prone to trying new experiences (Midgley and Dowling, 1978), such as interacting with new channels. Furthermore, this segment also reported higher shopping pleasure, which was signified by a higher enjoyment level (Konuş et al., 2008). They also tend to be more price consciousness (Konuş et al., 2008), which suggest that some customers with high interaction breadth pursue an economic goal during their routine (Balasubramanian et al., 2005; Barwitz and Maas, 2018).

2.3.3 The conceptualisation of customer interaction depth

Depth, in a general sense, relates to the level of sophistication that arises from the progression of cognitive complexity (Wang and Von Tunzelmann, 2000). Looking back at the study of Laursen and Salter (2006), the term depth was used to represent the extent of the usage of a particular search-channel. Adopting a similar conceptualisation, the omnichannel customer interaction depth portrays the degree of channel usage within an omnichannel retailer. Interaction depth also represents the level of exchange between a customer and a retailer. The more information exchanged between them, the deeper their interaction will be. These exchanges are facilitated by customer activities across purchase stages and interaction frequencies. Thereby, the two components are the central part of customer interaction depth. Based on these, customer interaction depth is defined as the degree of involvement that customers exert to interact with a retailer, through an array of activities performed at different level of frequency across stages in a customer journey.

The first aspect of interaction depth is the range of activities within the customer journey. Based on observable practices, Echeverri and Skålén (2011) classify customer activities into five groups: informing, greeting, delivering, charging, and helping. This classification is service-centric and from an organisation's perspective. It was based on a qualitative study pertaining to co-production and co-creation of value within a public service organisation. Similarly, but in a broader perspective, Ballantyne and Varey (2006) divided customer activities into three types: knowing, communicating, and relating. These two categorisations can be summed up into three areas consisting of communicational activities, transactional activities, and relational activities. Communicational activities capture the aspect of knowing, communicating (Ballantyne and Varey, 2006), and informing (Echeverri and Skålén, 2011), which concern activities that facilitate information sharing, dialogue building, and learning. Transactional

activities relate to customer activities that support service delivery and fulfilment, as seen within the practice of charging and delivering as studied by Echeverri and Skålén (2011). Transactional activities provide the means to transfer products/services in exchange for monetary compensation when a customer completes a payment, gets a product delivered home, or uses an option to buy-now-pay-later. The last category is relational activities which support relationship building between a customer and a retailer. It encapsulates the element of greeting and helping (Echeverri and Skålén, 2011), and relating (Ballantyne and Varey, 2006).

Another point-of-view is grouping customer activities based on the purchase stages when the activity happens: activities within the pre-purchase, purchase, and post-purchase stage. The discussion about customer activities was currently limited to whether customers use a particular channel for search and purchase (Konuş et al., 2008) and after-sales service (De Keyser et al., 2015). Konuş et al. (2008) used subjective data based on customer perceived appropriateness, while De Keyser et al. (2015) used objective self-report data about channel usage. As customers use a retailer's channel for more activities, they expect to gain more service outputs such as information provision, product assortment, and product fulfilment (Wallace et al., 2004).

Within each stage, there are multiple activities that a customer can execute. For instance, within a purchase stage where customers have decided which product to buy, they can still engage with activities related to finalising a payment, using a discount code or voucher, or picking up the ordered product. As linked above, some activities were performed to exploit certain channel service output or benefit. In this case, we take the example of picking up products. This particular activity falls into the service output category of product fulfilment. If customers conduct this activity in the offline channel, the product fulfilment is immediate. Depending on the shopping goals of a customer, the benefit of immediate product fulfilment from the offline channel can be perceived as

an advantage or disadvantage, contingent on the product a customer is purchasing purchase (e.g., a bag of oranges vs a mattress) or the mode of transportation (e.g., on foot vs driving a minivan). It is because a channel service output (e.g., product fulfilment) is evaluated based on the perceived benefits such as convenience, confidence, and assurance of quality (Hammerschmidt et al., 2016). Consequently, a channel service output shapes customers perception related to the value obtained from their customer journey (Lemke et al., 2011).

The second property of interaction depth discusses the frequency of activities. The frequency of customer interaction with a retailer plays a key role in forming what customers usually do and how they do it; this in turn creates a customer habit (Cambra-Fierro et al., 2020). Habitual behaviour is driven by the subconscious and is an automatic decision, hence, it requires less cognitive process and more experiential effort (Cambra-Fierro et al., 2020). From another perspective, interaction frequency contributes to the relationship between a customer and a retailer (Bolton et al., 2004), especially for newly-developed relationships (Dagger et al., 2009). Depth of interaction indirectly shows customer trust in the retailer. How often a customer performs activities in a particular retailer illustrates how much they trust that retailer to either (a) complete their journey and commit for a transaction, or (b) provide them the same service all over again. Understandably, relationship and habit are formed because frequency promotes familiarity which may improve a customer's knowledge about specific parts of the customers journey (Alba and Hutchinson, 1987). As a result, interaction frequency promotes positive brand attitude (Lane, 2000; Yaveroglu and Donthu, 2008) and sales response (Taylor et al., 2013).

2.4 Channel integration in omnichannel retailers

In most omnichannel research areas, the advancement of technology plays an important role in shaping retailers' new strategies and changing how customers behave

(Piotrowicz and Cuthbertson, 2014). The impact of increasing IT capabilities in retailers is reflected in the implementation of one particular channel strategy: channel integration. Channel integration is seen as an integral part of omnichannel retailing and even as the key requirement of being an omnichannel retailer (Picot-Coupey et al., 2016). It is therefore important to include channel integration in this research in order to understand its role in influencing customer interaction and customer experience.

Channel integration is defined as the extent to which multiple aspects of a retailer's channels and touchpoints are synced and coordinated for the advantage of retailer and customers (Bendoly et al., 2005; Cao and Li, 2015; Cao and Li, 2018). It is a spectrum that is characterised by numerous facets of the retail mix. In their early development, multichannel retailers aim at a different customer segment for each channel they have. As a result, product assortment in each channel can be varied depending on the target market. Even today, customers, from time to time, find that they cannot find a product in the offline channel, even though it is available in the online channel.

Another example is a customer loyalty scheme where points are added if customers shop from the same retailer. These points are usually tradeable and can be exchanged for rewards such as shopping vouchers. Some retailers allow customers to use online vouchers in the offline channel, but some insist that online vouchers can only be redeemed in the online or mobile channel. The examples above illustrate how channels can be integrated differently ranging from full integration to partial or asymmetrical integration to no integration at all (Emrich et al., 2015). The components of channel integration can be divided into two broad components: retail mix and information management (Bendoly et al., 2005; Oh et al., 2012; Cao and Li, 2015; Cao and Li, 2018; Zhang et al., 2018). The retail mix components include price, promotion (retail branding, advertisement, campaign), product (assortment, availability), place (order

fulfilment), and service support (return, exchange, repair). The information management component consists of information access and information record.

Implementation and level of channel integration are influenced by firm capabilities, retailer characteristics, and industry characteristics (Cao and Li, 2018). Operating with integrated channels requires specific capabilities, especially in information technology, supply chain management, and data analytics (Zhang et al., 2010; Piotrowicz and Cuthbertson, 2014; Cao and Li, 2018). These capabilities enable retailers to manage a strong online presence, coordinate order fulfilment, and provide a personalised customer experience.

Three areas highlight the importance of channel integration in omnichannel retailers. First, channel integration contributes positively to shopping utility (Melis et al., 2015) and encourages positive customer engagement (Lee et al., 2019). Second, it is an essential strategy to promote omnichannel behaviour (Herhausen et al., 2015; Shen et al., 2018) through incremental perceived service quality, convenience, and variety, and the decrease of perceived risk (Emrich et al., 2015; Herhausen et al., 2015). Third, channel integration has empirically proven to positively impact a retailer's performance (Zhang et al., 2010; Cao and Li, 2015) through building their explorative and exploitative competences (Oh et al., 2012).

2.5 Customer experience in an omnichannel retail environment

Omnichannel retailing is designed to provide a superior and seamless customer experience (Verhoef et al., 2015). Therefore, it is important to understand the definition, the origin, and the impact of customer experience in the omnichannel retail context. In accordance with the holistic and integrative approach of omnichannel performance evaluation, customer experience in an omnichannel retailer is evaluated based on the accumulative customer experience in all involved channels and touchpoints.

Understandably, when interacting with a retailer, customers will look back to their journey and create an overall evaluation rather than an individual assessment of a single channel or touchpoint (Verhoef et al., 2007).

The concept of experience has been discussed in marketing as one of the sources of economic value (Pine et al., 1999; Pine and Gilmore, 1998). Economic value progresses from commodities to goods to services and eventually to experience. An organisation that puts experience as its economic offering no longer focuses on customisation but rather on personalisation. Achieving personalised offerings through integrated marketing and operations functions contributes to the development of a competent omnichannel retailer (Bijmolt et al., 2004).

In response to the shift in focus on creating an experience as economic value, marketers started developing a framework to maximise customer experience. Schmitt (1999) is one of the earliest scholars to suggest the use of a multidimensional approach to formulate an integrated customer experience. He proposed five dimensions, namely sense, feel, think, act, and relate. These customer experience dimensions originate from the psychological aspects of a customer; sense relates to sensory experiences, think captures cognitive experience, feel relates to affective experience, act represents a physical or behavioural aspect of the experience, and relate is based on to social experience. The resurgence of this comprehensive approach is seen in studies related to brand experience, online customer experience, and omnichannel customer experience (Gentile et al., 2007; Brakus et al., 2009; Verhoef et al., 2009; Nambisan and Watt, 2011; Bleier and Eisenbeiss, 2015; Verhoef et al., 2015)

There are two relevant definitions of customer experience that can be used to deconstruct the elements of customer experience. Firstly, Gentile et al., (2007) define customer experience as a customer's personal response originating from a set of

interactions between a customer and a component of an organisation (e.g. a product, a brand, an employee) which denotes the customer's involvement at multiple levels (rational, emotional, sensorial, physical and spiritual). A customer evaluates their experience based on an assessment between their expectations and stimuli during an interaction regarding different events that occur through different channels and touchpoints (LaSalle and Britton, 2002; Gentile et al., 2007).

The second definition was offered by Verhoef et al. (2009 p. 32):

> *"…the customer experience construct is holistic in nature and involves the c**ustomer's cognitive, affective, emotional, social and physical** responses to the retailer. This experience is created not only by those elements which the retailer can control (e.g., service interface, retail atmosphere, assortment, price), but also by elements that are outside of the retailer's control (e.g., influence of others, purpose of shopping). Additionally, we submit that the customer experience encompasses the total experience, including **the search, purchase, consumption, and after-sale phases of the experience**, and may **involve multiple retail channels**. (Bold added)"*

From the two definitions above, it is clear that customer experience is rooted in an entire set of interaction which are sometimes being called moments of truth. Customer experience encompasses both direct and indirect encounters between a customer and a retailer (Meyer and Schwager, 2007) and occurs during all stages of the customer journey, search, purchase, usage, and service (Verhoef et al., 2009; Lemon and Verhoef, 2016). It also arises as a response to customer interaction with a retail mix such as pricing, merchandising, promotion, location, supply chain (Grewal et al., 2009).

Secondly, the customer experience is personal. The same stimuli may result differently depending on customers' characteristics. Moreover, current customer experience is affected by past experience and will influence future experience (Lemon and Verhoef,

2016). Hence, it combines pre-existing expectation and stimuli during encounters (LaSalle and Britton, 2002). This is why customer experience is largely subjective and reflects the customer's internal response (Pine and Gilmore, 1998; Holbrook, 2006; Gentile et al., 2007; Meyer and Schwager, 2007; Lemke et al., 2011; Stein and Ramaseshan, 2016).

Thirdly, customer experience stems from a set of contact points. In an omnichannel retail environment, contact points refer to channels and touchpoints. This aspect of customer experience emphasises the holistic approach, which moves away from analysing customer experience by looking at individual channels. Instead, the approach is interested in looking at multichannel, multi touchpoints evaluation along with customer journey (Baxendale et al., 2015; Homburg et al., 2017). Past literature related to specific-channel experiences, such as offline shopping experience (Donovan and Rossiter, 1982; Machleit and Eroglu, 2000; Brocato et al., 2012; Helmefalk and Hultén, 2017) and online or mobile experience (Manganari et al., 2009; Nambisan and Watt, 2011; Izogo and Jayawardhena, 2018; Bleier et al., 2019), are useful resources that shape the progression of customer experience conceptualisation in the context of an omnichannel retail environment.

Fourthly, customer experience is a projection of customer involvement. Gentile et al. (2007) suggest that the combination of commitment and involvement results in three types of relations: superficial, connected to collection practices, and profound. Involvement also affects how an individual’s subjective state of mind influences their shopping experience (Swinyard, 1993). It is because customer involvement influences how customers actively put effort into achieving their goals (Celsi and Olson, 1988; Swinyard, 1993) that they thereby willingly process more cognitive information (Clarke and Belk, 1979). Puccinelli et al. (2009) also discussed involvement as part of the

customer experience and similarly suggested how customer involvement influences motivations to engage in information processing.

Finally, from the definition, we can infer that customer experience affects different aspects of customer psychology. Gentile et al. (2007) mentioned that customer experience consists of aspects that includes rational, emotional, sensorial, physical, spiritual. This notion of the multidimensional concept of customer experience is largely similar to what was proposed by Schmitt (1999) with think, feel, sense, act, and relate. The multidimensionality of customer experience, repeated by Verhoef et al. (2009) and Lemon and Verhoef (2016), is the foundation by which this research to adopts five customer experience dimensions: cognitive, affective, behavioural, sensory, and social.

2.5.1 Cognitive experience

A large and growing body of literature has investigated the cognitive response as part of customer experience (Schmitt, 1999; Novak et al., 2000; Brakus, 2008; Brakus et al., 2009; Verhoef et al., 2009; Nambisan and Watt, 2011; Rose et al., 2011; Rose et al., 2012; Izogo and Jayawardhena, 2018; Bleier et al., 2019). This dimension relates to customers' ability to think, the mental process that follows, and the intellectual outcomes as a response (Schmitt, 1999; Gentile et al., 2007). Various terms and more specific concepts have been used to represent cognitive experience such as "think" (Schmitt, 1999; Brakus, 2008), "flow" (Novak et al., 2000; Rose et al., 2011; Rose et al., 2012), "intellect" (Brakus et al., 2009), "informativeness" (Bleier et al., 2019), "pragmatic" and "usability" (Nambisan and Watt, 2011). Most of these terms and concepts has been applied to situations that involve information processing, problem-solving, and creativity; all of these situation require intellectual analysis, analytical ability, knowledge application, and memory usage (Schmitt, 1999; Nambisan and Watt, 2011). Izogo and Jayawardhena (2018) adopted Mathwick et al.'s (2001) framework of

experiential values and categorised trust, expertise task, product, cost, convenience, and usability as part of the online cognitive experience.

Many studies examine the impact of cognitive response on customers' affective states, such as how flow results in positive affect (Hoffman and Novak, 1996; Novak et al., 2000). This is related closely to information processing theory, which holds the notion that humans process information that they received rather than merely responding to stimuli. Consequently, the affective response occurs as a result of cognitive evaluation, which in turn leads to behavioural consequences. The relationship between cognitive experience to a behavioural consequence is also reflected in a study by Jones et al. (2006) that showed a positive effect of cognitive experience on revisit intention. Cognitive experience also affects other marketing outcomes such as purchase intention (Emrich and Verhoef, 2015; Izogo and Jayawardhena, 2018), word-of-mouth (Izogo and Jayawardhena, 2018), satisfaction (Mosteller et al., 2014) and eventually trust (Rose et al., 2012). In a multichannel context, cognitive experience influences channel utilisation both for searching and purchasing across virtual and physical channels (Noble et al., 2005).

2.5.2 Affective experience

Affect is an umbrella term that is generally used to represent mood, emotion, and sometimes attitude (Bagozzi et al., 1999). It refers to the underlying experience of the subjective inner feeling state (Westbrook, 1987; Hogg and Abrams, 2007; Brakus, 2008). Over the past years, scholars have used multiple terms to represent affective experience, such as 'emotion' (McLean et al., 2018), 'mood' (Spies et al., 1997), 'playfulness and aesthetics' (Mathwick et al., 2001; Izogo and Jayawardhena, 2018), and 'entertainment' (Bleier et al., 2019). There are slight differences in how affective experience has defined and conceptualised, however, most studies can be referred to as reflections of customers feeling towards the overall customer journey.

Considering what customers feel, the affective experience can be translated into emotion and mood. While affect itself may comprise positive, negative, and neutral valence (Westbrook, 1987; Izard, 2013), emotion has been known to be the valenced affective response (Clore et al., 1987; Ortony et al., 1987; Richins, 1997). Although occasionally used interchangeably, emotion and mood are two different concepts. Bagozzi et al. (1999) discussed the differences and defined emotion as a mental state of readiness that stems from the cognitive assessment of stimuli. Emotion is, therefore, a premeditated response that differs from a mood, which is generally unintentional (Bagozzi et al., 1999). Emotions are high in intensity and may result in bodily experiences or overt actions. In comparison, mood is lower in intensity but lasts longer. There are three factors that can prompt moods (Frijda, 1986). First, mood can be caused by an after effect of emotion. Second, it is provoked by temporal states of physical condition such as illness, fatigue, etc. Third, physical surroundings such as heat, noise, and crowd can influence changes in mood and assessments of moods (Gardner, 1985). Mood has an ability both to influence and be influenced by a shopping experience (Swinyard, 1993).

An affective response may occur before or after a cognitive response. In the previous section, using information processing theory we mentioned that affective response can be caused by cognitive experience. However, there are some situations where an affective response may occur before a cognitive experience. During an impulsive shopping journey, customers may have little time to comprehend the cognitive attribute of a purchase. In this type of journey, the affective experience dominates the evaluation of the overall experience (Yeung and Wyer, 2004; Yim et al., 2014). As a result, customers with affective experience dominance are more likely to engage in influencing other customers through word-of-mouth activities (Jones et al., 2006).

2.5.3 Behavioural experience

There is a bodily response, that is a physical response, embodied within the customer experience which occurs when customers react to certain stimuli. Brakus (2008) argued that a bodily response shapes an individual's cognitive process which involves around making sense and understanding things. He used the metaphorical concept of 'warmth' as an example how some people translate it into a type of affection. The condition of warmth is originated from the rising temperature of a human body after being touched or hug. The human cognitive process helps an individual to understand the association between warmth and affection. Another example can be seen when the human body releases endorphins due to a mood-lifting, excited, or energetic episode. This episode can be applied on a shopping trip. It is well-known that a certain segment of customers embarks on a journey to what they called retail therapy, in which they expect the shopping trip to be a stress-reduced activity.

The human body is an essential source of information to interpret metaphors, therefore the physical experiences that the human body undergoes are able to transform metaphoric meaning into brand perceptions (Möller and Herm, 2013). Physical experience is not limited to a physical retail environment. Stimuli within the virtual or digital retail environment also influence a physical experience. A customer can potentially feel tired after conducting an extensive online search or feel exhausted after interacting with customer service via chatroom. It is, therefore, relevant to include behavioural experience into the omnichannel customer experience dimension.

Using the framework of experiential marketing proposed by Schmitt (1999) and Gentile (2007), retailers can stimulate physical experiences using product offerings or the consumption of products to create customer values and show an alternative lifestyle. Bodily experiences are supposed to transform behaviour or, at the very least, shape behaviour towards the lifestyle of customers and the perception of the retailer.

2.5.4 Sensory experience

Sensory experience deals with experiential aspects that engage customers' senses, including vision, audition, haptics, taste, and smell (Gentile et al., 2007; Krishna, 2012). Think about the smell of Lush's stores worldwide - it is so strikingly apparent from the outside that it becomes an invitation for customers to visit the store. Inside the store, customers can touch and smell bath bombs and even use their hands to dissolves them in a bowl of water, which projects future experience with the product upon purchase. Selling products that rely heavily on customers' senses might be the biggest reason why specialty retailers such as Lush, Jo Malone (smell), and Bose (hear) utilise sensory cues to sway customers perceptions, judgement, and behaviour. However, many other retailers also put effort to intriguing customers' sensorial experience, for example, lighting adjustment in different sections of a department store, ambient music in a fashion retailer, colour scheme and image style in ASOS mobile store, or how Sainsbury has an in-store bakery that bakes fresh pastries throughout the day. Consequently, such sensory experiences can arise regardless of the type of retailers and within both virtual and physical channels.

Sensory experience comes from sensory stimuli that results in sensory responses. When a sensory organ receives sensory stimuli, the human brain begins a neurological process that turns the stimulus into perceptions that shape both cognitive and affective responses (Krishna, 2012). In fact, marketers have long discussed how the five human senses contribute to positive customer experience (Donovan and Rossiter, 1982; Donovan et al., 1994; Cox et al., 2005; Krishna, 2012; Spence et al., 2014; Roggeveen et al., 2020). Sensory stimulus is more prominent in the offline channel shopping experience, as seen within the scope of store atmospheric research (Donovan et al., 1994; Spies et al., 1997; Massara et al., 2010; Spence et al., 2014; Helmefalk and Hultén, 2017). Nonetheless, recent study regarding online customer experience have included sensory experience as

one of its customer experience dimension (see Bleier et al., 2019), signifies the relevance of analysing sensory experience in the context of omnichannel retail environment.

Online and other virtual channels may lack taste as well as haptic and olfactory stimuli, however, audio and visual cues have a lot of potential to provide online sensory experience. In its simplest form, retailers use visual cues, such as images and graphic art, as well as verbal cues, such as a textual product information, to influence customers' attitude in the online channel (Kim and Lennon, 2008). In a more sophisticated strategy, retailers employ sensory enabling technologies (virtual try-on and 3D rotation view) to enhance customer experience through the increasing of perceived usefulness and perceived entertainment (Kim and Forsythe, 2008; Kim and Forsythe, 2009).

Sensory experience has been argued to be a potential source of shopping pleasure. Almost half of the sample in a study conducted by Cox et al. (2005) reported a pleasurable experience from sensory stimulation of a shopping journey, which corroborates findings by Wakefield and Baker (1998). They found that within an offline customer experience, sensory experience ranked even higher than social experience.

2.5.5 Social experience

Social experience considers the dynamics between customers and themselves, customers and their reference groups, customers and their social identity, and customers with others during a particular customer journey (Schmitt, 1999; Gentile et al., 2007; Nambisan and Watt, 2011; Bleier et al., 2019). This dimension starts from the perspective that humans are social beings and is not only about the interaction between customers or between customers and employees, but it also projects customers'

responses about how they want to be perceived by others and their position within their social groups.

Customers and employees interact during service delivery. In an offline retail environment, customers and employees encounter directly, while within a virtual retail environment, the interaction is mediated by technology (e.g., internet, telephone, computer). Regardless of how the interaction occurs, customers can feel a social presence from their interaction with the retailer's employees. Salespersons who are helpful, friendly, knowledgeable, and less pushy are found to contribute to a positive shopping experience (Arnold et al., 2005).

Furthermore, customer interaction can be directly or indirectly affected by the presence of other customers. Studies have shown how other customers can enhance or dismay one's customer experience. The pleasant behaviour of other customers can create a positive incident that inadvertently promotes a delightful experience (Grove and Fisk, 1997; Brocato et al., 2012). Differences can occur depending on whether a person is shopping by themselves or with others around them. Among younger customers, shopping with friends increases spending compared to shopping alone (Mangleburg et al., 2004). Generally, there is a notion that people behave differently when someone is watching them compared to when they are alone. In fact, it is also a matter of who is watching. As such, shopping with friends has been found to encourage purchases while shopping with family members can have the opposite effect (Luo, 2005).

Social dimension of customer experience also discusses how customers want to be seen by others. Customers convey their self-identity through decisions they made pertaining to shopping activities (Kleine et al., 1993). There are cases where customers avoid purchasing from an online or any virtual channel as an act to protect the earth and contribute less to the carbon footprint produced by an inefficient delivery system. Other

customers refrain from returning products, even when the option is viable, due to the issue of supply and waste management created by unsold products. These decisions are taken as a consequence of an appraisal process in a customer's mind that creates a dynamic between pride or shame (Laverie et al., 2002).

2.6 Customer effort and customer enjoyment as mediators

Prior sections have discussed the new conceptualisation of customer interaction breadth and customer interaction depth. These dimensions of customer interaction complexity are crucial within a customer journey. Customer interaction is an entity that builds up a customer journey (Lemon and Verhoef, 2016). Customer interaction with numerous channels and touchpoints within an omnichannel retail environment allows customers to personalise or customise their individual customer journey (Lemon and Verhoef, 2016). As such, innovative customer journey design and proactive personalisation are keys to winning against the competition in the customer journey (Edelman and Singer, 2015). Customers value an experience that is highly engaging and collaborative in the form of greater willingness to pay, purchase intention, and attitude toward a product (Franke et al., 2009). There are two vital factors that form an underlying mechanism for why personalised experience is valued higher - customer effort and customer enjoyment (Franke and Schreier, 2010). This is consistent with the implementation of social penetration theory, where individuals evaluate the progression of a relationship by assessing cost and benefit. In this framework, customer effort represents the cost element of an assessment because the effort involved is a nonmonetary sacrifice that customers have to spend (Baltas et al., 2010). Meanwhile, customer enjoyment represents the resulting benefit as it gives a customer something to gain, or more specifically, positive utility (Nowlis et al., 2004). These factors will be thoroughly explained below.

2.6.1 Customer effort

The amount of energy given by a customer to acquire a product or service reflects the degree of customer effort (Cardozo, 1965). It includes the cognitive, physical, and emotional effort as well as other resources such as financial and time effort (Cardozo, 1965; Clark and Bryan, 2013). Therefore, perceived effort is not always associated with tangible investment, but also the amount of thought given (cognitive) and how much emotion is spent on one particular journey. Customer effort increases as customers take part in more tasks (Cardozo, 1965; Sweeney et al., 2015) and contribute to customer value co-creation (Sweeney et al., 2015).

Customer effort is highly associated with convenience. As Berry et al. (2002) suggest, if customers can proceed with a task quickly, easily, and while paying less effort, then they have high transaction convenience. Effort is seen as a component to be exchanged in a transaction. Customers are willing to pay a premium price for products or services in exchange for acquiring them with minimum effort (Garbarino and Edell, 1997). For instance, customers pay a higher price to get a hairstyling service at home rather than at a salon. Past research has argued that customer effort increases at the expense of customer enjoyment (Cardozo, 1965; Garbarino and Edell, 1997). Additionally, empirical research has shown that high convenience shopping task evidently could affect customer satisfaction positively (Hunneman et al., 2015).

On the other hand, customers can use higher amounts of effort to signal how important a product or journey is for them, which in turn leads to a higher perceived value and ultimately affects satisfaction positively (Hult et al., 2019). Similarly, customers perceive the amount of effort as an indicator of quality, especially when the value of object being evaluated was challenging to determine (Kruger et al., 2004). For instance, in the case of acquiring an art object through a tough auction. Additionally, customer effort leads to choice-decision satisfaction and confidence (Klein and Yadav, 1989).

Customers feel more confident and satisfied with a choice, knowing that they have invested a lot of time and effort, especially in situations where there are abundant alternatives (Klein and Yadav, 1989).

Interestingly, customer effort is subjective to the nature of channels and touchpoints. Customers perceive and commit to a certain level of effort differently contingent on certain characteristics of the channels and the products. Due to less the less physical involvement and the fast technical performance in search, computer-mediated interaction is perceived to require less effort than human interaction (Bechwati and Xia, 2003). Hence, customers perceive lower search costs and are more inclined to spend a greater amount of time online (Chiu et al., 2019).

2.6.2 Customer enjoyment

Customer enjoyment is commonly linked with a customer segment who perceives shopping as a recreational task. The linkage is established from the perspective that enjoyment comes out of a process. However, enjoyment can also be derived from an outcome of the process itself which is not only experienced by recreational shoppers. Previous work showed that people who join a competition for the sake of the competition itself (the process) report higher enjoyment than those who expect a prize at the end (the outcome of the process) (Kruglanski et al., 1972). Arguably, this happens because enjoying a process does not necessarily depend on a positive or negative outcome.

Enjoyment from shopping can be activated by various types of interaction: before, during, and after the purchase. Enjoyment derived from before the shopping process has a lot to do with motivation, such as whether customers shop to keep themselves updated with current trends or, as briefly mentioned in the beginning of this section: seeing shopping as an adventure (Arnold and Reynolds, 2003). The latter accounts for a large

proportion of customers who happily spend more time and are involved in more activities during their journey (Bellenger and Korgaonkar, 1980). Meanwhile, the enjoyment that is stemmed from the process itself is related to the interaction that occurs during shopping activities such as social interaction (e.g. shopping with friends or conversation with other customers) or general interaction with the retail environment that is perceived as a stress-relief activity (e.g. being in the shop, feeling the atmosphere) (Arnold and Reynolds, 2003). Enjoyment subsequent to the shopping experience can be seen when customers shop for others (gift-giving or charitable task) or when receiving the best deal to purchase a product (Arnold and Reynolds, 2003). This illustrates that enjoyment does not necessarily come from hedonic motivation but also utilitarian motives.

Customers who do not enjoy shopping, in general, will limit their direct interaction with a retailer and instead complete shopping activities through salespeople (Reynolds and Beatty, 1999). Forcing direct interaction onto this segment may damage the enjoyment of the customers, however, facilitating and simplifying interactions could potentially enhance their enjoyment. Ultimately, it is about giving customers a sense of control and freedom in their journey, as well as allowing them to feel fun and enjoyment in whatever terms they have in their mind (Wolfinbarger and Gilly, 2001; Rose et al., 2011).

2.7 The gap within the consumer research in omnichannel retailing

Understanding customer experience creation within an omnichannel retail environment is pertinent because it is key to surviving and succeeding in an omnichannel era (Rigby, 2011). Past studies have mentioned that customer experience originates from customer interaction (Gentile et al., 2007; Jüttner et al., 2013), therefore, it is important to understand how customer interaction empirically links to customer experience. Many scholars have discussed the linkages between the two constructs in theoretical papers

(Prahalad and Ramaswamy, 2004; Ballantyne and Varey, 2006; Gentile et al., 2007; Grönroos, 2011) and concluded that customer interaction enables exchanges of value through transactional, relational, and communication activities that creates a customer experience. Gentile et al. (2007) suggested that customer interaction induces certain subjective responses that manifest within cognitive, affective, social, behavioural and sensory dimensions of customer experience.

Other qualitative studies have confirmed the suggested relationship. For example, Jüttner et al. (2013) showed that customer interaction at various touchpoints drives the affective and cognitive experience. Both conceptual papers and qualitative studies did not explicitly suggest whether the linkages between customer interaction and customer experience are positive or negative, linear or curvilinear. Using a different perspective, Echeverri and Skålén (2011) indicated that customer interaction influences not only customer experience creation but also destruction. This destruction can happen for a number of reasons, such as obstruction to information flow, inadequateness of attention, and complication of process. In their research, Echeverri and Skalålén hinted at the possibility of both positive and negative effect that customer interaction has on customer experience.

What is known so far is that customer interaction triggers an evaluation of its quality. Some researchers have used the SERVQUAL framework to analyse the impact of customer interaction on customer experience (Lemke et al., 2011; Klaus and Maklan, 2013). The qualitative research conducted by Lemke et al. (2011) indicates that customer interaction before, during, and after service encounters shapes customer experience quality. McLean et al. (2018) demonstrated that the ease of use, convenience, and customisation, positively affect mobile customer experience. Nonetheless, further empirical findings could assist us in establishing a stronger customer interaction-customer experience link. Using social penetration theory and

applying it to the customer-retailer relationship framework, this thesis looks at several studies that examined the link between customer interaction and relational outcomes such as patronage intention and customer engagement. Customer interaction, in terms of frequency of interaction at a specific channel (e.g., online, offline, social media), have been found to positively influence customer purchase (Hudson et al., 2016; Cambra-Fierro et al., 2020). Additionally, customer interaction through multiple search activities on the mobile channel could drive customer purchase intention (Rippé et al., 2017). Sopadjieva et al. (2017) found a positive relationship between higher channel mix in customer interaction and customers' shopping basket, however, this relationship was correlational and not causal. A higher frequency of customer-company interaction can also influence a positive brand attitude (Yaveroglu and Donthu, 2008).

Studies mentioned above mostly advocate the positive effect of customer interaction on the relational outcome. However, the relationship between customer interaction and relational outcome may not be as simplistic as it may appear. Single-channel customers were frequently found to be the most loyal segments (Konuş et al., 2008; De Keyser et al., 2015). This is because there is a tendency for the customer to always minimise their effort and find simplicity in their shopping journey (Spenner and Freeman, 2012; Sweeney et al., 2015). Moreover, every additional frequency in customer interaction can diminish the meaning of the previous interaction. Rather than stimulating the feeling of intimacy, it suggested a lack of understanding and became counter-productive in relationship building (Fournier et al., 1998; Reinartz et al., 2005; Venkatesan et al., 2007). The opposing results call for more explanations as there might be a certain contextual condition that changes the environment where customer interaction occurs. This condition can either be supporting a creation or a destruction of customer experience. There is also a need to reconsider how customer interaction is analysed before applying it into omnichannel retail environment context. Therefore, more gaps

will be presented in this section related to the need to integrate the current conceptualisation of customer interaction, the moderator variable, and the mediation mechanism that will be helpful in explaining the relationship between customer interaction and customer experience.

2.7.1 The fragmented analyses of customer interaction

Customer interaction has been examined widely but measured in various manners. It is a broad term that refers to a customer's direct and indirect encounters with a retailer's people, processes, and physical elements (Meyer and Schwager, 2007; Bolton and Saxena-Iyer, 2009). In the past, researchers have focused on different aspects of customer interaction, and hence, conceptualised and operationalised it differently. In the multichannel and omnichannel research streams, researchers have been particularly interested in channel and touchpoint usage (Konuş et al., 2008; De Keyser et al., 2015; Herhausen et al., 2019). These studies operationalised customer interaction as a variety of channels or touchpoints involved in the customer journey. Customers' channel and touchpoint repertoire is used as the basis for categorising customer segment. For example, customers are divided into multichannel customers, offline-focused customer, and online-to-offline. Each segment was profiled based on psychographic and demographic characteristics. For instance, multichannel customers are highly involved, have a high shopping enjoyment, and are younger (Konuş et al., 2008; Herhausen et al., 2019). Others have also used a variety of channels to analyse customer lifetime value which consists of customer purchase, share-of-wallet, and loyalty intention (Kumar and Venkatesan, 2005; Kushwaha and Shankar, 2013; Cambra-Fierro et al., 2016). There was a positive association between the variety of channels used and customer lifetime value, which was strongly positive for B2B customers but rather mixed for B2B customers, especially it was different between goods vs service. Multichannel customers spend the highest purchase value on the hedonic product category but

perform worse when it comes to utilitarian products (Kushwaha and Shankar, 2013). Multichannel customers, more specifically, all channels customers, were found to be less profitable than two-channels customers in the context of the financial service industry (Cambra-Fierro et al., 2016).

The second aspect that is commonly analysed as customer interaction is the frequency of interaction. Frequency of interaction has been part of concepts such as 'channel use' (Rodríguez-Torrico et al., 2017), 'channel interaction' (Hudson et al., 2016), 'channel habit' (Cambra-Fierro et al., 2016), 'touchpoint frequency' (Baxendale et al., 2015), and 'interaction characteristic' (Venkatesan et al., 2007). Rodríguez-Torrico et al. (2017) studied customer interaction frequency in the relationship between omnichannel behaviour and personality traits. They found that mobile channel use frequency is greater for high impulsiveness customers (Rodríguez-Torrico et al., 2017). Frequency of interaction often been used alongside other dimensions such as duration of time spent (Hudson et al., 2016; Rapp et al., 2013), number of customer-initiated contacts (Cambra-Fierro et al., 2020), and valence of interaction (Baxendale et al., 2015). These studies found a positive effect of customer interaction (i.e., frequency of interaction) on attitudinal loyalty, customer influence, relationship quality, and brand consideration (Venkatesan et al., 2007; Baxendale et al., 2015; Hudson et al., 2016; Cambra-Fierro et al., 2020). One finding was different in that is showed a curvilinear effect (i.e., U-shaped) between customer interaction with marketing communication and channel adoption duration (Venkatesan et al., 2007).

Rippé et al. (2017) captured customer interaction in mobile search and measured it with a multi-item scale. These items delineate the extent to which customers use the mobile channel to search, based on multiple search activities such as price comparison and product search, which eventually influence offline purchase. This brings us to the next dimension, customer activities. Theoretical papers have explored the numerous

activities that customers strive for during interactions with omnichannel retailers (Dholakia et al., 2010; Yadav and Pavlou, 2014). Dholakia et al. (2010) listed multiple groups of activities including pre-purchase search, choose, consume, post-purchase search, advocate, return, and complain. Few studies have provided a detailed perspective of these customer activities across stages, with most studies focusing on analysing the channel used in each stage, which is related to the first dimension of channel variety (Konuş et al., 2008; De Keyser et al., 2015; Herhausen et al., 2019). Wallace et al. (2004) gave an insight into channel service output (i.e., availability, information provision, delivery time) which was linked to a variety of activities in a customer journey. They observed a positive effect of channel service output on satisfaction (Wallace et al., 2004). However, these service outputs capture a bigger picture rather than detailed aspect of customer activities across channels. Köhler et al. (2011) divided interaction into functional and social categories, which both were able to influence salespeople's performance. This categorisation can also be seen in a study conducted by Sweeney et al. (2015) about customer activities in a healthcare institution. Customers are involved in social-oriented activities when building relationships with staff, other customers (i.e., patients), family, and friends. They are also involved in functional activities where they chose and managed treatment, a diet plan, or other procedural activities (Sweeney et al., 2015). Activities are not limited to functional type that lead to transactional relationship, because non-purchase activities are also important due to their virtue on nonmonetary outcomes such as brand awareness (Yadav and Pavlou, 2014).

As omnichannel retailing constitutes practices from several channel-specific strategies, our study also looks at research on customer interaction in a certain channel. The ability to conduct a face-to-face interaction in an offline retail environment promotes research related to customer interaction with other customers (Grove and Fisk, 1997; Brocato et

al., 2012; Tax et al., 2013). Tax et al. (2013) postulate that customer interaction with other customers in the retail environment can impact the overall evaluation of customer experience. Grove and Fisk (1997) noted that an exciting interaction between two customers may result in a positive experience for them but could also lead to dissatisfaction for other customers who were not in the same conversation group. This is a classic example of the impact of shared servicescape. However, specific types of customers actively seek social interaction when shopping, be it with their friends or with others they met in the offline channel. These customers possess an approach intention, and are positively influenced by other customers' similarity, physical appearance, and suitable behaviour (Brocato et al., 2012). In the online retail environment, the impact of other customers comes in the form of online touchpoints such as star ratings or textual reviews (Bleier et al., 2019). Customer interaction with this touchpoint drives customer experience in all dimension (i.e., informative, entertaining, social, and sensory experiences) (Bleier et al., 2019). Other touchpoints may impact customer experience differently; for instance, product description and use of a comparison matrix significantly influence cognitive experience, while product feature visualisation and video are useful to increase sensory experience in the online channel (Bleier et al., 2019).

Considering the above argument, this thesis seeks to highlight the complexity and multidimensionality of customer interaction. The aforementioned studies shown above have analysed customer interaction individually, either only for a certain dimension or a certain channel context. They have afforded insights into the broad discussion of customer interaction and its distinctive elements. While useful, the conceptualisation of customer interaction in the previous studies are insufficient to be applied to the omnichannel retail environment context. As such, there is a need to provide more nuanced coverage about the effect of customer interaction on customer experience. In

doing so, this present research offers a new conceptualisation of customer interaction complexity that encompasses two dimensions: customer interaction breadth and customer interaction depth. By analysing these two dimensions, this thesis attempts to answer whether a superior customer experience can only be driven by complex customer interaction. The new conceptualisation enables this present research to investigate the optimum levels for maximising customer experience.

2.7.2 The importance of investigating the effect of channel integration in the customer interaction – customer experience relationship

This thesis looks at past papers analysing linkages between customer interaction and behavioural/relational outcome to identify and understand factors that could change the strength of the relationship. The literature review provided in this chapter revealed that existing moderating variables could be grouped into four categories: product-related factors (e.g., Nambisan and Baron, 2007; Lemke et al., 2011; Kushwaha and Shankar, 2013), customer-related factors (e.g., Nambisan and Baron, 2007; Lemke et al., 2011; Hudson et al., 2016), retail strategies (e.g., Rapp et al., 2013; Hudson et al., 2016; Rippé et al., 2017), and customer interaction attributes (e.g., Köhler et al., 2011; Rapp et al., 2013; Polo and Sese, 2016). These categories will be discussed further; however, it is worth pointing out that past research overlooks the retailer's channel attribute when considering moderating variables. The importance of the channel attribute is significant due to its ability to change the retail environment in which the buying process takes place.

First, a lot of attention has been given to examining the role of product-related factors in moderating the relationship between customer interaction and certain behavioural or relational outcomes. These factors include product risk (Kushwaha and Shankar, 2013), product complexity (Lemke et al., 2011), and product category (Lemke et al., 2011; Kushwaha and Shankar, 2013). The moderating role of these factors relates to two main

points: (1) their ability to change a customer's perception about the importance of a customer journey, and (2) their fit within the channel employed to host the customer interaction. Product complexity, for instance, positively moderates the linkage between customer interaction and the value-in-use (Lemke et al., 2011). Customer interaction is more meaningful and produces a stronger value-in-use when product complexity is high (Lemke et al., 2011). This is because customers perceive higher importance in their journey as product complexity increases. Getting the right information and consulting with the salespeople when buying insurance for a house will result in a greater customer experience than doing the same for a box of pasta.

However, a box of pasta can be seen as a hedonic product if it is a special variant or especially handmade for an important occasion (e.g., anniversary, birthday, graduation). In this case, the importance of a product increases and moves to the emotional domain. Customer interaction will drive a greater affective experience because it activates hedonic value-in-use instead of another form of value-in-use (e.g., utilitarian, relational, economic value). Hedonic product category also relates to channel fit. Customers who pursue hedonic products commonly possess variety-seeking behaviour supported by customer interaction with multiple retailers' channels (Kushwaha and Shankar, 2013). Consequently, multiple channel customer interaction (high customer interaction breadth) drives a higher spending level for the hedonic product category. In another case, customer interaction with the offline channel yielded greater purchase for low-risk products (Kushwaha and Shankar, 2013). This is because low-risk products attract risk-averse customers, and interaction through offline channels facilitates their risk-aversion tendency.

The second group of moderators falls within the scope of customer-related factors. This includes community identification (Nambisan and Baron, 2007), uncertainty avoidance (Hudson et al., 2016), customer emotional involvement, and relationality/closeness

(Lemke et al., 2011). Community identification becomes a significant moderator when tested in the context of community in-group interaction. As customers identify themselves more with the larger community with whom they interact, personal integrative benefits (e.g., self-efficacy, expertise, self-esteem) will drive more customer engagement in the future (Nambisan and Baron, 2007). This is because there is a tendency for customers to look for recognition from a group that matters to them. Similarly, other factors also focus on the notion of what matters for a customer. Some customers highly involved in their purchase decision because there is a sentimental reason behind the journey; for example, buying one's first house or buying a wallpaper for the first child's nursery room. This involvement strengthens the effect of customer interaction on the expected value-in-use (Lemke et al., 2011).

Uncertainty avoidance, as a customer factor ingrained in the culture, plays a significant role in influencing the effect of social media interaction on shaping brand relationship quality (Hudson et al., 2016). In a country where uncertainty avoidance is predominantly high, social media interaction helps retailers stimulate customer engagement and build superior brand relationship quality. On the other hand, social media used to encourage customers-retailer interaction is ineffective in countries with low uncertainty avoidance (Hudson et al., 2016). Overall, customer-related factors indicate that customer experience is shaped by subjective responses and within subjective consumption context. Different traits in different customers may affect how customer interaction influences the customer experience.

The third theme discusses factors contributed by retailers' strategy such as adaptive selling (Rippé et al., 2017), anthropomorphism (Hudson et al., 2016), service ambidexterity and brand reputation (Rapp et al., 2013). Rippé et al. (2017) found that retailers are able to increase customers' purchase intention by implementing an adaptive selling technique to customers who interact with the mobile channel. Mobile channel

interaction increases customers' perceived control, and in return, customers understand exactly the level of knowledge they have and the remaining information they need from salespeople. Applying adaptive selling technique enables salespeople to cater their assistance to level that customers need. Anthropomorphism is a strategy related to brand communication in which an organisation uses a human characteristic to represent themselves. The use of this strategy facilitates interpersonal exchange, which is useful for enhancing the effect of social media usage on customer engagement and brand relationship (Hudson et al., 2016). The interpersonal perspective carries on especially towards reputable retailers. There is a significant positive relationship between retailer interaction on social media and customer interaction on social media (Rapp et al., 2013). Brand reputation has further reinforced this relationship because it enhances customer affirmation regarding self-image (Rapp et al., 2013). Simultaneously, a similar effect was found when retailers successfully balance their sales effort and relationship-building effort (i.e., service ambidexterity) (Rapp et al., 2013).

The last component that has been tested as a moderator is related to customer interaction itself, and includes the style of interaction (Köhler et al., 2011), the nature of the interaction (Polo and Sese, 2016), and interaction-based segmentation (Herhausen et al., 2019). Customer interaction style was examined from the perspective of salespeople. Functional-focused customer interaction that is met with a proactive interaction-style will generate greater journey effectiveness (Köhler et al., 2011). Salespeople who implement a proactive style are suitable for assisting customers' problem-solving activities, which are dominant in functional-focused customer interaction. Customer interaction can also be categorised based on the risk it holds. High-risk interaction, as observed during purchase-related interaction, will intensify the effect of customer attitude on channel choice. As for low-risk interaction (e.g., communication), the effect of marketing activities is more prominent on channel choice. Collectively, customer

interaction with purchase channel and communication channel make up customer interaction breadth, and as this chapter discussed before, has been used to characterise customer segmentation (Herhausen et al., 2019). As customer interaction breadth increases, the effect of product satisfaction on customer loyalty will decrease (Herhausen et al., 2019) because customers will attribute their satisfaction towards their own effort to collect information and not to the retailer. Therefore, the influence of journey satisfaction on customer loyalty will be stronger in conditions of high interaction breadth.

The four themes of moderators tested in the past have enriched our knowledge of the customer interaction complexity-customer experience relationship. Nevertheless, there is an opportunity to enhance our understanding of the current subject. One factor that this thesis views as an important moderator and has not been discussed in the past is channel integration. The level of integration between channels in an omnichannel retailer will influence the shopping process in which customers encounter (Dholakia et al., 2010). Channel integration can increase the ease of processing information (Shen et al., 2018) and the perception of variety assortment (Emrich et al., 2015).

Moreover, it becomes a vessel for achieving a more personalised service through increased interactivity (Yadav and Varadarajan, 2005; Hughes, 2006). Second, channel integration consists of many elements of which the implementation can vary across retailers. This creates circumstantial differences for the customer journey, which might affect customer perceived control (Zhang et al., 2018) and subsequently prompt future engagements (Rippé et al., 2017). Accumulatively, there are enough arguments for placing channel integration as a promising moderator for a relationship between customer interaction complexity and customer experience.

2.7.3 The moderating role of channel type (offline versus online)

The offline channel and online channel are arguably the two most prominent shopping mediums in a retail environment. They are the most common channels found in omnichannel retailers' channel choices (Sousa and Voss, 2006). Thus, it is vital to understand how the creation of customer experience differs across channels. As seen in section 2.5, existing studies of customer experience are specific to a certain channel. These studies discussed offline and online customer experience separately.

Offline shopping experience usually focuses on store atmospherics, salespersons, and other customers in the store (Donovan and Rossiter, 1982; Roggeveen et al., 2020). Olfactory cues, when implemented correctly, encourage favourable shopping behaviour. A simple scent, rather than a complex one, works better in promoting greater sales (Herrmann et al., 2013); meanwhile, a combination of ambient scent and sound on a visually dominant store can enhance customer emotions (Helmefalk and Hultén, 2017). The offline retail environment provides a communal space shared with other people, including salespersons and other customers, hence, its evaluation is influenced by the presence and behaviour of others. Salespersons who are helpful, friendly, knowledgeable, and less pushy are found to contribute to a positive shopping experience (Arnold et al., 2005). Similarly, the pleasant behaviour of other customers could create a positive incident that inadvertently promotes a delightful experience (Grove and Fisk, 1997; Brocato et al., 2012).

Online shopping experience similarly focuses on virtual atmospherics, interactivity, and online customer-to-customer contact (Manganari et al., 2009; Nambisan and Watt, 2011; Harmeling et al., 2017; Bleier et al., 2019). The aesthetics of the online retail environment have an impact on customer patronage intention and advocacy (Izogo and Jayawardhena, 2018). The aesthetics factor discusses the look and feel of a webpage, the verbal elements, and the consistency of visual cues and brand perception (Rose et

al., 2012; Mosteller et al., 2014). Although no longer perceived as a novelty, customers possess different levels of knowledge and skill when navigating online channels. The ease of navigation, together with the web aesthetics have been proposed to influence interactivity, which impacts positively on customer attitude (Dennis et al., 2009). An online store that allows customers to search and purchase easily will benefit from a positive experience (Novak et al., 2000; Mathwick and Rigdon, 2004). The functional quality of the online retail environment, such as the interaction speed and customisation, also positively impact online customer experience (Novak et al., 2000; Rose et al., 2011; Rose et al., 2012; McLean et al., 2018).

Offline versus online comparison, however, has been studied a lot regarding other topics. A recent study by Hult et al. (2019) showed that the effect of service quality on customer satisfaction is more pronounced in the offline channel, while the effect of perceived value is stronger in the online channel. The online channel is perceived as the economical mode of shopping due to the lower search cost (Chintagunta et al., 2012) and the ease of obtaining information (Shankar et al., 2003). However, price dispersion is greater online than offline due to the increasing number of online retailers (Zhuang et al., 2018). Furthermore, the positive effect of customer satisfaction on loyalty is greater in the online channel (Shankar et al., 2003; Hult et al., 2019).

The online channel is also advantageous for well-known brands (Degeratu et al., 2000; Danaher et al., 2003; Saini and Lynch, 2016). The limited sensory cues in the online channel shift customers' reliance to more heuristic cues, such as brand name, to assist in the decision-making process (Saini and Lynch, 2016). Customers also rely on themselves in making judgements online, and tend to feel in control when navigating through the online medium (Koo and Lee, 2011). The level of control felt by online customers increases their level of tolerance towards a lower level of service recovery than offline customers (Harris et al., 2006). Online customers, however, can experience

a higher level regret if they find a cheaper option after having engaged in a high level of customer effort (Park et al., 2015).

Despite extensive research, no study has investigated how customer interaction influences customer experience differently across the offline and online channels. Understanding the similarities and differences between the offline and online channels will guide retail managers in taking decisions pertaining to channel design. Moreover, it has the potential to enable managers to infuse ideas that could potentially maximise customer experience in both channels, resulting in the superior evaluation of their omnichannel retailers.

2.7.4 The lack of existing mediating variables that fit the interpersonal views of the customer – retailer relationship building

The current literature offers a different mechanism in explaining how customer interaction can lead to a certain relational outcome. Aligned with the interpersonal relationship perspective that this thesis follows, evaluation of cost and benefit is pertinent to progressing the customer–retailer relationship. This framework of cost-benefit analysis has been used in past research with variance in the application. Konuş et al. (2008) and De Keyser et al. (2015) analysed cost and benefit to calculate total utility based on customer psychographic. The cost aspect includes traits such as price consciousness and time pressure; meanwhile, the benefit part is indicated by customer innovativeness (Konuş et al., 2008; De Keyser et al., 2015). Although these studies used a cost and benefit analysis, the estimated factors were not derived from the process or the journey, instead, they are extracted from customers' personality and psychology characteristics.

Similarly, Balasubramanian et al. (2005) also used total utility to explain how customer interaction goals and motivation can result in certain channel choice. For instance, customers with an affirmation of expertise will be prone to using online channels for

extensive searches and learning but visit an offline channel to inspect a product closely and ensure its quality. Customer motivations play a role in determining expected value-in-use that mediates customer interaction and customer engagement (Lemke et al., 2011). Therefore, rather than stemming from the customer journey, the mediators above originate from customers themselves before the purchase process begins.

In mobile customer interaction, cost and benefit were assessed using timeliness and enjoyment (McLean et al., 2018). In this case, the timeliness represented cost and measured the efficiency of performing intended shopping activities. The higher the interaction quality, the less time spent to complete the interaction. Subsequently, having an efficient interaction will increase the overall mobile customer experience (McLean et al., 2018). McLean et al.'s work seems to offer a balanced analysis of cost and benefits, however, the caveat of using timelines is twofold: first, it is a channel-specific variable that is most appropriately be used within an online or mobile retail environment; and second, it is limited to a single dimension of 'cost' (i.e., time spent). Other studies have not offered an integrative framework as they used either cost or benefit as a mediator. For instance, Cambra-Fierro et al. (2020) suggested that customer interaction depth increases retailers' service usage via increased switching costs. Others have introduced service benefits (i.e. convenience, information provision, product fulfilment) (Wallace et al., 2004) or perceived control (Rippé et al., 2017) as factors that positively mediates customer interaction and patronage intention.

There is still a need to test mediating variables relevant to the omnichannel retail environment and represent customers' cost and benefit analysis derived from the customer journey. This present study offers customer effort and customer enjoyment as mediators between customer interaction and customer experience. These mediators are seen as suitable mediators for our research due to several reasons. First, both customer effort and customer enjoyment are variables that are highly applicable in an

omnichannel retail environment. They do not have a contextual bias, as found on timeliness, and they appropriately represent cost and benefit, respectively. Second, in particular, customer effort captures a wide range of 'costs', from cognitive effort to emotional effort, time effort, and physical effort (Clark and Bryan, 2013). Lastly, customer effort and customer enjoyment portray the perceptual response stemming from the process within a customer journey. As Franke and Schreier (2010) pointed out in their research, customer effort and customer enjoyment are "the psychological reaction(s) elicited by the process" (p.1022).

2.8 Chapter summary

This chapter presented a systematic overview of relevant omnichannel literature that was used to identify research gaps for this study. There has been a considerable amount of research focusing on customer behaviour in the omnichannel retail environment, however, no study has attempted to thoroughly analyse customer interaction using social penetration theory. This theory is fundamental in understanding the role of customer interaction within the customer-retailer relationship. It further aids the conceptualisation of customer interaction in conjunction with organisational complexity and external knowledge search.

Past studies have been linked customer interaction to marketing outcomes such as customer purchase, customer satisfaction, and customer loyalty. However, to this date, there has been no research that examines the impact of the customer interaction complexity on customer experience. It is crucial to understand customer experience creation in an omnichannel retail environment because it has become the ultimate objective of omnichannel retailers and is believed to be the key to win the competition. This chapter discussed the definition of customer experience, including its five dimensions: cognitive, affective, behavioural, sensory, and social. Subsequently, other important constructs in this research were reviewed, such as channel integration,

customer effort, and customer enjoyment. In Chapter 3, constructs discussed in this chapter will be used to formulate a research framework, and the relevant theories will be used to outline the relationship between constructs.

Chapter 3 Development of Conceptual Framework

3.1 Introduction

This chapter provides the rationale behind the development of our conceptual framework. It further explains the relevant theories, concepts, and current understanding of how the relevant constructs, discussed in Chapter 2, are related. The theoretical background will be discussed, and links between construct will be drawn. Furthermore, a series of hypotheses will be formulated to be tested in the following chapters.

3.2 Conceptual framework

Myriad channels and touchpoints within an omnichannel retail environment exist to facilitate customer interaction with a retailer (Lemon and Verhoef, 2016). The proliferation of ways to interact with these channels and touchpoints encourage personalisation in the customer journey (Barwitz and Maas, 2018; Herhausen et al., 2019). Every personalisation of the customer journey comprises of customer decisions concerning which channels and touchpoints they want to interact with, what kind of activity they want to perform, and how many times the recurrence should be. Building upon the social penetration framework, these decisions affect the progression of the relationship development between a customer and a retailer (Taylor, 1968; Altman and Taylor, 1973).

There are five aspects of the social penetration theory that can be unfolded and put in the context of the omnichannel customer-retailer relationship. First, the social penetration theory is applicable considering that the relationship between a customer and a retailer is increasingly personal. A retailer's ability to store and track historical purchases makes it possible for them to customise offerings to customers, making every interaction become personal. For instance, retailers can combine customers' preferences

that are captured from social media, with the ranking algorithm in the search engine, to boost clickstream of a lower rating product (Ghose et al., 2014).

Second, the social penetration theory gives guidance on how to look at the development of a relationship by determining the breadth and depth of penetration, which inspired this thesis to adopt customer interaction breadth and depth. The notion behind the breadth of penetration is that individuals exchange topics of discussion that are perceived as equally important. To implement this to customers' channel repertoire would be a good fit because in an omnichannel environment, channels are and should be interchangeable (Verhoef et al., 2015). No channel is superior to others, and the reason customers choose to interact with one and not the other is that they have assessed their needs and preferences (Hosseini et al., 2018). A relationship can also progress based on the depth of penetration which signifies layers of a relationship's intimacy. This present research associates these layers of intimacy to be similar to a marketing funnel in which layers of different journey stages invites customers to a different level of relationship. For illustration, a customer using a retailer only to search for information has a less intimate relationship than another customer who is searching for and performing a transactional exchange with that retailer.

The third aspect is the consideration of situational conditions or physical environment (Werner et al., 1992). Taylor et al. (1969) pointed out that interpersonal exchange depends on the environment of the exchanges. This thesis posits channel integration and channel type as conditions that could change the outcome of customer interaction with an omnichannel retailers. Thus, the present research specifically focuses on retailer channel attributes to be the moderators in the conceptual framework. Channel integration is a degree to which a retailer's channels are synergistically aligned through consolidated configuration related to objectives, design, and retail mix (Cao and Li, 2015). The level of channel integration arguably will define the situation where

customer journey eventualise. This situation is pertaining to shopping convenience and the ease of navigation across channels (Oh et al., 2012). Similarly, channel type will directly define customers' shopping environment. In this case, two most prominent channel types are tested, the offline channel and online channel. Both channel types exhibit distinct characteristics that could influence conditions where customer interaction takes place.

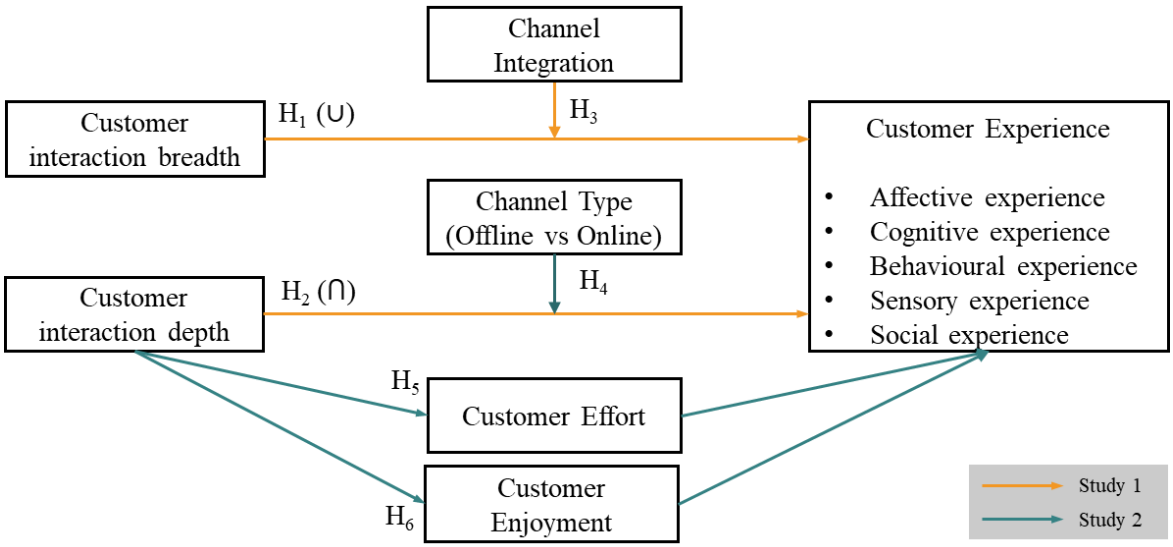
The fourth aspect of social penetration theory is related to the checks and balances process of the interaction outcome. Reward and cost play an important role in continuing a relationship (Taylor et al., 1969). This thesis put customer effort and customer enjoyment to play this role. It has been discussed in the previous chapter how both constructs appear to form the mechanism for customers to evaluate a personalised and heavily interpersonal service (Franke and Schreier, 2010). Customer effort is the cost or sacrifice expended by customers when interacting with a retailer, while customer enjoyment is seen as the reward of such a process. Consequently, the level of breadth and depth are simultaneously checked against the level of effort and enjoyment produced.

Finally, we discuss how a relationship progresses through a satisfactory interaction. Satisfaction judgments are thought to be comprised of both affective (Westbrook, 1987; Mummalaneni, 2005) and cognitive elements (Oliver, 1993), but it are a distinct concept from both of these (Hunt, 1977). Similarly, these two elements are part of customer experience, and so as a whole, social penetration theory aids this thesis in laying the path for the ties between interaction and experience.

The conceptual framework Figure 3.1 illustrates two dimensions of customer interaction complexity within an omnichannel retail environment: customer interaction breadth and customer interaction depth, as the antecedent of customer experience. In this conceptual

framework, channel integration acts as a moderator of the relationship between customer interaction breadth and customer experience. As such, it is predicted to alter the strength and the nature of the relationship between customer interaction breadth and customer experience. Differently, channel type (i.e., offline versus online) is expected to moderate the relationship between customer interaction depth and customer experience. Furthermore, this thesis postulates the effect of customer interaction depth and channel type is mediated by customer enjoyment and effort. The relationships between constructs are colour-coded based on the study on which they will be tested. Details on the methodology of each study will be further explained in the methodology found in Chapter 4.

Figure 3.1 Conceptual framework



3.3 Research hypotheses

3.3.1 Direct effects

3.3.1.1 Customer interaction breadth and customer experience

The relationship between customer interaction breadth and customer experience can be predicted using three different routes. First, it can be explained using the linkages between customer interaction breadth and customer shopping basket. Researchers have

found that customer shopping basket and total purchase value are positively associated with customer interaction breadth (Kumar and Venkatesan, 2005; Thomas and Sullivan, 2005; Neslin et al., 2006; Sopadjieva et al., 2017). As such, the more channels and touchpoints involved in a customer journey, the higher the shopping basket will be. The size of a customers' shopping basket is often linked to the formation of a relationship between a customer and a retailer. Customer with low and high shopping basket form relationships with a retailer faster (Venkatesan et al., 2007). Venkatesan et al. (2007) argued that customers with small basket sizes usually engage in unplanned fill-in shopping trips. This customer segment obtains higher utility from getting their immediate needs fulfilled by a retailer. In contrast, customers with large shopping basket sizes commonly participate in planned visits and are more likely involved in repeat purchases. This customer segment derives higher utility from being satisfied with the retailer's offerings. In both cases, shopping utility drives satisfaction and contributes to the acceleration of relationship development. Simultaneously, when shopping utility drives satisfaction, it also signals a proportionate effect on customer experience (Pansari and Kumar, 2017).

Instead of building a relationship, customers with moderate sizes of shopping basket focus more on getting and finding a lower price (Mazumdar and Papatla, 1995). The customer experience of this price-conscious segment tends to be one-dimensional to the factor of price. There is an inclination to disregard social experience due to the tendency to dehumanise personal interaction (Henkel et al., 2018), making the overall customer experience lower.

The second route is through the creation of customer satisfaction. Customer satisfaction can be contributed by product satisfaction and journey satisfaction (Herhausen et al., 2019). The former is driven by the outcome-thinking process that focuses on achieving the end of a journey (Thompson et al., 2009). This is commonly signified by the limited

interaction, the low emphasis of the search process, and the reliance on the final product in shopping evaluation (Herhausen et al., 2015). On the other hand, journey satisfaction is driven by process-oriented thinking (Herhausen et al., 2019) that stresses the need for stimulation (Menon and Kahn, 1995) and the importance of taking elaborate steps in the decision-making process (Thompson et al., 2009). At low levels of customer interaction breadth, the overall customer satisfaction is dominated by product satisfaction, while at the high levels, journey satisfaction is more prevalent. Nonetheless, both will result in higher levels of customer experience. Differently, at moderate levels of customer interaction breadth, the overall customer satisfaction is evaluated against both product satisfaction and journey satisfaction. Customers weigh in more factors to make a more critical assessment that scrutinises the overall customer experience. Subsequently, at moderate levels, customer experience reaches the lowest point.

The third is related to customers' learning curve in understanding channels and touchpoints' navigation. Based on Mitchell and Dacin (1996), one of the avenues used to learn and build expertise is direct experience of a specific service and the information acquisition from external sources. As customer interaction breadth increases, so does the expertise towards the retailer's channels and touchpoints. Between low to moderate levels of customer interaction breadth, incremental expertise results in a decreasing customer experience. The negative effect arises because learning and acquiring expertise is a high cognitive task (Bettman et al., 1990). This cognitive process may produce some levels of fatigue or confusion and eventually lead to negative affect (Wang and Shukla, 2013). At the same time, as expertise increases, customers may misunderstand the true level of their knowledge (Alba and Hutchinson, 1987). As a result, they deliberately ignore certain cues or abbreviate certain processes resulting in a premature decision that jeopardises the interaction outcome (Alba and Hutchinson, 1987). This tendency to generalise will evaporate as customer interaction breadth

continually increases from moderate to high levels (Haleblian and Finkelstein, 1999). Between these points, the customer will appropriately weigh both surface and underlying features of channels and touchpoints, making them able to exploit the benefits on which they can gain. Eventually, this affects customer experience positively.

There appears to be a strong rationale for a nonlinear relationship between customer interaction and customer experience from the three routes explained above. In sum, the hypothesis can be stated as:

Hypothesis 1*: There is a U-shaped relationship between customer interaction breadth and customer experience*

3.3.1.2 Customer interaction depth and customer experience

One of the component of customer interaction depth, frequency of interaction, has been known to positively influences perceptual outcomes such as brand attitude (Lane, 2000; Yaveroglu and Donthu, 2008) and behavioural outcomes such as customer purchase (Taylor et al., 2013). As the frequency of interaction increases, a customer-retailer relationship is built through mutual trust (Morgan and Hunt, 1994). This influence only lasts up to a certain threshold where customers feels that the interaction has no additional value to the relationship and instead has a worsening impact (Venkatesan et al., 2007). The link between frequency of interaction and the development of a relationship is therefore nonlinear (Reinartz et al., 2005); for those with low or high levels of customer interaction depth, the customer-retailer relationship develops slower (Venkatesan et al., 2007).

Customers also shape a deeper interaction by engaging with different activities. Activities are performed to unlock a channel's or touchpoint's service output (Wallace et al., 2004). For example, a customer browses a product catalogue to unravel the capability of a certain channel or touchpoint in providing information. Activities are

also performed to achieve specifics goals in a customer's mind, such as economic goals, symbolic meaning, or social influence (Balasubramanian et al., 2005). The attainment of service outputs and the fulfilment of goals increases the total utility perceived by customers (Balasubramanian et al., 2005). It accumulatively aids customers to move on to the next marketing funnel stages (Balasubramanian et al., 2005; Colicev et al., 2019). For example, a customer with an economic goal during the consideration stage would be involved in extensive price-related activities such as comparing prices, seeking discounts, or couponing. Once their goal is achieved, they will move on to the purchase intent stage.

Although additional activities increase customers' total utility, evaluation is subjective to their perceived benefits. Customers evaluate total utility based on the effectiveness (i.e., the consumer's beliefs about the activities to perform desired functions) and efficiency that each activity contributes to their journey (Thompson et al., 2005). This aligns with its relationship to service output and goal attainment as the number of activities positively influences journey effectiveness (Thompson et al., 2005). In contrast, it negatively affects efficiency (Thompson et al., 2005) because every additional activity requires more time to complete, greater mental effort, and a higher propensity to result in missteps (Nielsen, 1993; McLaughlin and Skinner, 2000; Lacka and Chong, 2016).

Customers consider effectiveness more prominently at the beginning of an interaction, then move their emphasis to efficiency at the later stages (Thompson et al., 2005). Thus, it is predicted that customer experience increases from low-to-moderate levels of customer interaction depth due to the greater effectiveness obtained from incremental activities. However, customer experience increases at a diminishing rate because the effect of efficiency slowly takes over. After a certain point and towards high levels of customer interaction depth, customers shift their focus into the usability aspect of

interaction and evaluate the ease of completing a journey. At these levels, customer experience decreases following the negative effect of journey efficiency.

Moreover, when customers continue to conduct activities, it signals their need to reach an effective customer journey. In other words, the current interactions were felt insufficient to reach a goal, indicating a problematic customer journey. Arguably, at these points, previous activities were not satisfactory. This phenomenon is reflected in the analysis of after-purchase activity, such as return. Customer interaction for return positively affects satisfaction only when it is solved at the beginning. Other returns overtime signalling a bad customer service level and, therefore, that the influence is deteriorating (Venkatesan and Kumar, 2004; Venkatesan et al., 2007). As customers engage in more shopping activities, their expectation increase and they becoming harder to please (Shankar et al., 2003), or more susceptible to disappointment in the choice decision (Park et al., 2015). Accordingly, this suggests a negative return in customer experience after a certain level of depth. Based on these arguments, this thesis proposes that:

Hypothesis 2*: There is an inverted U-shaped relationship between customer interaction depth and customer experience.*

3.3.2 Moderating effects of channel integration on the customer interaction breadth-customer experience link

On the subject of interaction breadth, channel integration is largely responsible for creating a seamless customer journey. According to the Oxford dictionary, the word ‘seamless’ refers to an adjective that translates into “without spaces or pauses between one part and the next” (Oxford Learner’s Dictionaries, 2020). In an omnichannel context, seamless refers to the ability to move between channels and touchpoints without boundaries and limitation (Brynjolfsson et al., 2013). Channel integration is the factor that creates a seamless transition between channels and touchpoints (Homburg et

al., 2017). It indicates that channel integration has the ability to change the environment where customers interact with retail channels or touchpoints.

First, the presence of channel integration will increase the navigation between channels and touchpoints. Channel integration increases connectivity across channels and touchpoints (Homburg et al., 2017). Once customers feel the increased connectivity, they will feel greater benefit from having a higher interaction breadth, resulting in a superior customer experience. Without the presence of channel integration, customers will feel the extra work when more channels are involved in their routine. Consequently, this extra effort weighs down customers' pleasure.

Second, higher channel integration increases the ease of processing and accessing information. This is due to the incremental of perceived fluency (Shen et al., 2018). The previous argument proposed in Hypothesis 1 states that customers face difficulties in interacting with more channels because each channel requires a different set of operating knowledge. The higher the integration of channels within a retailer, the more likely those difficulties will fade away. By committing to provide higher integration between channels, retailers pass on multiple cues, so customers better understand how to interact through channels and touchpoints. For instance, retailers can give a hyperlink to access their call centre via their website, which automatically displays the call centre number on the customer's phone. Without this link, customers have to search for the phone number and separately dial the number manually on their phone. In this way, customers rely more on the provided cues and not on their own knowledge, liberating them from processing more information and improving their customer experience.

Nonetheless, customers engage in a learning process, albeit an incidental one, in which learning is not the primary goal (Biehal and Chakravarti, 1982). There is less information retained in incidental learning; nevertheless, customers take part in an

increasingly cognitive task to retain accumulative information as customer interaction breadth increases. There is an increasing complexity that negatively affects information and knowledge coordination (Cummings and Kiesler, 2007). The cost of coordination gets similar that found in forms of physical and mental exhaustion (Gittell and Weiss, 2004). Specifically, mental exhaustion can hinder customers' ability to produce creative and adaptive solutions (Chen et al., 2019), exposing them to failure and disappointment. The positive effect on customer experience only lasts from low levels to moderate levels of customer interaction breadth. Towards the higher levels, the increasing coordination of knowledge and information takes a toll on customer experience. Based on the arguments above, this thesis proposes that the relationship between interaction breadth and customer experience becomes less negative, and even positive, along with the intensification of channel integration. This thesis hypothesises it as:

Hypothesis 3*: Channel integration moderates the relationship between customer interaction breadth and customer experience in such a way that* ***(a)*** *at low levels of channel integration, the customer interaction breadth – customer experience relationship is U-shaped, while* ***(b)*** *at high levels of channel integration, the customer interaction breadth – customer experience relationship flips to an inverted U-shaped.*

Channel integration and customer interaction depth

This thesis does not hypothesise the moderating effect of channel integration on the relationship between customer interaction depth and customer experience due to two reasons. First, the component of customer interaction depth does not include an attribute directly linked to retailer's channels. Unlike customer interaction breadth, that represents a number of channels in a customer's channel repertoire, customer interaction depth focuses on the activities within a retailer touchpoint and the frequency of those activities performed by customers regardless of the channel in which the interaction occurs. Second, one can suggest that channel integration improves journey effectivity

through the increased perceived interactivity (Yadav and Varadarajan, 2005; Hughes, 2006; Yadav and Pavlou, 2014) which positively influences customer attitude towards retailers (Johnson et al., 2006). Interactivity is attached to channels' features commonly found in computer-mediated channels such as a build-your-own comparison matrix, online agent, or technology-enhanced product image (e.g., 360° image rotation, zoom-in function, or colour swapping). While customer interaction depth captures the activities in which customers are possibly using these features, it does not directly signify the level of interactivity in the overall customers' journey. Moreover, the encounter between customer and interactive features does not guarantee the formation of perceived interactivity unless customers actively engage with them. Again, the engagement with interactive features was not captured by our operationalisation of customer interaction depth. Customers may have actively been look for product visualisation, but whether they came across an interactive image or a static one, was not specified in this study.

3.3.3 The moderating role of channel type and the mediating role of customer effort and customer enjoyment on customer interaction depth and customer experience link

Customer interaction depth and channel type

The offline and online retail environments offer unique characteristics that influence customer perception and judgement differently. The offline retail environment provides a rich touch and feel sensation for customers which presents greater assurance on customer perceptions of product and journey quality (Degeratu et al., 2000; Laroche et al., 2005). The face-to-face interaction afforded by offline channel forms reinforces service quality by granting access to trustworthy information that facilitates a personalised service that many customers are after (Laroche et al., 2005). The offline channel poses a lower shopping risk compared to online the channel and brings more

certainty to the customer journey (Zhuang et al., 2018). However, there are multiple transaction costs incurred during offline shopping such as travel costs (e.g., bus fare, car petrol, parking fee), physical costs (e.g., carrying grocery bags, picking up products from an aisle, pushing a shopping cart), and time spent travelling as well as in-store (Chintagunta et al., 2012).

In contrast, the online channel presents more risk as it is filled with uncertainty (Dimoka et al., 2012). First, there is a risk that products ordered are not as expected. For instance, colours may be different, quality could be lower, or a product could be ill-fitting. Delivery of products are also risky; there is a possibility of cancellations or delays due to non-immediate fulfilment. There is also a chance that the product delivered is incorrect or faulty upon arrival. In addition to the process risk, customers face financial risk related to transaction security and privacy concerns (Dai et al., 2014). The online channel can increase a customer's experience simply by allowing them to organise, access, and obtain relevant information quicker and more easily (Shankar et al., 2003). Part of this information is price-related. Price transparency is higher in the online channel because customers are able to compare prices from multiple retailers (Dai et al., 2014). Access to price information and lower search cost create a perception that the online channel offers a lower price point. It is therefore perceived to be more efficient in terms of time and effort and less expensive to use.

The online environment grants more control to customers that enables them to easily participate in more activities (Harris et al., 2006). As a consequence, customers rely upon their own effort to evaluate the outcome of the shopping process. Any service failure is seen as customers' own responsibility and therefore they will be more satisfied with lower level of remedies from retailers (Harris et al., 2006). In other words, customer control plays a key role in how customers evaluate their experience. In the online channel, customers perceive their experience proportionately to the depth of

interaction. First, customers feel greater control and therefore greater responsibility for the outcome. The increase of customer interaction depth has a positive effect on customer experience. Differently, in the offline channel, customers do not only count on themselves but also on the retailer (e.g., salespeople, retailer's products or services). They share responsibility for the journey outcome. Customers develop greater anticipation for service outcome in addition to an increase of customer interaction depth, which is placed on the shoulders of the retailer. The effect of customer expectation in generating customer satisfaction is stronger in the offline channel (Hult et al., 2019). The built-up expectation costs customers the positive experience which results in a negative return at high levels of customer interaction depth. Thus, this thesis posits the following:

Hypothesis 4: *Channel type moderates the inverted-U shape relationship between customer interaction depth and customer experience such that* ***(a)*** *for offline channel, customer interaction depth – customer experience relationship is inverted U-shaped, while* ***(b)*** *for online channel, the effect of customer interaction depth on customer experience is linear and positive.*

Channel type and customer effort

Aligned with the explanation in the literature review, customer interaction depth depicts the degree of elaboration of customers' decision-making process within the shopping journey. This process is assembled from a range of customers activities (Sweeney et al., 2015) consisting of instrumental and non-instrumental elements of the shopping process (Balasubramanian et al., 2005). Each activity entails physical effort, time effort, mental effort, and cognitive effort (Balasubramanian et al., 2005), which make up the actual effort and perceived effort (Clark and Bryan, 2013). The more extensive the decision-making process within a customer journey, the more activities carried out by customers, and as a result, the more effort they put in (Sweeney et al., 2015). Hence, customers will

perceive greater effort along with the increased customer interaction depth, both through the wider range of customer activities and higher frequency of activities (Clarke and Belk, 1979; Desai and Hoyer, 2000). This explains the tendency of a positive relationship between customer interaction depth and customer effort.

However, this thesis postulates a nonlinear effect of customer interaction depth on customer effort because it consists of subjective perceptions of value relating to evaluations (Dunn et al., 2017). In particular, this is because one of the components of customer interaction depth is frequency. Hawkins et al. (2001) suggested that the frequency of activities will lead to repetition, which supports habit formation (Neal et al., 2012; Cambra-Fierro et al., 2020). Activities that have been turned into a set of habits will be conducted automatically (Neal et al., 2012; Cambra-Fierro et al., 2020) without a conscious decision (Ouellette and Wood, 1998; Lin and Wang, 2006) and naturally require less deliberate effort (Henderson et al., 2011). However, habit is only formed after a certain level of repetition (Ouellette and Wood, 1998; Jolley et al., 2006), which implies that it arises at higher levels of customer interaction depth. Consequently, at high levels of customer interaction depth, the additional activities and frequency will require less effort.

This thesis is also aware that offline and online activities have different perceptual effort. Customers perceive effort subjectively depending on the nature of the activity (Hornik, 1984) and the complexities of surrounding stimuli (Fasolo et al., 2009). Customers can obtain easier access to information within an online environment than the one that is offline (Shankar et al., 2003; Johnson and Payne, 1985). This condition makes customers willingly engage with more activities online to maximise potential benefit (Shankar et al., 2003). Subsequently, they become involved in the high processing of information while receiving more complex stimuli. This leads to the

underestimation of effort spent (Fasolo et al., 2009) and perceived lesser effort when dealing with online interaction (Bechwati and Xia, 2003; Chiu et al., 2019).

Bem's theory of self-perception (Bem, 1972) suggests that individuals identify their internal states based on the assessment of their overt behaviour and the accompanied occurrences. Drawing on this theory, there are at least two major reasons to expect customer effort to have a positive relationship with customer experience. One reason is the carryover effect of positive self-perception. Customers observe the amount of effort expend when interacting with a retailer and shape subsequent judgement about themselves. For instance, evidence has suggested that customer effort draws some self-affirmations about being a smart-shopper or an expert (Balasubramanian et al., 2005). The positive image one has towards themselves is projected to the evaluation of one's shopping journey (Miller et al., 2019) and subsequently reflected on the customer experience. A second reason to expect customer effort to have a positive relationship with customer experience is through the activation of self-control (Bijmolt et al., 2019). As customers devote more effort to their repertoire, they gain more control over the journey's outcome (Dabholkar and Bagozzi, 2002). It successively influences overall service quality assurance and encourages a positive evaluation of customer experience (Chan et al., 2010). Thus, this thesis proposes the following hypothesis:

Hypothesis 5*: Customer effort mediates the effect of customer interaction depth and channel type on customer experience.*

Channel type and customer enjoyment

Customer interaction depth gives an indication of the level of customer involvement, specifically related to the shopping process. Involvement, here, denotes the actualised response of mental or behavioural reaction (Houston and Rotschild, 1978; Stone, 1984; Laaksonen, 1994). Performing various customer-initiated activities, as a component of customer interaction depth, reflects this definition. The more customer-initiated

activities done by customers, the more active role they play in their customer journey. Customers' active role across purchase stages and within each stage also depicts customer participation (Fang, 2008; Fang et al., 2015). Hence, the effect of customer interaction depth on customer enjoyment can be seen by examining the link between customer involvement and customer participation to customer enjoyment.

Customer involvement has been linked positively with customer enjoyment (Cai and Xu, 2006; Anton et al., 2013; Franke and Schreier, 2010). Increasing customer involvement allows customers to absorb a more functional quality of services provided by a retailer and affords the feeling of self-efficacy, determination, and competence (Davis et al., 1992). Thus, fulfilling both utilitarian and hedonic advantages of interactions (Anton et al., 2013). Customer participation is also known to be positively related to enjoyment (Auh et al., 2019) through higher economic and relational values obtained. Customers who are highly involved and actively participate will enjoy higher economic value because they can maximise the journey utility (Chan et al., 2010). For example, customers can engage in various activities to find the best deal or the best instalment plan by searching, consulting with a salesperson, and reviewing other customers' past experiences. Additionally, customers gain relational value due to the relationship built throughout their journey with a retailer (Chan et al., 2010).

By participating extensively, customers also engage in designing their own journey, which stimulates positive emotional reactions (Franke and Schreier, 2010). Participating in service customisation increases an immersive experience (Teng, 2010; Yim et al., 2017), facilitating the expression of self-identity (Teng, 2010). However, it comes with a price. As customisation increases, so does the risks it entails, such as service failure and uncertainty of service success (Stump et al., 2002). At higher levels of customer interaction depth, customers may shift their focus to the opportunity lost and feel a withdrawal of positive emotions (de Bellis et al., 2015; Turner et al., 2020). At these

levels, customers start evaluating the efficiency of the service and the uncertainty of the result. Although repeated exposure to customer activities benefits trust-building (Nicholson et al., 2001), it can also lead to over-expectation (Shankar et al., 2003). As such, high expectations leave customers with minimal tolerance towards service failure.

Moreover, there is always a risk that customers do not actually know what is best for them, and a high iteration of interaction can instead signify a lost journey which can potentially cause frustration (Massey et al., 2001). Therefore, this thesis predicts that the positive relationship between customer interaction depth and customer enjoyment will occur between low to moderate levels of customer interaction depth. At high levels, the effect of customer interaction depth will be negative, thus creating an inverted U-shaped curve.

The effect of customer interaction depth to enjoyment explained above differs across channel type. The online retail environment offers a more stable and consistent environment, and as a result, a negative return from customer interaction depth can be reduced (Shankar et al., 2003). When it comes to the pre-purchase stage, the online channel offers a richer environment with its ability to sort, filter, and compare items, making customers more confident about their choice (Park et al., 2015). However, Rohm and Swaminathan (2004) discovered that customer enjoyment is less salient within an online channel, possibly due to the delayed gratification from product fulfilment as an evaluation of the overall customer journey. In addition, the online channel struggles from replicating the sensory and physical experience that are heavily generated in the offline channel (Rohm and Swaminathan, 2004). Hence, lower customer enjoyment is expected in the online channel compared to the offline channel between low to moderate levels of customer interaction depth. However, the negative return of customer enjoyment will be weaker in the online channel.

Taken together previous arguments, this thesis hypothesises as follows:

Hypothesis 6*: Customer enjoyment mediates the effect of customer interaction depth and channel type on customer experience.*

3.4 Chapter summary

This chapter began with the presentation of an overarching theory used to guide the development of our conceptual framework. The conceptual framework shown portrays the linkages between constructs used in this research and a brief detail concerning the study plan. There was discussion pertaining to the theoretical rationale behind the linkages between constructs which were synthesised from past studies and research. These hypotheses will be tested in the following chapters and are expected to answer the research questions of this thesis.

Chapter 4 Research Methodology

4.1 Introduction

This chapter outlines the methodology and methods employed for testing hypotheses within the conceptual framework. It begins by addressing the methodology issues around research philosophy and research design. Subsequently, it discusses more practical consideration of the research methods, including sampling design, data collection technique, and analytical approach to examine the collected data. A summary of the chapter and a study plan is presented at the end.

4.2 Research philosophy

Research philosophy in social science predominantly refers to two distinct polar opposites: positivism and interpretivism. More schools of thought have been born to fill the existing gap or to serve as critique of it, diminishing the polarisation of what constitutes acceptable knowledge. Critical realism, pragmatism, and postmodernism emerged and offer a different perspective, ontologically and epistemologically. Ontology is a concept concerned with the study of being, which deals with the assumptions of the nature of reality and the relationship between elements of society (Barron, 2011). Meanwhile, epistemology is the study of knowledge that concern how we understand reality, what constitutes acceptable, valid and legitimate knowledge, and how we can communicate knowledge to others (Byrne, 2017). The differences between the ontology and epistemology of existing research philosophies, intentionally or eventually, shapes the way a researchers see research objects (Burell and Morgan, 1979; Saunders et al., 2009). It then determines the decision on what research methods should employed by a researcher.

This present study adopts a positivist approach. The ontological position of positivism is the existence of the ultimate truth. It retains that an objective reality exists

independently from human perception (Sale et al., 2002). Epistemologically, the researcher and the subject of research lies on separate independent entities. It puts the researcher outside the subject and allows them to investigate without being affected or affecting the subject (Guba and Lincoln, 1994). The aim is to generate generalisation by determining and examining the causal relationships between variables within a value-free framework. Positivist social scientists usually employ a similar method used by natural scientists to understand the social phenomenon. Techniques such as experiment, mathematical analysis, and hypothesis testing are commonly used (Lee, 1991).

4.3 Research design

Research design is a guided plan toward a research goal. It consists of detail research activities in each step of the research project. It is classified into two broad types: exploratory and conclusive research design (Malhotra, 2012). Exploratory research design aims to provide insight and understanding of an unknown cause of a particular problem (Malhotra, 2012). It focuses on collecting data using an unstructured format or informal procedures, which allow some flexibility throughout the process (Hair et al., 2003; Malhotra, 2012). Commonly, this type of research design employs rigorous qualitative research methods as the primary data collection technique, such as interviews or focus groups (Hair et al., 2003). The results of exploratory research are typically used as a basis of further research, another exploratory research or conclusive research.

On the other hand, there is a conclusive research design that focuses on providing aid and assistance to a decision-making process. It includes goals such as determining, evaluating, or selecting the best suitable approach to a problem. Unlike explorative research design, a conclusive research design is characterised by a formal and structured research process that utilises clearly defined information and uses large sample data. Two subtypes of conclusive research design are causal and descriptive research design.

Their differences lie in the objective, characteristics and data analysis techniques (Malhotra, 2012).

Causal research design concentrates on the cause-and-effect relationships between market variables. It aims to provide an answer to the question of why a certain phenomenon occurs. By using an experimental design, researchers are able to identify causality through the manipulation of one or more independent variables. An experiment can be done in a laboratory setting or a field experiment. The difference is whether a researcher can control the testing environment or not (Silver et al., 2012). A laboratory setting enables a researcher to isolate variables of interest and therefore produce a higher internal validity compared to a field experiment. However, due to its lack of realism, a laboratory setting could have lower external validity. A field experiment, on the other hand, offers a more realistic setting. This can be an advantage but also a problem because potentially, there will be many uncontrollable variables. Recruiting a collaborator, for example a retailer, will also be challenging and expensive. As a consequence, this present study employs a laboratory setting experiment as one of its data collection technique.

Descriptive research seeks to describe the characteristics of a market or population. It answers the question of how, what, when, who, and where regarding different attributes of a market or population. It is characterised by a structured design that mostly employs quantitative research method such as a cross-sectional study, longitudinal study, and panel data. A cross-sectional study captures information from a sample of a population at one point in time (Malhotra, 2012a; Silver et al., 2012). When the information is gathered from the same sample of a population on several occasions over a period of time, it refers to a longitudinal study. This present study may benefit from employing panel data due to its accuracy and ability to detect changes. However, creating a panel of respondents is challenging in terms of recruiting and maintaining a representative

sample. In contrast, the cross-sectional study offers more ease in participant recruitment, and because it is one time only, it can reach a more representative sampling for the research. Hence, this present study chose to conduct a cross-sectional study, particularly through a sample survey.

All types of research designs explained above should not be perceived as separate entities but rather complementary to each other (Malhotra, 2012). A researcher may apply a combination of various research designs depending on their research goal. Therefore, this present study incorporates both descriptive and causal research design to study the impact of customer interaction on customer experience. By doing so, this study is able to describe the creation of customer experience in an omnichannel retail setting as well as to explain the causal effects between interaction and experience. Our research begins with a cross-sectional survey (*descriptive research*), which collects data at one particular period of time within a specific population. It then goes on to a *causal research design* employing experimental study that is conducted to confirm the cause-and-effect relationship between variables in this research framework.

4.3.1 The need for combining descriptive and causal research

Each research method possesses its own benefits and limitations. Using multiple methods also has its own advantages and disadvantages. The decision was made considering how these benefits outweigh the drawbacks. For this reason, we will run through the positives and negatives of each research methods.

Descriptive research through a cross-sectional survey is characterised by a high degree of structure, both in the process and instruments (Silver et al., 2012). Consequently, the difficulty in designing its survey instruments, such as a questionnaire, is perceived to be one of the disadvantages of the survey. Moreover, a researcher can hardly get an in-depth view from respondents due to the nature of structured questions that might erase

the possibility of having a customised follow-up question. Particularly for the self-administered questionnaire, there is a difficulty in determining whether respondents are giving honest answers (Hair et al., 2003). These are the reasons why there are various steps taken to ensure the reliability and validity of the data gathered from a survey. Each analysis, which will be discussed later in this chapter, is useful to overcome the limitation of the survey.

Nonetheless, the survey offers several benefits; according to Hair et al. (2003), it has the ability to accommodate a large sample size and therefore increase the generalisability of the results. Using a survey, collecting a large sample size can be done more efficiently than other techniques such as an interview or focus group discussion. This is equal to a shorter period of data collection time, less resource allocation, and a cost-effective option. From participants' point-of-view, the survey is easy to administer; and from the researcher's point of view, the survey's results are easy to record. Moreover, the results can be analysed using multiple statistical analyses according to the diversity of variables. These analyses include some relationships that are not directly measurable.

As mentioned previously, a cross-sectional survey only portrays responses at one time. As a result, it is unable to identify the cause-and-effect relationship between variables because both cause and effect are measured simultaneously. Ideally, the researcher uses a longitudinal survey to capture the causality, for example, by analysing independent variables in the first survey against the dependent variable collected from the second survey. However, the difficulties in recruiting the survey panel have hindered the researcher from employing longitudinal study. For this reason, an experimental study is employed. An experimental study has the ability to provide the direction of cause and effect, determining which variable causes the other (Cozby and Bates, 2015).

Both survey and experimental study may face some issues from confounding variables. Confounding variables refers to an uncontrolled third variable that exists and influences both the independent variable and dependent variable (Cozby and Bates, 2015). There are three types of confounding variables based on their sources: operational, procedural, and person confounding variables.

The issue of operational confounding arises either when indicators of one construct measure another construct that is theoretically different or when two distinct constructs are measured with similar indicators (Thoits, 1981). To avoid having operational confounding, a researcher can implement a well-established scale to measure constructs in their research project. Furthermore, using an experimental study, the researcher could implement a manipulation check to ensure that the manipulation of an independent variable runs as intended (Cozby and Bates, 2015).

Procedural confounding variable occurs when a third variable is mistakenly allowed to change along with the manipulated independent variable (Pelham and Blanton, 2006). To eliminate the issue of procedural confounding, it is important to keep all extraneous variables constant. In this way, the only difference is contributed by the manipulated independent variable.

The last issue is regarding the person confounding, which is related closely to the individual differences of participants. Participants' demographic profile could contribute an effect to the result, such as gender, income, or education level. Randomisation can be put in place to remove such an effect. The idea is to ensure that the effect of participants' characteristics would affect one experimental group as likely as it would affect another group (Cozby and Bates, 2015).

Limitations and benefits are presented to show how the combination of two methods, survey and experiment, can complement each other and provide stronger research. This

present research is able to analyse a large sample size and provide a descriptive explanation due to the implementation of the survey. Meanwhile, experimental studies allow this present research to confirm the causality effect, which is not provided merely from analysing a cross-sectional survey. Similarly, applying multiple approaches to analyse a phenomenon aligns with the principle of triangulation, particularly methodology triangulation. The value of methodology triangulation is to enhance research credibility and establish corroborating evidence to eventually answer the research questions (Morris, 2018).

4.4 Design of the Studies

4.4.1 Design of the survey

A survey is classified based on how it is distributed, and how the data is gathered. Hair et al. (2003) and Malhotra (2012) divided it into four categories: person-administered, self-administered, telephone-administered, and computer-assisted survey. This present study applies a computer-assisted survey, specifically an internet survey. Using this method, the researcher distributes questionnaires via an online platform on which participants could access the link and complete the survey individually. To an extent, this type of survey is a self-administered survey. However, since the researcher uses the internet to record responses from participants, it falls under computer-assisted or online survey.

Adding to the benefit of using a survey in general, an online survey enables the researcher to contact respondents beyond geographical limitation. It provides an accurate time stamp and allows the researcher to minimise missing data compare to when using a paper-based survey. The absence of face-to-face contact increases the level of anonymity and thus, keeping the social desirability level low. This condition also removes the interviewer bias. Online surveys cost less compares to other methods

of survey and arguably are able to collect responses quicker. Finally, an online survey offers respondents to complete the questionnaire at their most convenient time, giving them flexibilities.

Despite the abundant benefits of an online survey, there are still a few disadvantages to using one. Without a sufficient strategy to target participants, an online survey could lead to a low response rate. A researcher has no to low control over the sample and the environment in which respondents are responding. Obviously, this type of survey will only reach a population who has access to the internet, which cause participant selection bias. For the present study, however, the reach of an online survey is suitable since we target a population of customers who have experienced an omnichannel shopping experience. Other limitations can be minimised by implementing a strategy in sampling and recruitment, which will be explained in the later section.

4.4.2 Design of the experiment

Discussing experimental design implies the consideration about how participants are assigned to the experiment and how many independent variables are manipulated in each treatment (Cozby and Bates, 2015). The former discusses whether a researcher implements a *between-subject* or *within-subject* experimental design. The latter focuses on the discussion regarding *one-way* design and *factorial* design.

4.4.2.1 Between-subject designs vs within-subject designs

In a between-subject design, participants are randomly assigned to one out of various experimental treatment. In this case, each participant will only be exposed to one condition. Therefore, at the end of the experiment, each condition has a different group of participants. In order to estimate the causal effect, the researcher compares the dependent variables in one experimental condition with the result in another. In other words, a researcher has to compare the difference *between* the groups (Oeldorf-Hirsch,

2018). The key is to ensure that randomisation occurs across conditions. Randomisation needs to be done to reduce the effect of the person confounding variable discussed previously, as removing it completely is, perhaps, unattainable. The critique of between-subject design revolves around statistical power and analysis (Charness et al., 2012). It is relatively simple to analyse the between-subject design, however, there is a trade-off between statistical power and the number of experimental conditions. Another potential issue is the number of participants needed for a study. Due to its requirement to have a different group of participants for each experimental condition, it could require numerous participants. That said, a between-subject design is beneficial to avoid carryover effects between conditions (Oeldorf-Hirsch, 2018). A carryover effect arises when the outcome of an experimental condition persists long after the treatment is administered (Foley, 2011), resulting in an influence on a subsequent experimental condition (Oeldorf-Hirsch, 2018).

In contrast to a between-subject design, participants in a within-subject experimental design are exposed to all experimental treatment in the study (Cozby and Bates, 2015). It is also called a repeated measure design because participants repeatedly measure dependent variables under different experimental conditions. In this type of experimental design, the causal estimate is obtained by comparing how the participants' assessment of dependent variables changes when the experimental treatment changes (Charness et al., 2012). Unlike between-subject design, the internal validity of within-subject design does not depend on randomisation; hence, individual differences can be detached from the error term (Charness et al., 2012; Kim, 2012). The advantage of using this type of design is the utilisation of participants. Both the elimination of individual differences and the collection of a larger sample contribute to increasing the statistical power to detect the treatment effect (Draeger, 2020; Kim, 2012). The pitfall of within-subject design is that it is more susceptible to experience a carryover effect. This effect

could inadvertently increase or decrease the subject's performance, creating a confound. This carryover effect can either be a learning effect or a fatigue effect (Cozby and Bates, 2015). The learning effect arises when participants use a condition to practice and learn to get a better performance in the following condition. Whereas a fatigue effect is caused by tiredness for having done multiple tasks, which might decrease subjects' performance.

A between-subject design is an experimental design that is applied in this present research. The approach is more conservative and requires more subjects. However, it is more suitable for testing the proposed relationships.

4.4.2.2 One-way designs and factorial designs

There are two type of experimental study designs, a one-way design and a factorial design. The difference between them is related to the number of independent variables tested. In a one-way design, there is only one independent variable that is manipulated throughout conditions. However, when the number of independent variables is increased, the design of the experiments can be classified as factorial design (Cozby and Bates, 2015). This may appear when testing a moderation analysis, using one independent variable and another independent variable that acts as a moderator. In this design, two variables – an independent variable and a moderating variable – change in every condition simultaneously.

In the experiment with factorial design, the number of experimental conditions depends on the number of levels of each independent variable. For instance, there are three levels tested of independent variable A and two levels tested of independent variable B, otherwise known as 3 x 2 factorial design. The total experimental conditions will be six, resulting from the multiplication of all independent variables' levels. The assessment of the main effect of each independent variable represents the effect each variable has

itself. In comparison, the interaction effect indicates that "the effect of one independent variable is different at different levels of the other independent variable" (Cozby and Bates, 2015 p. 207). The factorial design is the one that is applied in our research, specifically for Study 2. More details on the design and procedures are explained in Chapter 6.

4.5 Sampling design

There are five steps within the sampling design process which comprises population definition, sampling frame determination, sampling technique selection, sample size determination, and the execution of the sampling process (Malhotra, 2012).

4.5.1 Target population definition

Population, as a statistical term, refers to a group of entities that shares a common set of attributes that are of interest to the researcher and relevant to the research objective (Hair et al., 2003). This group can consist of people, products, organisation, or other physical entities. The subset group of the population that is selected for the study is called a sample (Malhotra, 2012). The set of attributes within the population consist of objects that have informational value to the researcher; this is called a target population (Malhotra, 2012). In this study, there are two target population based on the type of data collection technique.

In our survey, the target population is grocery or fashion retail customers in the United States who have interacted with an omnichannel retailer in the past year. The aim is to examine how customers' interaction with channels and touchpoint within an omnichannel retailer could impact their assessment of their customers' experience. Therefore, it is important that the target population have interacted with an omnichannel retailer in the first place, even though it is not necessarily that they interacted with multiple channels and touchpoints. The decision to include only grocery and fashion

retail customers is due to the popularity of these categories amongst retail customers. Fashion products are consistently on the top three of global omnichannel purchase, and the grocery product category is growing rapidly (Nielsen, 2018).

In our experiments, the target population is simpler, retaining the age limit of 18 and the geographical location of the United States but omitting the omnichannel experience. The age limit is based on the Convention on the Rights of the Child (UNICEF, 1989) regarding the definition of a child. It identifies that every human being under 18 years old is defined as a child; thereby, consumers who are over 18 years old are considered as adults and capable of making a decent purchase decision.

4.5.2 Sampling frame

A sampling frame defines as a representation of components of the target population (Malhotra, 2012). It usually refers to identifying the target population and enabling a sampling process. In past studies, a sampling frame commonly used in research was in the form of a business directory (e.g. Lenox et al., 2010), list of customers in a loyalty program (Lemon and Wangenheim, 2009), or a database (e.g. Venkatesan et al., 2007; Cuneo et al., 2012). Nonetheless, it is also known that getting an accurate sampling frame is not necessarily straightforward. Depending on the situation, a sampling frame could have over-registration or under-registration conditions (Hair et al., 2003). The ideal scenario in this study would be to employ a list of customers from omnichannel retailers. However, these lists can be very expensive or simply unavailable to attain, considering protection of customers' privacy. For a survey that is conducted online, a website or an online platform can be used as a sampling frame (Hall, 2011). Hence, the sampling frame that is used in this study is within the Amazon Mechanical Turk (MTurk) crowdsource platform. This platform enables us to hire "workers" as participants of the study. It only allows people over 18 years old to be on the platform

and allows us to limit the scope of participants into a certain geographical area, such as United States.

4.5.2.1 MTurk sampling: potential issues and remedies

The decision of using Murk sampling in our data collection comes with its inherent issues, which have ignited a debate among researchers, especially concerning the quality of the data (see Kees et al., 2017a; Kees et al., 2017b; Ford, 2017; Cheung et al., 2017; Mascarenhas et al., 2006; Wessling et al., 2017). As Hair et al. (2003) have pointed out, MTurk potentially carries an over-registration problem, meaning that this sampling frame has additional elements that may not be useful for the research. This issue arises due to the fact that potential participants include those who never experienced any interaction with an omnichannel retailer. The over-registration problem also links to sample representativeness which can be fixed by implementing some filter questions at the beginning of the survey. The filter questions were: "Have you ever interacted with an omnichannel retailer in the past one year?" and is followed by another question, "Could you please tell us the retailer that you think about?". The objective of the follow-up question is to verify the participant’s answer to the filter question. These questions enable us to exclude those who answered "No" in the first question and mentioned a non-omnichannel retailer in the second one. This approach also suffers from under-registration because the sampling frame only includes those who are registered with MTurk. The under-registration problem is not perceived as a threatening problem since MTurk has been widely used in consumer research and is perceived to have similar characteristics as using student samples (Goodman and Paolacci, 2017; Kees et al., 2017a).

Other inherent issues from employing MTurk are related to the validity of the data. Cheung et al. (2017) identified ten methodological issues that could potentially threaten internal validity, external validity, construct validity, and statistical conclusion. For that

reason, multiple measures can be applied to increase validity, as shown in Table 4.1. First, we chose to use Qualtrics as our survey and online experiment platform to be embedded on MTurk to ensure the consistency of the tool. In addition, a pilot study was conducted before the main data collection to identify the source of extraneous variables such as the suspicion of bot involvement with identical IP addresses in more than two users, the average completion time, and the browser experience. Second, we advertised our study without disclosing too much information in the beginning. Using a generic description of the study minimises the self-selection risk (Goodman and Paolacci, 2017) and avoids the threat of external validity and construct validity (Cheung et al., 2017). Keeping a generic description is also useful to conceal the eligibility criteria, which avoid MTurk workers fabricating their identities to participate in a study (Cheung et al., 2017 p. 353).

Third, we set several qualification requirements to limit the characteristics of workers who could participate in the study. We only allow MTurk workers who have done more than 50 tasks. This qualification requirement aims to ensure that the participated MTurk workers are experienced enough to navigate the task. The second requirement is that the location of the MTurk workers is set to be restricted in the United States. This decision is taken because the retail landscape in the United States is one of the most advanced ones in which the omnichannel retail business has become a common business model. Therefore, we believe that the MTurk workers in the United States would not find it difficult to refer their experience with an omnichannel retailer. In one way, MTurk has less of an issue regarding range restriction due to its heterogeneity. However, the qualification requirements put in place by the researcher could affect the population size. Our study aims to capture the general population and targets a diverse range of demographics profiles. For this reason, we set certain qualification requirements that do

not directly affect our participants' demographics. In doing so, we tried to ensure the quality of external validity, construct validity, and statistical conclusion.

Fourth, two attention checks were utilised to detect the issue of subject inattentiveness. In order to give fair treatment to MTurk workers, we indicated the use of attention checks on the introduction page as a basis of the task's approval. The attention checks were assigned at the beginning of the task and in the middle of the survey. Responses that recorded two failures would be rejected, and the MTurk workers would not be compensated. However, we compensated workers who passed only one attention check, although we excluded their responses for the final analysis.

Mturk itself offers a diverse participant pool; nonetheless, most workers are within the productive age who are well-aware of the use of the internet. This characteristic of MTurk is deemed appropriate for our research which examines the omnichannel interaction, which naturally includes online interactions. Therefore, increasing consistency between construct explication and study operation (Cheung et al., 2017).

Table 4.1 Summary of methodological issues concerning the use of MTurk

Methodological issue	Type of threat	Remedies
Subject inattentiveness	A, C, D	Applying attention checks and implementing data screening technique.
Selection biases	B, C	Provide a generic description of the study (Goodman and Paolacci, 2017).
Demand characteristics	A, C	Avoid cues signalling eligibility criteria.
Repeated participation	A, C	Customise the workers' qualification and monitor the IP address.
Range restriction	D	Set a qualification requirement.
Consistency of treatment	D	Use a standardised measurement tool and conduct a pilot study prior to the main one.
Extraneous factors	A, C, D	Include possible extraneous variables in the data analyses.
Sample representativeness	B, C	Set a follow-up question to verify the filter question's answer.
Consistency between construct	C	Evaluate the appropriateness of research topic with MTurk population
Method bias	C	Examine the emergence of method variance

Source: Cheung et al. (2017) Note: A = internal validity, B = external validity, C = construct validity, D = statistical conclusion

4.5.3 Sampling technique

There are two types of sampling techniques, probability and nonprobability sampling (Malhotra, 2012). In a probability sampling technique, a sample is created through random selection, or completely by chance. In a nonprobability sampling technique, the researcher uses their own appraisal and convenience to select elements that create a sample (Hair et al., 2003; Hall, 2011). This present study employs nonprobability sampling, particularly convenience sampling. The use of the MTurk platform to recruit participants falls under this convenient sampling. As one of the advantages of convenience sampling, it is relatively quick to gain a large number of responses. The

drawback of this technique, however, is the lack of generalizability due to the absence of randomisation when selecting subjects.

4.6 Analytical procedure

This section explains the analytical procedures that are conducted in the entire study. In a broader classification, it contains both descriptive statistics and inferential statistics. As the name implies, descriptive statistics describe and provide the outlook of the sample. Inferential statistics, on the other hand, aims to provide an estimation of parameters and to test hypotheses (Tabachnick and Fidell, 2013).

4.6.1 Descriptive analysis

After the completion of data collection and the finalisation of data preparation, a descriptive analysis is conducted. The descriptive analysis contains the analysis of descriptive statistics, which commonly include the frequency, the measure of central tendency, and the measure of dispersion (Hair et al., 2003). The measure of central tendency can be represented by the value of the mean, which portrays the average value or centre of the distribution. The measure of dispersion, represented by range and standard deviation, indicate the variability of a distribution. The range is frequently shown in the form of a minimum and maximum value. Another measure is a standard deviation, which implies the average distance between the observed value from the mean. A high standard deviation reveals that the observed values tend to be farther away from the mean, signifying that the data is spread out over a wider range (Malhotra, 2012).

The descriptive statistics above also link to the shape of the data distribution. However, two measures are frequently utilised when describing the shape of the data distribution, namely skewness and kurtosis (Hair et al., 2014). Skewness reflects the balance of the data distribution; a balanced data distribution is symmetrical and centred, whereas an

unbalanced data is skewed to the left (positive skewness) or right (negative skewness) (Hair et al., 2014). Kurtosis measures the peakedness of the data distribution, which denotes the height of the distribution (Tabachnick and Fidell, 2013). According to Kline (2011) and Finch et al. (1997), values of skewness lower than |2| and of kurtosis smaller than |7| indicate a moderate departure from a univariate normal distribution.

4.6.2 Validity

The term validity can be interpreted differently depending on the type of study. In general, it refers to the accuracy of the research (Hair et al., 2014). The following sections discuss the validity in causal research through an experimental study and validity in descriptive research using a cross-sectional survey.

4.6.2.1 Validity in an experimental study

In the experimental study, validity relates to internal validity and external validity. Internal validity can be reached when the causal effect on a dependent variable is actually affected by the independent variable (Malhotra, 2012; Cozby and Bates, 2015). It is a measure of accuracy and ability to produce a causal relationship between the independent and dependent variable. Cozby and Bates (2015) discuss three aspects as requirements of strong internal validity. Firstly, the manipulated independent variable (the causal) should have occurred before the dependent variable (the effect); this principle is called temporal precedence. Secondly, there must be covariation between the causal variable and the effect. This exists respective to the treatment condition. The effect of an experimental condition only affect the participants in that particular condition and not others in a different condition. Thirdly, there is a need to establish non-spuriousness. This refers to a situation that the independent variable is the only one that is responsible for the effect. Hence, other alternative explanations should be ruled out. This brings attention back to the discussion in section 4.3.1 about confounding

variables. Several procedures to avoid the existence of confounding variables are implemented to increase internal validity.

External validity in an experimental study refers to the ability to draw a similar causal effect in a different sample or larger population (Malhotra, 2012; Cozby and Bates, 2015). It relates to the reproducibility and generalisability of the study. The issue of external validity is especially great in a laboratory setting due to its artificial nature. Creating a realistic scenario within every experimental condition is one of the ways to tackle the issue.

4.6.2.2 Validity in a cross-sectional study

In a cross-sectional survey, validity concerns the ability of the measures used to effectively capture, or measure, attributes of interest (Fink, 2018). To label a measure as a valid one, it should contain no random error or no systematic error, or at least be minimally affected by them (Malhotra, 2012; Fink, 2018). The validity analysis that is performed in this study is mainly a construct validity. Construct validity can be analysed through convergent validity and discriminant validity.

Convergent validity refers to the extent to which the indicators of a specific construct are highly correlated (Malhotra, 2012; Hair et al., 2014). Hair et al. (2014) suggest that a confirmatory factor analysis (CFA) can be used to assess measurement validity. CFA provides a confirmatory test to measurement theory that specifies how measured variables represent a latent construct that is not measured directly. Several indices were recommended to assess the goodness of the CFA model in general (Hu and Bentler, 1999; Bagozzi and Yi, 2012; Hair et al., 2014). They include both absolute (e.g., chi-square and RMSEA) and relative (e.g., NFI and CFI) fit indices. Table 4.2 below sum up the common indices and their recommended threshold, which are used in this study.

Table 4.2 Summary of Fit Indices

Measurement index	Recommended threshold
Chi-square (χ^2)	χ2 as small as possible, p > .05
Normed chi-square (χ^2/df)	≤ 5 or ≤ 2
Root mean square error of approximation (RMSEA)	≤ 0.05 or 0.05 – 0.08
Goodness-of-fit index (GFI/AGFI)	≥ 0.9
Normed fit index (NFI)	≥ 0.9
Comparative fit index (CFI)	≥ 0.9
Standardised root mean squared residual (SRMR)	≤ 0.05

To establish convergent validity, Hair et al. (2014) provides three requirements. First, the standardised loading estimates should ideally be 0.7, or exceeding 0.5. Second, the average variance extracted (AVE) should be more than 0.5. AVE is calculated using the formula below:

$$AVE = \frac{\sum_{i=1}^{n} L_i^2}{n}$$

Where L_i represents the standardised factor loading, and i is the number of items. Therefore, for n items, the value of AVE is computed as the sum of squared standardised factor loadings divided by the number of items.

Third, the minimum value of construct reliability (CR) should be 0.7. It is computed using the formula below, where the squared sum of factor loadings (L_i) for each construct divided by the accumulation of itself and the sum of the error variance terms for a construct (e_i):

$$CR = \frac{(\sum_{i=1}^{n} L_i)^2}{\left(\sum_{i=1}^{n} L_i\right)^2 + \left(\sum_{i=1}^{n} e_i\right)}$$

Discriminant validity aims to define whether two purportedly distinct constructs are indeed statistically different (Malhotra, 2012). In the simplest way, two theoretically distinct constructs should be uncorrelated. Fornell and Larcker (1981) suggest assessing discriminant validity by examining the square root of AVE, which should be greater than the highest shared variance with other constructs in the model.

4.6.3 Reliability

Similar to validity, the reliability issue differs between experiment and survey. In an experimental study, reliability is achieved when the same design produces the same result in a different group of participants; in other words, it mimics what was discussed as external validity. The issue becomes more prominent in a survey, especially one that employs a multi-item scale, as seen in this study.

Scale reliability measures whether a scale used in the study would produce a consistent result in repeated measurement (Hair et al., 2003; Malhotra, 2012). The approach that is used in this study is internal-consistency reliability, which is commonly used when dealing with a composite measure. The composite measure is formed based on multiple indicators or items that measure the same construct. The consistency of each of these items in representing the construct is what is captured by internal-consistency reliability (Malhotra, 2012). One of the most prevalent technique for assessing reliability is the coefficient Cronbach's alpha (α). The coefficient value varies between 0 to 1, where the cut-off point of a reliable scale is usually 0.6 (Hair et al., 2014) or 0.8 depending on the application to the research level (Nunnally, 1978).

4.6.4 Common method bias

Method bias occurs from "response tendencies that raters apply across measures, similarities in item structure or wording that induce similar responses, the proximity of items in an instrument, and similarities in the medium, timing, or location in which measures are collected" (Edwards, 2008 p. 476). In other words, method bias arises when the research instrument introduces a bias which can be seen in the form of archival biases, key-informant prejudices or limitations, halo effects, and social desirability (Bagozzi et al., 1991). This method bias creates method variance, which is part of measurement error. The existence of measurement error, include systematic error and random error, potentially influences validity, reliability, and covariations between

constructs (MacKenzie and Podsakoff, 2012). Hence, it is crucial to detect the presence of method variance and to apply some statistical remedies accordingly.

There are several ways to identify the presence of common method variance; two of these are used in this study. The first technique is Harman's single-factor test (Harman, 1976). Using an exploratory factor analysis, all items were loaded into one single factor. The unrotated solution then examined to account for the variance in the variables. The common method variance presence can be seen if a single factor emerges from the factor analysis. There are limitations from this analysis, which encompasses the fact that this technique does nothing to statistically control the method effect and have a low sensitivity level (Podsakoff et al., 2003).

A second technique was introduced after that to provide a more robust analysis. It is called a partial correlation technique with a marker variable (Lindell and Whitney, 2001). Marker variable is a variable that should be theoretically unrelated to the rest of the constructs tested in the model; hence, its expected correlation coefficient is nearly zero or very minimal. An estimate of the common method variance is computed from the smallest correlation coefficient between the marker variable and the manifest variables or using the second smallest one for a more conservative estimate (Lindell and Whitney, 2001; Malhotra et al., 2006). This would then be further calculated using the following formula (Lindell and Whitney, 2001, p. 116):

$$Partial\ correlation\ (r_{yi-M}) = \frac{r_{ys} - r_s}{1 - r_s}$$

$$Significance\ (t) = \frac{r_{yi-M}}{\sqrt{(1 - r_{yi-M}^2)/(N-3)}}$$

Where the r_{yi-M} in the above formula represents the partial correlation coefficient of the manifest variable, r_{ys} is the raw correlation coefficient between the manifest variables, and r_s indicates the second smallest raw correlation coefficient.

Some limitations still arise following the use of this technique. Firstly, it assumes that the method factor represented by the marker variable does not interact with the manifest variables (Podsakoff et al., 2012). Secondly, it controls the method bias at the scale level and not the item level (Williams et al., 2010). Nevertheless, due to its ability to estimate the common method variance along with statistical significance, this technique is perceived as a more appropriate alternative to assessing common method bias (Malhotra et al., 2006).

4.6.5 Correlation analysis

Correlation analysis is a statistical analysis conducted to determine the strength and direction of linear association between two variables (Hair et al., 2003; Malhotra, 2012). Pearson correlation coefficient (*r*) is the statistical measures that depict those strength and direction. The value of the Pearson correlation coefficient ranging from -1 to +1. The positive (+) and negative (-) sign in the coefficient signify the direction of the relationship. A positive coefficient indicates that an incremental of one variable is associated with an additional in another variable. While the negative coefficient means as one variable decreases, the other one increases. To analyse the strength of the relationship, a Pearson correlation coefficient value should be seen as an absolute value; negative and positive are merely suggesting the pattern and not the magnitude of the relationship. In this way, a Pearson correlation coefficient of +0.6 is as strong as -0.6, and 0 indicates that there is no association between the two variables.

4.6.6 Hypothesis testing

Several analyses were conducted to test all the hypotheses in this research. They are mainly focused on the analysis of nonlinear relationships, including moderation and mediation analysis of such relationships. Following the approach taken by previous studies (Laursen and Salter, 2006; Zhang and Bartol, 2010; Haans et al., 2016), a

regression analysis was employed to test these relationships. However, some data needs to be analysed differently, particularly data from experimental studies. When analysing the differences between experimental conditions, an analysis of variance (ANOVA) was conducted. Moreover, a Post-Hoc test was also used to further examine the differences when there are more than two experimental groups. More analyses were also performed as part of robustness check to the respective hypothesis. Depending on the specific analysis, different statistical software was used, such as Statistical Pack for Social Sciences (SPSS 26) and Stata (Stata SE 16).

4.6.6.1 The analysis of the indirect effect

The traditional approach by Baron and Kenny (1986) is perhaps one of the most widespread approaches used in testing mediation. Nonetheless, more contemporary approaches have emerged in the last decade that improve how mediation can be analysed (Preacher and Hayes, 2004; Zhao et al., 2010). It focuses on developing the typology of mediation (Zhao et al., 2010) and offering a more rigorous method to estimate the effect's strength, such as via bootstrapping (Preacher and Hayes, 2004). The caveat is that the approach mainly concentrates on the indirect effect within a linear relationship.

Hayes and Preacher (2010) suggested a different treatment should be given when the predicted path between an independent variable (X) and a mediator (M) is curvilinear, as proposed in this study. Rather than predicting an overall indirect effect, an indirect effect should be quantified at a specific value of X (Stolzenberg, 1980), which is defined as an instantaneous indirect effect. The X value, in this case, should represent a meaningful point in a dataset, for example, values that indicate a low, moderate, and high level of interaction.

There are various combinations of mediation model that include a nonlinear path(s). The nonlinear path could either be in between X → M, or M→ Y, or X → Y, or it appears in both or all part of the model. In the case where predictions for relationship between X → M is curvilinear and M → Y is linear, the instantaneous indirect effect of X on Y through M can be calculated using the following formula (Hayes and Preacher, 2010 p. 633):

$$(a_1 + 2a_2X)b$$

Where, a_1 is the beta coefficient of the linear term of x, a_2 is the beta coefficient of the quadratic term of x, and b is the beta coefficient of the mediator when predicting Y.

4.7 Summary

This chapter presented the overarching methodology and methods employed throughout this study. A positivist approach was used in the study, emphasising a quantitative approach in data analysis and causal explanation provision. The research design follows a conclusive research design which combines both descriptive and causal research design, represented by the implementation of a cross-sectional survey and experimental studies. The research sample was discussed, and more specifically, the issue concerning the use of MTurk to collect data was addressed. The chapter ends with a series of analytical procedures conducted in the studies. A more detailed discussion on questionnaire development, experimental studies' procedures, and operationalisation of variables are discussed in subsequent chapters. Each study is presented separately, as Table 4.3 displayed. Chapter 5 will discuss the methods taken when developing a cross-sectional survey (Study 1) and the analyses that follow to test H_1 – H_3. Chapter 6 focuses on the methods and analysis concerning the Study 2, which aim to test H_4 – H_6, using an experimental design study.

Table 4.3 Summary of the studies in this research

	Hypothesis statement	Study 1 (Chapter 5)	Study 2 (Chapter 6)
H_1	Breadth – Customer Experience (∪)	✓	
H_2	Depth – Customer Experience (∩)	✓	
H_3	Channel Integration moderates Breadth – Customer Experience	✓	
H_4	Channel Type moderates Depth – Customer Experience		✓
H_5	Customer effort mediates Depth x Channel Type – Customer Experience		✓
H_6	Customer Enjoyment mediates Depth x Channel Type – Customer Experience		✓

Chapter 5 Determining the relationship between customer interaction complexity and customer experience (Study 1: H_1 – H_3)

5.1 Introduction

This chapter outlines the overview of the methodology and the statistical procedures conducted to analyse the data in the cross-sectional survey, called Study 1, from this point forward. The goal is to provide an initial test of H_1 and H_2 that customer interaction complexity (customer interaction breadth and customer interaction depth) has curvilinear effects on customer experience. Additionally, Study 1 seeks to examine the changing nature of the relationship between customer interaction breadth and customer experience under a different level of channel integration (H_3). The chapter begins with an overview of the research method employed in this study. It will then go on to data preparation and examination, providing preliminary analysis to identify the goodness of the data. The third part then moves on to present the results of hypotheses testing and several posthoc analyses. A summary of the main findings will be discussed at the end of this chapter.

5.2 Overview of the methodology

Following the discussion in the previous chapter, both descriptive and conclusive research design was employed in this research project as part of methodology triangulation. Study 1 is a cross-sectional study, and part of the descriptive research design, which aims to provide an understanding of the relationship between customer interaction and customer experience. It collected responses from a crowdsourced population of the online platform MTurk, using an online survey developed on the online platform Qualtrics. More on the questionnaire development and distribution are discussed later in this chapter. Analytical procedures employed in Study 1 comprises a descriptive analysis, validity and reliability analysis, common method analysis, correlation analysis, and hypotheses testing using hierarchical regression.

5.3 Operationalisation of construct

Constructs used in a research framework are concepts that exist in a higher level of abstraction (Malhotra, 2012). This abstraction frequently refers to a construct that is unobserved and so-called as a latent variable. Especially in multi-item scales, a construct is measured by observable components (Malhotra, 2012). Identifying these components should be done using an underlying theory which is part of a process called operationalisation. Operationalisation is a process of defining measurement terms by specifying the activities or operations necessary to measure them (Hair et al., 2003). The procedure seeks to collect the needed data structure by focusing on the design and use of questions and scale measurements (Hair et al., 2003). The consistency between the operationalisation process and theory is crucial not only to define but also to interpret the result into a deliverable recommendation.

5.3.1 Customer interaction breadth

The operationalisation of breadth followed a similar approach as Laursen and Salter (2006) who operationalised the breadth of external search of knowledge. Breadth is constructed as a combination of the eight channels and touchpoints used by participants in the past year within a specific omnichannel retailer. Breadth, in this research, refers to the variety of channels employed by customers during their shopping journey. Other researchers have also used the same operationalisation, although it may be called under a different construct name or simply defined as a ‘variety of channels’ by Käuferle and Reinartz (2015) or a ‘number of channels’ by (Fürst et al., 2017).

The list of channels in the questionnaire consists of an offline channel, online channel, mobile app, company-owned social media, catalogue, call centre, in-store technology, and external contact point (e.g., independent pick-up points). Participants were asked to select all channels they have used to interacted with their chosen retailer using checkbox options. As a starting point, each channel is coded as a binary variable, 0 being no use

and 1 being used. Subsequently, the eight channels are added up so that each respondent gets 1 when they only use one channel and maximum 8 when they use all channels.

5.3.2 Customer interaction depth

Examining depth as one of the dimensions of customer interaction is a novelty contributed by this research. Depth is defined as the degree of channel usage by customers. There are two identified relevant aspects of channel usage: frequency of use of each channel and the *number of activities involved* in each channel. These two aspects were used to operationalise depth. The core idea is to investigate the level of the customer's interaction across channels. The more frequent a customer uses a channel and the more activities involved in a customer's journey, the deeper interaction they have with the retailer. Therefore, to capture the overall interaction, depth is measured by aggregating the frequency of activities in all used channels.

In order to develop metrics to measure depth, several analyses and studies were conducted. The process was iterative, which involves both secondary research and primary research. First, secondary research was carried out to list the most common customer activities. A customer review report by Deloitte consulting company published in 2016 (see Fenech et al., 2016) was utilised to establish the foundation on customers' activities. In the report, Deloitte used a survey result from 2,084 adults in the UK to identify a comprehensive framework of a shopping journey to analyse customer experience. Activities were identified according to different stages of the shopping journey. This list was then compiled and analysed to create an elaborate version to be tested on a group of customers and academics.

Once a list of shopping activities was created, it was circulated among several PhD colleagues at Leeds University Business School to identify any potential improvement or missing activities. The same list was also distributed to 30 random customers using a convenient sampling method. This process aims to identify whether the list has captured

the essence of customers activities in the most efficient way. Several important insights were assembled into new activities such as ‘Look for social interaction’, ‘Exchange a product’, and ‘See how a product works & visualised’. Some discussion with marketing academics in consumer research also resulting in the amendment to the list, such as the merging of similar activities (e.g., couponing and finding offers) to simplify the questionnaire. Lastly, the accessibility of each activity was identified to analyse whether it could be performed in a specific channel or not. The channels used in the list were identical to those which were used in Breadth. Table 5.1 shows the list of activities used to measure depth and their accessibility in each channel. It is presented in three different stages: pre-purchase, purchase, and post-purchase.

The question regarding depth was asked after participants selected channels, as explained in the previous section regarding breadth (see 5.3.1). Depending on the chosen channels, participants were presented with a list of possible activities within a particular channel they selected before. Participants were then asked to indicate the frequency of each activity using a 4-point Likert scale from 0 to 3 (Never, Rarely, Occasionally, Frequently, respectively). Participants would not be presented with a list of activities for channels they did not select.

Table 5.1 Customer activities in each channel used in the survey

Activities	Offline	Online	Mobile	Catalogue/ newsletter	Call Centre	Social Media	In-Store Technology	External
Pre-purchase								
Visit	✓	✓	✓	✓	✓	✓	✓	
Browse	✓	✓	✓	✓	✓	✓	✓	
Receive/seek offers/coupon	✓	✓	✓	✓	✓	✓	✓	
Check for availability	✓	✓	✓		✓	✓	✓	
Compare price & payment methods	✓	✓	✓	✓	✓	✓	✓	
Product demo & visualisation	✓	✓	✓	✓		✓	✓	
Look for social interaction	✓	✓	✓		✓	✓		
Find product reviews	✓	✓	✓	✓		✓	✓	
Get a free trial	✓	✓	✓	✓	✓	✓		
Purchase								
Place an order	✓	✓	✓	✓	✓		✓	
Redeem a coupon	✓	✓	✓		✓		✓	
Complete a payment	✓	✓	✓		✓		✓	✓
Track an order	✓	✓	✓		✓		✓	✓
Receive a product	✓							✓
Post-purchase								
Share an experience	✓	✓	✓	✓	✓	✓		
Review a product	✓	✓	✓	✓	✓	✓		
Report an issue/ a complaint	✓	✓	✓	✓	✓	✓		
Identify know-how (installation)	✓	✓	✓	✓	✓	✓		
Exchange/return	✓	✓	✓	✓	✓			
Total Activities	**19**	**18**	**18**	**13**	**16**	**13**	**11**	**3**

5.3.3 Customer experience

Customer experience, as defined by many scholars (Verhoef et al., 2015), is a multi-dimensional construct. It should capture many facets of customers' internal response, including affective, cognitive, behavioural, sensory, and social aspects. In measuring this, a brand experience scale by Brakus et al. (2009) was used since the scale itself able to capture most of the dimensions of customer experience. The brand experience scale, however, does not have a social experience dimension. The inclusion of the social

experience dimension is especially important in an omnichannel business setting because the combination of physical and virtual channels allow customers to have actual social contact with an employee or with another customer. In doing so, the social value scale is adopted, combining scales developed by Sweeney and Soutar (2001).

The adaptation made, including the changes of some wordings such as the word 'brand', was replaced with 'retailer' to put the scale into the context, and additional explanation in the parentheses for item Behaviour2. The statements were introduced after the opening sentence, "Please indicate to what extent do you agree or disagree with the following statements." A seven-point Likert scale was employed to measure customer experience, ranging from 1 (strongly disagree) to 7 (strongly disagree). Table 5.2 shows the items used in the study to measure customer experience.

Table 5.2 Scale for customer experience

Construct	Code	Items	Source
Affective experience	Affective1	This retailer induces my feelings and sentiments.	Brakus et al. (2009)
	Affective2	I do not have strong emotions for this retailer. *	
	Affective3	This retailer is an emotional brand.	
Cognitive experience	Cognitive1	I engage in a lot of thinking when I shop from this retailer.	
	Cognitive2	This retailer does not make me think. *	
	Cognitive3	This retailer stimulates my curiosity and problem-solving.	
Behavioural experience	Behaviour1	I engage in physical actions and behaviours when I shop from this retailer.	
	Behaviour2	This retailer results in bodily experiences (e.g. becomes well, hungry, relief, energised, talkative, strong).	
	Behaviour3	This retailer is not action-oriented. *	
Sensory experience	Sensory1	This brand makes a strong impression on my visual sense or other senses.	
	Sensory2	I find this brand interesting in a sensory way.	
	Sensory3	This brand does not appeal to my senses.	
Social experience	Social1	This retailer helps me feel socially accepted.	Sweeney and Soutar (2001)
	Social2	Shopping from this retailer makes a good impression on other people.	
	Social3	This retailer improves the way I am perceived.	

* = *reversed coded*

5.3.4 Channel integration

The channel integration scale was adopted from Bendoly et al. (2005). They identified eight common characteristics of retailers who operate with physical and virtual channels. These eight characteristics were translated into measurement items that capture channel integration, including product, price, promotion, order fulfilment, information access, and customer service. Compared to the more recent study, such as a work undertaken by Oh et al. (2012) that results in 27-items to measure channel integration, Bendoly et al.'s items capture similar dimensions in a simpler way, an important point to be considered in the long survey. The items measuring channel integration are shown in Table 5.3. These items were proposed after an introductory sentence of "Please indicate to what extent does this retailer practice the following statements?" Respondents were asked to indicate each statement with a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly disagree).

Table 5.3 Scales for channel integration

Construct	Code	Items	Source
Channel integration	Integrate1	Advertise their Web sites at their local stores.	Bendoly et al. (2005)
	Integrate2	Advertise their local stores through their Web site	
	Integrate3	Provide information regarding the list of goods offered at specific stores through their Web sites.	
	Integrate4	Allow consumers to receive non-product information on their stores (e.g., driving directions) via e-mail contact or other electronic communication made available through their Web sites.	
	Integrate5	Allow customers to purchase items through their Web sites and pick them up in one of their stores.	
	Integrate6	Have employees at their stores that are knowledgeable and helpful regarding the use of their Web sites.	
	Integrate7	Have kiosks (stations for accessing their Web sites) within their stores.	
	Integrate8	Accept returns at their stores for purchases made through their Web sites	

5.3.5 Market mavenism as a marker variable

Marker variable was included in the questionnaire to analyse the common method bias. The marker variable should be theoretically unrelated to other constructs. In this instance, a construct of market mavenism was used. Respondents were asked to answer to what extent they agree with the statement, "My friends and neighbours often come to me for advice." Using a 7-point Likert scale, similar to other constructs, respondents were indicating whether they were agreed with the statement, from 1 (strongly disagree) to 7 (strongly agree).

5.3.6 Control variables

Table 5.4 Operationalisation of control variables

Construct	Operationalisation	Source
Tenure	Number of months between the customer's first purchase and the current time period.	Kumar and Venkatesan (2005), Bilgicer et al. (2015)
Dollar spent	The average spending per visit in dollar	
Gender	Female Male Others	
Income	Below $9,999 $10,000 to $19,999 $20,000 to $34,999 $35,000 to $49,999 $50,000 - $74,999 $75,000 to $99,999 over $100,000	
Age	18 – 24 25 – 34 35 – 44 45 – 54 55 – 64 65 and over	

The operationalisation of control variables can be seen in Table 5.4 above. Five variables were used as control variables; these were classified as customer characteristics and customer demographics. The customer characteristics include the

length of the relationship (tenure) and the amount of spending (dollar spent). At the same time, customer demographics include age, gender, and income.

5.4 Questionnaire development

The previous chapter discussed the survey design employed in Study 1. This section elaborates further on the instrument used in that survey, namely the questionnaire. Hair et al. (2003) defined a questionnaire as a formalised framework used to collect raw data comprising a set of questions and scales. These measurement scales should be taken or adapted from an established set of scales to ensure their validity and reliability. The questionnaire development involves configuring these scales into a complete instrument for communicating with and collecting information from respondents. Hair et al. (2003) suggest four integrated theoretical components of questionnaires. The following discussion is organised based on these four components, which are: questions, words, formats, and hypotheses, and an additional section of pilot testing. Each component's discussion describes the elements of the design process involved, as suggested by Malhotra (2012).

5.4.1 Questions

The list of questions in a questionnaire should be given based on the information needed in the research. The data commonly includes construct-related information, respondents' demographic profile, or other information that may be useful to signal data quality (for example, attention check). Once the information is specified, the type of collection method needs to be addressed. The questionnaire for Study 1 used a self-administered method wherein respondent fill out the questionnaire themselves without the presence of the researcher. This method can eliminate the researcher's bias and give respondents more authority to answer sensitive questions. Another issue is the effectivity of questions. Ambiguous questions may lead to unwanted responses or responses that does not reflect the actual condition. Focusing on the clarity of each

question and retaining a single main idea in each question can aid respondents in giving the correct answer.

5.4.2 Words

Words are the most dominant element in a questionnaire. Words can relate to language. Using the population strictly in an English-speaking country enable us to use English in the questionnaire. Apart from language, words also imply intention and create meaning behind a question or an instruction. Using academic terms might be ineffective when collecting information from the general public. Some statements in the questionnaire were adapted exactly for this reason. Simple terms equipped with example were used to replace higher academic terms (see the adaptation of Behavioural Experience scale section 5.3.3). The wording in the questionnaire should also be specific. Respondents in Study 1 were asked about their experience in the past year related to either grocery shopping or fashion shopping. By being specific, researchers set a standard for guiding respondents to give the information they were supposed to provide. A problem arises when respondents are reluctant to share some information. From a technical perspective, this problem creates missing values that may impact data analysis. However, more than a technicality, reluctancy creates a piece of missing information, and an incomplete overview of the research problem researchers are trying to see. Providing an explanation of the objective for each set of questions could increase respondents' confidence and willingness to answer.

5.4.3 Formats

The structure, flow, layout, and reproducibility of a questionnaire were components of format. Study 1 used a set of structured questions with scales, especially for collecting data about the main construct. Structured multiple-choice questions were used to collect demographic profile and customer characteristics information. Using structured questions is suitable for large surveys and self-administered surveys. The flow of the

questions should go from general to specific. Arrangement of the order of the questions is important to ensure respondence attention and focus. An introduction is useful to set respondents expectation pertaining to completion time and the objective. The previous chapter discussed how an objective should not be too specific not to influence respondents' response. Easy questions related to shopping habit and retailer's information were placed in the beginning and after opening questions. This was followed by the main constructs of customer interaction, customer experience, and channel integration. The questionnaire ended with multiple-choice questions related to respondents' personal information without asking for any data that could identify them individually.

The questionnaire used in Study 1 utilised the online platform Qualtrics. The advantage of using Qualtrics is its ability to cater to a complex layout and organise questions into several pages. Each section of the questionnaire (e.g., Introduction, Experience, Demographics) was displayed on one page, and respondents had to click next to go to the next section. Another benefit of Qualtrics is its ability to create a layout compatible with multiple devices, such as a computer, tablet, or smartphone. Qualtrics also facilitates randomisation in distribution. As Study 1 has two retail sectors in interest, the grocery retailer and fashion retailer, a randomisation option enables the researcher to divide the responses equally. Lastly, there is an issue with reproducibility. It is related to the question of whether the questionnaire has a consistent quality throughout its reproduction process. This problem may be more prominent in a paper-based questionnaire and not in an online questionnaire. However, elements like colours, fonts, and symbols, may not be available widely and could appear differently on the respondent's device. The questionnaire used for this study employed a default design of Leeds University Business School, which predominantly utilised neutral black and white colour.

5.4.4 Hypotheses

This final component focuses on the notion that questionnaires are designed for collecting meaningful raw data to test a hypothesis rather than merely to gather facts about objects under investigation (Hair et al., 2003). An issue regarding hypotheses is determining whether the questions are important or something that is probably 'nice to have'. Nice-to-have questions, although they can be useful in analyses, potentially increase respondent's fatigue and hence shifting their focus away from the important questions. The key is to prioritise and balance and be aware of the length of time needed to read questions and answer them.

5.4.5 Pilot testing

Pilot testing is the last step suggested by Malhotra (2012) that facilitate the researcher to test four components of the questionnaire (Hair et al., 2003) to a small sample of respondents. The objective is to eliminate potential problems and implement some changes needed before the questionnaire is rolled out to a larger sample. It allows the researcher to adapt, correct, and amend before the final data collection.

The pilot test in Study 1 was conducted using the sample from MTurk to obtain the result from the same population as the main data collection later. In total, 70 responses were collected and equally distributed between grocery retailers (N = 35) and fashion retailers (N = 35). Two major amendments were done tackling problems with format and question.

First, the format of the questionnaire was slightly changed with an additional captcha as a filter question. Captcha is an 'automated test that humans can pass, but current computer programs cannot pass' (Ahn et al., 2003, p. 294). This layer of question acts as a protection or security to ensure that all respondents were human and not a computer program (bot). It is apparently crucial to attach a captcha to the online questionnaire to exclude bots since it was found out that many entries had identical IP addresses

indicating they were coming from the same source. A captcha was placed on the first page of the questionnaire right after the introduction.

Second, the display of the question regarding customer interaction was amended. Initially, respondents were asked to fill in a large table consisted of 19 rows and 8 columns. Then it was changed into conditional options. To begin with, respondents were presented with eight possible channels to interact with a retailer. They had to select all channels they had interacted with in the past year. Then, depending on selected channels, respondents fill out follow up questions regarding the frequency of their interaction for every possible activity in each channel. In this way, participants did not feel obliged to fill out all table and therefore reflected closer to their actual experience. The full questionnaire can be seen in Appendix B.

5.5 Data collection

5.5.1 Questionnaire distribution

As previously brought up, questionnaires were circulated on the MTurk platform. Several restrictions were put in place to limit the distribution of the questionnaire and to increase the validity of the study. These restrictions were (1) the location of participants, which was set to be in the United States, (2) the number of tasks previously completed, which was set to 50 tasks, and (3) the exclusion of those who participated in a similar survey previously. The number of required responses was set to 500, and by the nature of MTurk, the respondents are all over 18 years old. All respondents were financially compensated ($1.5) for their time spent in completing the questionnaire (average = 10 minutes). The compensation value aligns with the minimum wage regulation in the United States.

5.5.2 Overview of the sample

A total of 500 responses were gathered through an online survey. After screening out some potential pitfalls discussed in the previous section, 485 responses were used throughout Study 1. Table 5.5 illustrates the respondent's profile based on gender, age group, education level, occupation, and income. The gender proportion was slightly dominated by the male participants (56%). The largest percentage of age was age group 25 – 3, which is accounted for 53% of the sample, followed by the age group 35 – 44 (23%). Most of the respondents had a bachelor degree (59%), while only less than 8% had a high school degree or less. Lastly, the majority of participants identified themselves as full-time employee (80%).

Table 5.5 Respondent profile in Study 1

Demographic		N	%
Gender	Male	274	56%
	Female	199	41%
	Identified as others	12	2%
Age Group	18 – 24	57	12%
	25 – 34	259	53%
	35 – 44	111	23%
	45 – 54	36	7%
	55 – 64	19	4%
	65 and over	3	1%
Education level	Less than high school degree	2	0%
	High school degree or equivalent (e.g., GED)	34	7%
	Some college but no degree	61	13%
	Associate degree	36	7%
	Bachelor degree	285	59%
	Graduate degree	67	14%
Occupation	Employed full time	387	80%
	Employed part-time	61	13%
	Unemployed looking for work	11	2%
	Unemployed not looking for work	16	3%
	Retired	3	1%
	Student	7	1%
Income	Below $9,999	26	5%
	$10,000 to $19,999	46	9%
	$20,000 to $34,999	94	19%
	$35,000 to $49,999	112	23%
	$50,000 - $74,999	111	23%
	$75,000 to $99,999	56	12%
	over $100,000	40	8%

5.6 Data preparation and examination

Missing values may lead to insufficient information to analyse the data. In this dataset, missing value analysis identified only a few missing values, all of which were found within the demographic variables. The case of missing values in the demographic variables is understandable since respondents were not obliged to answer demographic questions. Only two out of five demographic variables had missing values, namely education and employment, of which five and two cases accounted for 1 % and 0.4 % of total data in each variable, respectively. The percentages of these missing values were under 10%, which is considerably low and can be ignored (Hair et al., 2014). Nevertheless, the missing values were corrected using the median substitution method. Using this method, both missing values were treated to belong to the majority group of respondents.

Furthermore, attention checks were in place to ensure the quality of the data. Attention checks were needed due to the platform that this research employed for data collection, Amazon MTurk. As suggested by Goodman et al. (2013), screening questions were needed to measure respondents' attention. There were two attention check questions in the beginning and the middle of the questionnaire. The final step to gauge respondents' attention was by investigating the time stamp of each respondent. Respondents who spent less than 5 minutes completing the survey were excluded from the analysis. Using three filters, 15 responses were deleted, leaving 485 usable responses to be examined for further analysis.

5.6.1 Descriptive statistics of items and testing the normality

As explained in Chapter 4, descriptive statistics give an overview of how the data was disperse and the central tendency of the data. The first is signified by the range and standard deviation. Using a minimum and maximum value, the range of the data can be seen in Table 5.6.

For items measured using a Likert-scale, participants' answers include all values in the scale (from minimum 1 to maximum 7). The independent variable, Breadth, also consists of a 1 to 8 value, which represented all possible variation of the number of channels. Another measure to assess data dispersion is a standard deviation, which in this instance, ranged from min 1.381 (Sensory1) to 42.735 (Depth). Depth has a large value of standard deviation because the variable itself is an accumulated frequency (see 5.3.2 Customer interaction depth), therefore it is understandable to have such a disperse data point.

Table 5.6 Descriptive statistics and test of univariate normality

	Min.	Max.	Mean	SD	Skewness		Kurtosis	
					Statistic	Std. Error	Statistic	Std. Error
Breadth	1	8	2.819	1.474	1.403	0.111	2.617	0.221
Depth	5	245	70.532	42.735	1.244	0.111	1.590	0.221
Cognitive1	1	7	4.870	1.457	-0.680	0.111	-0.011	0.221
Cognitive2	1	7	4.777	1.619	-0.499	0.111	-0.457	0.221
Cognitive3	1	7	4.928	1.601	-0.771	0.111	-0.043	0.221
Affective1	1	7	4.771	1.622	-0.597	0.111	-0.365	0.221
Affective2	1	7	4.720	1.702	-0.561	0.111	-0.541	0.221
Affective3	1	7	4.594	1.792	-0.490	0.111	-0.762	0.221
Behaviour1	1	7	4.971	1.485	-0.794	0.111	0.172	0.221
Behaviour2	1	7	4.703	1.636	-0.607	0.111	-0.343	0.221
Behaviour3	1	7	4.969	1.486	-0.611	0.111	-0.147	0.221
Sensory1	1	7	5.173	1.381	-0.890	0.111	0.674	0.221
Sensory2	1	7	5.157	1.497	-1.012	0.111	0.801	0.221
Sensory3	1	7	5.231	1.440	-1.076	0.111	1.065	0.221
Social1	1	7	4.765	1.691	-0.720	0.111	-0.284	0.221
Social2	1	7	4.889	1.639	-0.740	0.111	-0.104	0.221
Social3	1	7	4.860	1.738	-0.727	0.111	-0.307	0.221
Integrate1	1	7	4.5010	2.035	-0.314	0.111	-1.209	0.221
Integrate2	1	7	4.3423	1.893	-0.298	0.111	-1.127	0.221
Integrate3	1	7	3.6990	1.920	0.157	0.111	-1.138	0.221
Integrate4	1	7	4.3340	1.962	-0.310	0.111	-1.150	0.221
Integrate5	1	7	4.4351	1.988	-0.313	0.111	-1.180	0.221
Integrate6	1	7	4.5093	2.058	-0.336	0.111	-1.226	0.221
Integrate7	1	7	4.3567	1.680	-0.369	0.111	-0.831	0.221
Integrate8	1	7	4.4825	2.020	-0.333	0.111	-1.176	0.221

The test of normality provides an overview related to the spread of the data. It covers two elements of normality, skewness, and kurtosis. Skewness represents the symmetry of the distribution, while kurtosis represents the peakedness of a distribution (Tabachnick and Fidell, 2013). According to Kline (2011) and Finch et al. (1997), the values of skewness lower than |2| and of kurtosis smaller than |7| indicate a moderate departure from a univariate normal distribution. The skewness of the data (see Table 5.6) ranged between |0.157| (Integrate3) and |1.403| (Breadth), while kurtosis value ranged between |0.011| (Cognitive1) and |2.617| (Breadth). This value indicates that the variable items are within the acceptable range of normality.

5.7 Measurement assessment

After preliminary data analyses, this section will discuss the assessment of the measurements used in the study. Using AMOS, a Confirmatory Factor Analysis (CFA) was performed to assess the construct validity and reliability.

5.7.1 Convergent validity and discriminant validity

CFA was performed on the reflective measurements, comprising six multi-items variables: cognitive experience, affective experience, behavioural experience, sensory experience, social experience, and channel integration. To categorically define the goodness of CFA result, there are some criterion and indices to follow, these usually refer to global fit indices and local fit indices. Firstly, the local fit indices were inspected to assess the fit of individual construct measures and structural relationship. Item-construct loading (λ) should reach at least 0.50 in an attempt to establish construct validity (Hair et al., 2014) and statistically significant (t-value $\geq$ 1.96). The initial result showed that two items in the channel integration construct found to be problematic. The factor loadings of Integrate3 (0.233) and Integrate7 (-0.043) were both less than the minimum 0.5. Hence, they were deleted, leaving the channel integration construct with

six out of eight items at the end. The final factor loadings and t-values of all items are presented at Table 5.7.

Table 5.7 Item-construct loadings and t-values

Constructs	Items	Standardised loading	T-values
Cognitive Experience	Cognitive1	0.782	18.139
	Cognitive2	0.914[a]	
Affective Experience	Affective1	0.865a	
	Affective2	0.891	26.904
	Affective3	0.894	27.042
Behavioural Experience	Behaviour1	0.711[a]	
	Behaviour2	0.821	16.254
	Behaviour3	0.806	16.022
Sensory Experience	Sensory1	0.823[a]	
	Sensory2	0.858	22.103
	Sensory3	0.884	22.969
Social Experience	SocialEx1	0.877[a]	
	SocialEx2	0.871	26.278
	SocialEx3	0.903	28.169
Channel Integration	Integrate1	0.849	22.044
	Integrate2	0.865	22.657
	Integrate4	0.898	23.948
	Integrate5	0.809	20.553
	Integrate6	0.786	19.755
	Integrate8	0.810[a]	
Customer Interaction Breadth	Breadth	0.977[a]	
Customer Interaction Depth	Depth	1.000[a]	
Gender	Gender_fem	0.815[a]	
Dollar Spending per trip	Dollar	0.949[a]	
Length of Relationship	Tenure	0.948[a]	
Age	AgeGroup	0.945[a]	
Income	IncomeLevel	0.979[a]	

Global Fit Indices: χ^2 = 451.979; df = 253; χ^2/df = 1.789; p = 0.000; NFI =0.949; CFI =0.976; AGFI = 0.902; GFI = 0.935; RMSEA = 0.040; SRMR = 0.023; a = fixed parameter

Next, the convergent validity was assessed by the average variance extracted (AVE), which should meet the criterion 0.5 set by Fornell and Larcker (1981). The initial result was that all constructs have AVE score greater than 0.5, ranging from 0.610 (Behaviour Experience) to 0.781 (Social Experiment). Using the result of AVE, discriminant validity was assessed.

The initial result of discriminant validity showed that the square root of the AVE for Cognitive Experience was less than the absolute value of the correlation with Affective Experience (0.829 vs 0.831). Due to these circumstances, items of Cognitive Experience were inspected, and Cognitive3 was deleted for having the least factor loading. The average variance extracted were recalculated, resulting in the increase of the AVE for Cognitive Experience to the value of 0.851 and decreasing its correlation with Affective Experience to the value of 0.763. As a result, the issue with discriminant validity was no longer present (see the bold number in Table 5.8).

Once the construct validity has been established, the construct reliability was measured—reliability concerns about the internal consistency of a construct towards repeated measurement (Malhotra, 2012). The most common indicators for reliability are Cronbach's alpha coefficient and Composite Reliability (CR). The lower limit of accepted Cronbach's alpha coefficient is between 0.6 – 0.7 (Hair et al., 2014) or 0.8 if applied to basic research, according to Nunnally (1978). Similarly, the cut-off point of 0.6 is deemed desirable for composite reliability (Bagozzi and Yi, 1988). The method recommended by Fornell and Larcker (1981) was employed to calculate the composite reliability, and the result shows that the value range between 0.824 and 0.933. Correspondingly, Cronbach's alpha coefficient all shows more than 0.8, with 0.825 (Behavioural Experience) is the lowest and 0.933 (Channel Integration) is the highest. All of the results of validity and reliability can be found in Table 5.8.

After the application of some changes to the model, including the deletion of three items, the global fit indices of the final model can be estimated as follow: χ^2 = 451.979, df = 253, χ^2/df = 1.789, p = 0.000, NFI =0.949, CFI =0.976, AGFI = 0.902, GFI = 0.935, RMSEA = 0.040, SRMR = 0.023. Comparing these indices with the standard threshold shown in Table 4.2, it is sufficient to conclude that the CFA model has a good fit. The normed chi-square (χ^2/df = 1.789) is within the threshold of a conservative threshold (≤ 2), and all other fit indices (AGFI, GFI, NFI, CFI) are above 0.9.

Table 5.8 Construct validity, reliability, and bivariate correlation

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	**Cognitive**	**0.851**												
2	**Affective**	0.763	**0.883**											
3	**Behaviour**	0.677	0.765	**0.781**										
4	**Sensory**	0.623	0.761	0.762	**0.855**									
5	**Social**	0.636	0.874	0.742	0.773	**0.884**								
6	**Integrate**	0.291	0.365	0.311	0.347	0.356	**0.837**							
7	**Breadth**	0.043	0.003	0.035	0.008	0.020	-0.066	**N/A**						
8	**Depth**	0.332	0.335	0.285	0.236	0.333	0.143	0.760	**N/A**					
9	**Dollar**	-0.002	0.035	0.018	-0.012	0.025	0.084	-0.009	0.056	**N/A**				
10	**Tenure**	-0.177	-0.250	-0.169	-0.133	-0.290	-0.028	-0.012	-0.183	-0.057	**N/A**			
11	**Age**	-0.124	-0.176	-0.143	-0.110	-0.231	0.013	-0.017	-0.105	-0.038	0.279	**N/A**		
12	**Gender**	0.121	0.132	0.090	0.080	0.036	-0.017	0.008	0.048	-0.052	0.046	0.139	**N/A**	
13	**Income**	-0.126	-0.110	-0.097	-0.087	-0.111	-0.045	0.005	-0.080	0.058	0.162	0.203	0.002	**N/A**
	Cronbach α	0.830	0.913	0.825	0.889	0.914	0.933	-	-	-	-	-	-	-
	CR	0.839	0.914	0.824	0.891	0.915	0.933	-	-	-	-	-	-	-
	AVE	0.723	0.780	0.610	0.731	0.781	0.701	-	-	-	-	-	-	-
	MSV	0.582	0.764	0.585	0.598	0.764	0.133	-	-	-	-	-	-	-

5.7.2 Analysis of common method bias (CMB)

The first method to assess the presence of common method bias is by applying Harman's single factor technique. This is done by conducting an exploratory factor analysis by including all construct items and extracting only one factor. The variance explained by this factor should not exceed 50% to establish that there is no common method variance concern. This is resulted in a single factor that explains 29.945% of the variance, well below the threshold.

Harman's single factor technique offers a simple method to detect common method bias; however, it does not statistically control common method variance itself (Podsakoff et al., 2003). The method becomes less conservative as the number of variable increases. Hence, this research conducted another technique commonly known as the partial correlation technique using a marker variable (MV) as recommended by Lindell and Whitney (2001).

A single-item variable measuring market mavenism was used as a marker variable in this research. The first step is to calculate raw correlations between main variables as well as marker variables. All main variables but one (breadth) are significantly correlated to each other as suggested theoretically. Within the same test, it was revealed that the marker variable did not significantly correlate with all other variables, indicating a discriminant validity (Lindell and Whitney, 2001). After obtaining a raw correlation coefficient, the partial correlation coefficient and its significance can be estimated using the formula by Lindell and Whitney (2001), as discussed in Chapter 4.

The second smallest raw correlation coefficient was found to be the correlation between breadth and affective experience, having a coefficient of 0.004. To rule out the CMB concern, there should be a consistent result in terms of correlation sign and significance between raw versus partial correlation. In total, there are 22 significant correlations which remain significant after the partial correlation test (lower versus upper diagonal

of Table 5.9). Moreover, there are no changes in their signs, which conclude the absence of CMB concern.

Table 5.9 Correlation and partial correlation matrix

	1	2	3	4	5	6	7	8	9
1 Affective exp.	1	0.669***	0.655***	0.689***	0.798***	0.335***	0.000	0.317***	-0.017
2 Cognitive exp.	0.670***	1***	0.567***	0.548***	0.550***	0.257***	0.038	0.308***	0.044
3 Behavioural exp.	0.656***	0.569***	1	0.648***	0.633***	0.274***	0.024	0.250***	0.018
4 Sensory exp.	0.690***	0.550***	0.649***	1	0.701***	0.318***	0.004	0.223***	0.050
5 Social exp.	0.799***	0.552***	0.634***	0.702***	1	0.327***	0.013	0.313***	0.032
6 C. Integration	0.337***	0.260***	0.277***	0.321***	0.329***	1	-0.071	0.130***	0.005
7 Breadth	**0.004**	0.041	0.027	0.008	0.017	-0.067	1	0.759	0.002
8 Depth	0.320***	0.311***	0.253***	0.226***	0.316***	0.133***	0.760***	1	-0.005
9 Mavenism	-0.014	0.047	0.021	0.054	0.036	0.009	0.006	-0.001	1

5.7.3 Creating a measurement index

Prior to running the analyses, the researcher created composite variables of multi-item measures corresponding to the result from CFA in the previous section. This step is done by calculating the mean of the multi-item construct, which is called a composite variable.

5.7.3.1 Composite for main variables

The variable Customer Experience was treated as a second-order construct as it was suggested as a multi-dimensional construct in the original paper by Brakus et al. (2009). In this case, instead of using five composite experience constructs as an independent variable, one variable called Customer Experience was computed. This computation was done by treating the composite experience variables as items of Customer Experience and creating the average of them. However, before the composite variable of Customer Experience was created, the construct reliability needs to be investigated (Nunnally, 1978). We use Cronbach's alpha coefficient to decide whether the five composite experience variables can be merged into Customer Experience variable. The

same threshold was used, and the Cronbach's alpha coefficient for Customer Experience was 0.901, indicating a good reliable construct.

5.7.3.2 Composite for quadratic and interaction terms

In order to avoid the possibility of multicollinearity issue in the regression analysis, this research used mean-centred variables. This procedure was done by extracting the value of a variable to its respective mean. This was applied for variable Breadth, Depth, Breadth^2, Depth^2, and Channel Integration. Moreover, interaction terms between Breadth and Channel Integration as well as between Breadth^2 and Channel Integration were also computed to test the moderating effect. These interaction terms were calculated by multiplying the mean-centred Breadth/Breadth^2 with mean-centred Channel Integration.

The summary of the descriptive statistics of multi-item variables and quadratic terms used in the analysis can be seen in Table 5.10 below.

Table 5.10 Descriptive statistics for reflective measures and quadratic terms

Construct	Number of items	Mean	Standard deviation	Skewness	Kurtosis
Cognitive Experience	2	4.832	1.423	-0.697	0.030
Affective Experience	3	4.695	1.575	-0.711	-0.352
Behavioural Experience	3	4.881	1.322	-0.712	0.093
Sensory Experience	3	5.186	1.303	-1.114	1.359
Social Experience	3	4.838	1.561	-0.898	0.057
Customer Experience	5	4.886	1.221	-0.610	-0.078
Channel Integration	6	4.435	1.723	-0.258	-1.238
Breadth^2	1	10.113	11.880	2.927	9.821
Depth^2	1	6797.245	8687.986	2.643	8.257
Breadth x C.Integration	1	-0.179	2.3516	0.210	2.283
Breadth^2 x C.Integration	1	-1.008	6.723	-1.637	17.062
Depth x C.Integration	1	9.7348	66.734	-0.055	2.413
Depth^2 x C.Integration	1	-120.862	5454.751	-0.471	18.780

5.7.3.3 Control variables

There are five control variables used in the hierarchical regression analysis. Two of these were shopping behaviour related variable; they are the amount of dollar spending per trip (Dollar) and the length of the relationship between a customer and a retailer (Tenure). The other three variables were demographic variables which include Age, Gender, and Income.

5.8 Hypotheses testing

This section discusses the effect of customer interaction's dimension on customer experience, followed by four additional analyses as a robustness check. The second part discusses the moderating role of channel integration in the tested framework. The first step was to include the only effects of control variables on Customer Experience, as seen in Model 1 at Table 5.11. Afterwards, customer interaction's dimension of Breadth and Depth were added in Model 2, and their quadratic terms were added in Model 3. Channel integration was introduced in Model 4, and the interaction terms were added in Model 5. These interaction terms include Channel Integration x Breadth, Channel Integration x Breadth^2, Channel Integration x Depth, and lastly Channel Integration x Depth^2.

Table 5.11 Hierarchical Regression Result

DV: Customer experience	**Model 1**		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
Control variables	**β**	**t**	**β**	**t**	**β**	**t**	**β**	**t**	**β**	**t**
Spending per trip	0.013	0.294	-0.026	-0.660	-0.034	-0.887	-0.048	-1.300	-0.036	-1.121
Length of tenure	-0.182	-3.968***	-0.079	-1.896†	-0.046	-1.120	-0.057	-1.466	-0.034	-0.967
Income	-0.063	-1.399	-0.024	-0.600	-0.009	-0.216	-0.003	-0.075	-0.018	-0.536
Age	-0.116	-2.501*	-0.084	-2.036*	-0.058	-1.443	-0.072	-1.856†	-0.059	-1.746†
Gender	0.102	2.293*	0.069	1.735	0.058	1.495	0.069	1.868†	0.037	1.136
Linear effect										
Breadth			-0.518	-8.373***	-0.678	-9.544***	-0.589	-8.530***	-0.121	-1.638
Depth			0.708	11.206***	0.887	12.588***	0.757	10.839***	0.571	8.872***
Quadratic effect										
Breadth^2					0.337	5.147***	0.361	5.767***	0.169	2.738**
Depth^2					-0.328	-4.967***	-0.310	-4.904***	-0.383	-6.691***
Moderating effect										
Channel integration							0.264	6.874***	0.575	11.356***
Breadth x Channel integration									0.547	8.969***
Breadth^2 x Channel integration									-0.374	-6.177***
Depth x Channel integration									0.005	0.094
Depth^2 x Channel integration									0.010	0.170
Highest VIF		1.107		2.817		3.538		3.867		5.324
Adjusted R^2		0.064		0.256		0.300		0.362		0.505
Changed in R^2				0.193		0.046		0.062		0.144
F	(-5, 479)	7.635***	(7, 477)	24.833***	(9, 475)	24.021***	(10, 474)	28.45***	(14, 470)	36.278***
Changed in F				62.895***		15.789***		47.258		35.274***

† = 0.1; * = 0.05; ** = 0.01; ***= 0.001; Numbers in parentheses are degree of freedom (regression, residual)

5.8.1 Effect of customer interaction complexity on customer experience

Hypotheses H_1 and H_2 sought to examine the effects of customer interaction breadth and depth on customer experience. Specifically, this research hypothesises that customer interaction affects customer experience curvilinearly, where Breadth takes a U-shaped relationship (H_1), and Depth takes an inverted U-shaped relationship to customer experience (H_2).

A significant regression model emerged in Model 3 (Table 5.11), where $F_{9,475} = 24.021$, $p < 0.001$, Adjusted $R^2 = 0.300$. It shows a significant improvement, compare to the linear model in Model 2, with F statistics increased by 15.789 ($p < 0.001$). The standardised beta coefficient for Breadth is negative and significant ($\beta = -0.678$, $t = -9.544$, $p < 0.001$) while $Breadth^2$ is positive and significant ($\beta = 0.337$, $t = 5.147$, $p < 0.001$). This supports H_1 which indicates that there is a U-shaped relationship between Breadth and Customer Experience. Depth is positive and significantly related to Customer Experience ($\beta = 0.887$, $t = 12.588$, $p < 0.001$) while $Depth^2$ shows negative and significant beta coefficient ($\beta = -0.328$, $t = -4.967$, $p < 0.001$).

Following Lind and Mehlum (2010) suggestion in testing a curvilinear relationship, the researcher examines whether both ends of the curve have significant slopes and whether the turning point was within the data range. It is considered insufficient to conclude a curvilinear relationship merely based on the beta coefficients. The presence of a curvilinear implies the following equation (Lind and Mehlum, p.111, 2010):

$$\text{U-shape: } \beta + 2\gamma x_l < 0 \text{ and } \beta + 2\gamma x_h > 0 ,$$

$$\text{Inverted U-shape: } \beta - \gamma x_l^{-2} < 0 \text{ and } \beta - \gamma x_h^{-2} > 0$$

β is a beta coefficient of linear term of x, and γ is a beta coefficient of quadratic term of x, x_l is the minimum value of x, and x_h is the maximum value of x within the data range.

To do this, additional analysis, *utest* analyses, were performed in STATA. As seen in Table 5.12, both slopes of Breadth and Depth are significant at $p < 0.05$. Moreover, the turning points of both Breadth and Depth are within the data range, hence confirming the presence of U-shaped in both Breadth and Depth.

Table 5.12 The estimates of Breadth and Depth curves

DV: Customer Experience	**Breadth**		**Depth**	
	Lower bound	*Upper bound*	*Lower bound*	*Upper bound*
Interval	1	8	5	245
Slope	-0.884	0.356	0.041	-0.015
t-value	-8.379	2.271	9.178	-2.062
P>|t|	0.000	0.012	0.000	0.020
Turning point	5.989		179.466	
Fieller interval	[5.187; 7.577]		[151.535; 239.984]	
Overall test of a U-shape				
t-value	2.270		2.060	
P>|t|	0.012		0.020	

5.8.1.1 Hypothesis testing with randomised subsamples

Following an approach conducted by Li et al. (2009), a regression analysis was run using three randomly selected subsamples (90%, 80%, and 70%) of the total observation. The aim of this test is to test the consistency of the results which are not supposedly contributed by the small sample of observation. The result finds consistent outcomes in comparison to the full sample, both Breadth and Depth retain their shape regarding customer experience (U-shaped and inverted U-shape, respectively). The more detailed result can be seen in Appendix C.1.

5.8.1.2 Test of the alternative specifications

To rule out the possibility that the curvilinear relationships were merely a convenient result, the researcher tested several other specifications such as cubic and logarithmic specification. Subsequently, the value of the Aikake information criterion (AIC) and Bayesian information criterion (BIC) were compared to aid the model selection. The

absolute value of AIC is not interpretable; however, the computation of the difference between two AIC can help to decide which model is the best. If the difference yields a value that is less than 2, it means that the compared model has substantial support to be chosen (Burnham and Anderson, 2004).

Based on the result, the quadratic model that was already used in the main hypotheses testing had the lowest AIC value, and there is no other model that yielded differences less than 2. Therefore, it provides support that the quadratic term is a better model. In addition, this quadratic model also has the smallest value of BIC, suggesting that it is a preferred model. Detail of the comparison of the results can be seen in Appendix C.2.

5.8.1.3 Analysis with winzorised independent variables

Winsorization is a technique to limit extreme observation in the dataset to minimise the influence of outliers (Dixon, 1960). Re-estimation of the quadratic model using winzorised data is useful to ensure that the current result was not driven by a few extreme values. Hence, it is expected to have the main findings remain (Haans et al., 2016). Using winzorised Breadth and Depth, there were no apparent changes in terms of the pattern of relationships and their significance toward customer experience. The comparison between AIC values ($AIC_{original}$ = 1406.917 vs $AIC_{winsorized}$ = 1406.856) generates a difference value of less than 2, implying substantial support for the original model. In conclusion, the main results are not produced by a few extreme observations.

5.8.1.4 Analysis of the significance of each point in the curvilinear

The main findings from the previous analyses conclude that the proposed model *predicts* positive returns (Breadth) and negative returns (Depth). However, whether the data from this research could confirm the significance of those returns is uncertain. In order to examine this issue, a procedure used by Laursen and Salter (2006) was employed. This method involved the researcher creating categorical dummies for Breadth and Depth, which specify segments of X-values. The categorical dummies were

then used to estimate the previously tested model. The categorical dummies for Breadth were created for the ranges of 1 channel; 2 – 4 channels; 5 channels; 6 – 7 channels; and 8 channels. Similarly, eight categorical dummies were created for Depth. A benchmark dummy is set for each variable as a reference point which represents the area of the turning point (as suggested from Table 5.12).

Following up the U-shaped curve of Breadth, it is expected that the benchmark dummy would be the lowest range of values in the data. As an implication, the beta coefficients of all other dummies of breadth were expected to have a positive value indicating its higher position along the curve. Conversely, as the curve of Depth is inverted U-shaped, the benchmark dummy would be the highest range of value. Thus, other categorical dummies of depth were expected to have a negative sign. Overall, to confirm the positive/negative returns in the model, the dummies beyond the benchmark point should be significant with their intended sign.

As Table 5.13 shows, the relationship pattern of all categorical dummies lies on the intended sign. All dummies of Breadth above the benchmark are positive, although only the dummy for the value 1 and 2 – 4 are significant. Correspondingly, no evidence of negative returns was found for Depth. The dummy above the benchmark point is negative, as expected. However, it is insignificant, providing no support for a negative return on Depth. To sum up, the model in this research *predicts* positive return on Breadth or negative returns on Depth; nonetheless, the evidence is insufficient to be certain that those returns are statistically significant. The visualisation of these significant points of Breadth and Depth can be seen in Figure 5.1and Figure 5.2. Further visualisation of significant points of Breadth and Depth under different condition of channel integration is displayed in Appendix C.3.

Table 5.13 Regression Analysis with Categorical Dummy Variables

DV: Customer experience	**β**	**t**
Control variables		
Spending per trip	-0.005	-0.116
Length of tenure	-0.083	-1.951*
Income	-0.030	-0.723
Age	-0.047	-1.096
Gender	0.036	0.896
Breadth		
Dummy Breadth 1	0.592	4.104***
Dummy Breadth 2 - 4	0.329	1.942†
Dummy Breadth 5	0.047	0.508
Dummy Breadth 6 - 7, benchmark		
Dummy Breadth 8	0.042	0.692
Depth		
Dummy Depth 5 - 30	-0.689	-5.895***
Dummy Depth 31 - 55	-0.658	-4.596***
Dummy Depth 56 - 85	-0.443	-3.156**
Dummy Depth 86 - 115	-0.146	-1.259
Dummy Depth 116 - 140	-0.107	-1.418
Dummy Depth 141 - 150	-0.008	-0.148
Dummy Depth 151 - 215, benchmark		
Dummy Depth 216 - 245	-0.009	-0.209
R^2		0.273
F		10.928***

Note: † = 0.1; * = 0.05; ** = 0.01; ***= 0.001

Figure 5.1 The effect of customer interaction Breadth on customer experience and its significant points based on dummy variables

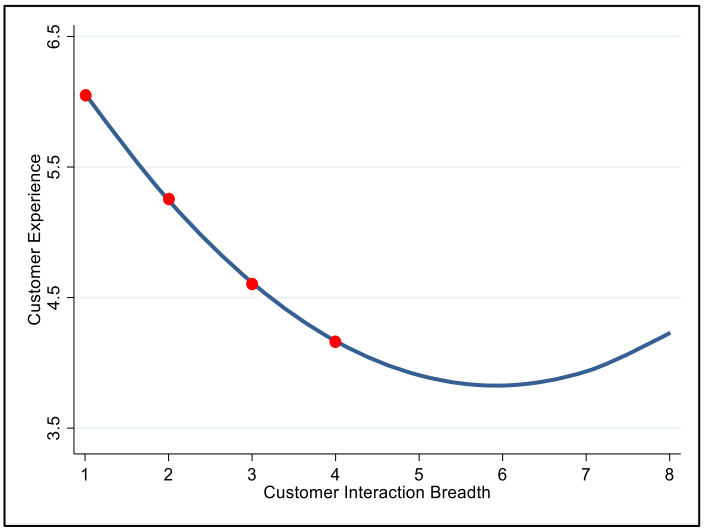
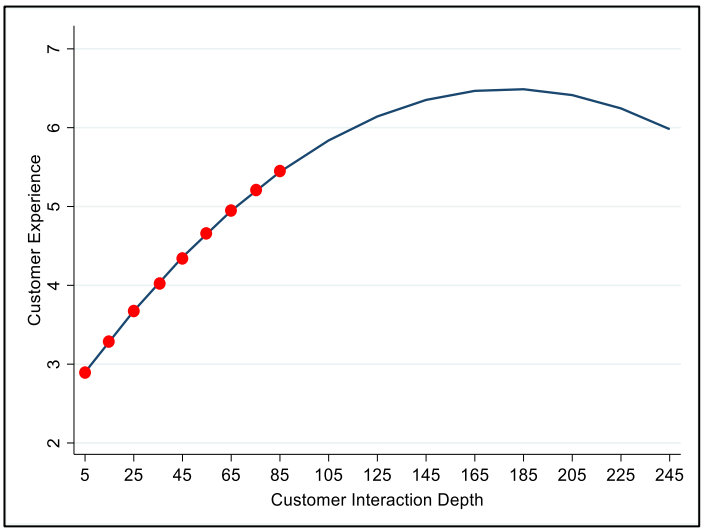


Figure 5.2 The effect of customer interaction Depth on customer experience and its significant points based on dummy variables



5.8.2 The moderating effect of channel integration on the relationship between customer interaction breadth and customer experience

The next set of analyses is interested in investigating the moderating effect of Channel Integration. Specifically, under what condition the relationship between Breadth and Customer Experience could change. Using interaction terms mentioned previously, moderation analysis was conducted using regression analysis. Although the main focus of this test was an examination of a moderation role, it is worth pointing out the direct effect of channel integration itself on customer experience. Model 5 in Table 5.11

shows that channel integration has a direct and positive effect on customer experience ($\beta = 0.575$, $t = 11.356$, $p < 0.001$).

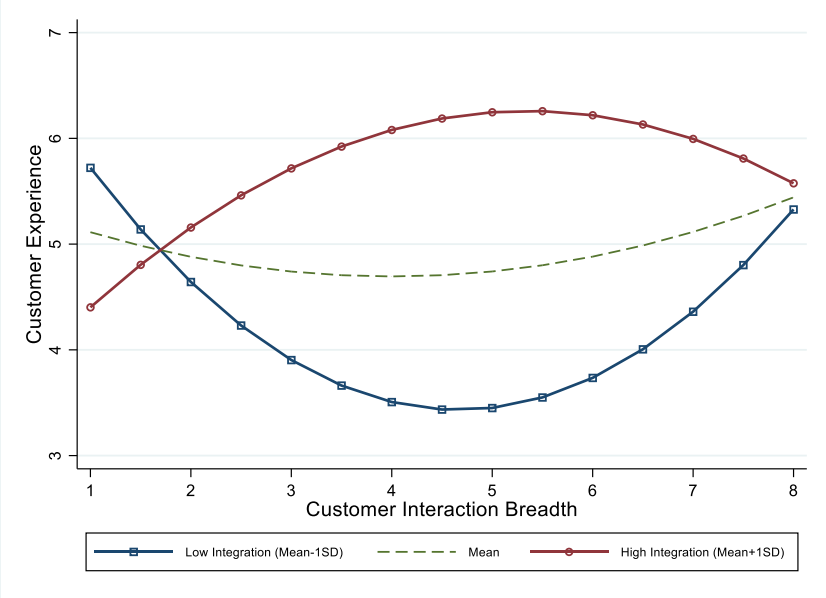
The researcher hypothesised that the relationship between breadth and customer experience is moderated by channel integration in a way that the U-shaped relationship is retained at the low level of channel integration but attenuated at the high level of channel integration, creating an inverted U-shaped relationship instead. To test the significance of the moderating effect, both interaction terms were added to Model 5. The beta coefficient of Channel Integration x Breadth could identify whether there is a shift in the turning point of breadth, while the beta coefficient of Channel Integration x $Breadth^2$ could indicate whether there is a change in the shape of the curve (Haans et al., 2016).

The result of the regression analysis shows that the interaction term between Channel Integration x Breadth is found to be positive and significant ($\beta = 0.547$, $t = 8.969$, $p < 0.001$), while the interaction term between Channel Integration x $Breadth^2$ is found to be negative and significant ($\beta = -0.374$, $t = -6.177$, $p < 0.001$). The former signifies that the turning point has shifted, while the latter indicates that the curve is flattening. The introduction of interaction terms shifts the turning point of breadth from the value of 5.989 to 4.794.

In order to assess whether the flattening curve would eventually lead to turning the shape from a U-shaped relationship to an inverted U-shape, the researcher had to determine the meaningful values of the moderator (Haans et al., 2016). Two values were set to identify the relationship at two different points: low level and high level of Channel Integration. The values were computed +/- 1 standard deviation to denote high level/low level of Channel Integration. An additional mid-point was added as a comparison, set at the mean value of Channel Integration. A two-way interaction graph was plotted to visualise the interaction, as seen in Figure 5.3. From the figure, it is clear

to see that the effect of Breadth on Customer Experience is different between retailers who were perceived to have low Channel Integration versus those who were perceived to have high Channel Integration. This provides evidence that, as the level of Channel Integration increases, the curve is flattening to a certain point that it flipped its shape from a U-shaped into an inverted U-shaped.

Figure 5.3 Two-way interaction between Breadth and Channel Integration



Channel Integration x Depth

Although this thesis does not hypothesise the moderating role of Channel Integration in the relationship between Depth and Customer Experience, the effect is tested as seen in Model 5 in Table 5.11. As predicted, there are no significant effects found at the interaction term of Channel Integration x Depth ($\beta = 0.005$, $t = 0.0941$, $p = 0.925$), as well as Channel Integration x Depth^2 ($\beta = 0.010$, $t = 0.170$, $p = 865$). The results suggest that Channel Integration neither changes the strength nor the relationship pattern of Depth on Customer Experience. There is no significant shift in the turning point and there is no significant change in the curve's shape.

5.8.2.1 Analysis of the significance of each point in the curvilinear of two groups based on channel integration

As discussed in the moderating analysis, more evidence needs to be gathered to prove the positive or negative returns of Breadth in Low Integration and High Integration groups. To do this, a similar approach as the previous section was used where the researcher created categorical dummies and tested the significance of each dummy. To assist the researcher in creating benchmark ranges for both groups, the *utest* command was once again performed on STATA (see Lind and Mehlum, 2010), to identify the turning points for Breadth and Depth.

In the group of low Channel Integration, the turning point for Breadth lies at a value of 4.7, making dummy Breadth of 4 – 5 channels set as a benchmark range. Three other categorical dummies were created to account for 1 channel, 2 – 3 channels, and 6 – 8 channels. Meanwhile, the turning point for Depth lies at a value of 119, 5 which is included in the range of dummy Depth 86 – 215. Four other categorical dummies were then created to account for Depth 5 – 30, 31 – 55, 56 – 85, and 216 – 245. The regression analysis result shows that there are no significant returns for both Breadth and Depth in Low Integration group. The only significant result comes from Dummy Breadth 1 channel ($\beta = 0.592$, $t = 3.551$, $p < 0.001$), Dummy Depth 5 – 30 ($\beta = -0.740$, $t = -4.642$, $p < 0.001$), and weak support for Dummy Depth 31 – 55 ($\beta = -0.238$, $t = 1.887$, $p < 0.1$). All signs for breadth were positive as intended, and all signs for depth were all negative as intended, however, there no significant returns beyond the reference point.

In the group of high Channel Integration, the turning point for Breadth lies at a value of 3.33 while the turning point for depth is at 131. Since there were only 76 observations in our data that fit into the description of high Channel Integration, some cases were absent, such as no observation for 1 channel, and all other channels more than 5.

Dummy Breadth 3 – 4 was set as a benchmark range, and two other categorical dummies were created for 2 channels and 5 channels. Meanwhile, six categorical dummies were created for Depth: 5 – 30, 31 – 55, 56 – 85, 86 – 115, 116 – 185 (benchmark point), and 186 – 215. In this group, both Breadth and Depth were expected to have an inverted U-shaped relationship to customer experience; hence all parameters for dummies were expected to be negative. This is shown in the result, except for Dummy Depth 186 – 215. Again, there is no support for negative returns both for Breadth and Depth. Some significant points are found at Dummy Depth 5 – 30 and Dummy Depth 31 – 55. The visualisation of these results can be seen in Appendix C.3.

5.8.3 Control variables

None of the control variables has a significant effect on Customer Experience, with the exception of Age. Age has a direct negative effect on customer experience which is significant at $p < 0.1$ ($\beta = -0.059$, $t = -1.746$). This finding indicates that younger respondents rate customer experience higher than the older group. All details regarding the hierarchical regression analysis and their model fit are presented in Table 5.11.

5.8.4 Additional robustness tests

5.8.4.1 The endogeneity tests

The endogeneity concern commonly emerges in many areas of marketing research, of which the main focus is to obtain causal inferences using regression-based analyses (Jean et al., 2016; Zaefarian et al., 2017). In some cases, a reverse causality occurs where the main explanatory variable or independent variable is reversely caused by the dependent variable. In other cases, the independent variable may be related to another variable (a third variable) that partially explains the variation of the dependent variable (Jean et al., 2016). In this instance, there could be a risk of providing inconsistent estimates, which appear when the independent variable correlates with residuals of a specified model (Rutz and Iv, 2019). Endogeneity, therefore, may influence

misinterpretation of conclusions regarding hypothesised relationships between variables in the specified model, which may render incorrect theoretical and managerial implications (Semadeni et al., 2014; Zaefarian et al., 2017).

The findings in this particular study carry the risk of endogeneity due to plausible reverse causality. Customer interaction breadth and depth may be reversely caused by customer experience, especially because both independent and dependent variables were collected simultaneously. In order to eliminate the risk of endogeneity, we conducted three-stage least squares (3SLS) using an instrumental variable. In 3SLS, the instrumental variable is usually the moderating variable. However, a good instrumental variable is supposed to be strongly related to the independent variables but unrelated to the dependent variable.

For this reason, our moderator—channel integration—is not the ideal variable to be applied as the instrumental variable (see Gao et al., 2021). Due to this condition, we decided to use another variable as the instrumental variable, namely extraversion. Extraversion is one of the customers' personality traits characterised by the attributes such as being sociable, energetic, and enthusiastic (Costa and McCrae, 1992). This personality trait is related closely to market mavenism (Steenkamp and Maydeu-Olivares, 2015), which suggests the tendency to influence others, not because of the expertise but because of motivation to share information and experience (Feick and Price, 1987). We perceive there is a stronger synergy between extraversion and omnichannel customer interaction than its relation to customer experience; these individuals like to interact and enjoy the opportunity to acquire more experience by using higher complexity in their journey.

In the first stage, Breadth is regressed against Extraversion to assess the relationship between the two variables and obtain residuals for Breadth that exclude the effect of Extraversion. The same procedure was conducted for Depth, as well as the quadratic

term of Breadth and Depth. From each regression analysis, the regression residual was saved. We checked the relevance of the chosen instrument variable by inspecting the F statistic in this first stage against the threshold of 8.96 according to Stock et al. (2012). The results shows that the instrumental variable passed the relevance test (Breadth: $F_{(1,483)} = 10.054$, $p < 0.001$); Depth: $F_{(1,483)} = 50.899$, $p < 0.001$), so we proceed to the next stage. In the second stage, the residuals of Breadth and Depth, including their quadratic terms, were employed as independent variables to examine their effect on customer experience. In the third stage, four interaction terms were entered into the model as predictors of customer experience. We use mean-centred variables in the computation of the interaction terms to avoid collinearity issues.

Table 5.14 Test of Endogeneity

	Model 1		**Model 2**		**Model 3**	
Control variables	**β**	**t**	**β**	**t**	**β**	**t**
Spending per trip	-0.009	-0.206	-0.013	-0.306	-0.020	-0.587
Length of tenure	-0.119	-2.683 **	-0.096	-2.170 *	-0.070	-1.880 †
Income	-0.035	-0.803	-0.021	-0.501	-0.028	-0.792
Age	-0.109	-2.472 *	-0.093	-2.120 *	-0.091	-2.521 *
Gender	0.099	2.346 *	0.098	2.355 *	0.065	1.855 †
Linear						
$Breadth_{residual}$	-0.411	-6.251 ***	-0.535	-6.899 ***	0.055	0.706
$Depth_{residual}$	0.482	7.223 ***	0.602	7.802 ***	0.311	4.595 ***
Quadratic						
$Breadth_{residual}$			0.237	3.328 ***	0.068	1.035
$Depth_{residual}$			-0.205	-2.827 **	-0.289	-4.656 ***
Moderating effect						
Channel Integration					0.417	11.059 ***
$Breadth_{residual}$ x C.Integration					0.579	8.794 ***
$Depth_{residual}$ x C.Integration					-0.394	-6.970 ***
$Breadth_{residual}$ x C.Integration					0.025	0.402
$Depth_{residual}$ x C.Integration					0.010	0.176
Model fit						
R^2		0.17		0.191		0.450
ΔR^2				0.02		0.259
F		13.989		12.435		27.468
ΔF				5.975 **		44.320 ***

Note: ***= 0.001; ** = 0.01; * = 0.05; † = 0.1

The results in Table 5.14 show that both curvilinear effects of Breadth and Depth remain the same as the initial analysis (Model 2) as well as the interaction effects, in which case, only $Breadth_{residual}$ x C.Integration and $Breadth2_{residuals}$ x C.Integration influence customer experience significantly. In conclusion, we can rule out the possible endogeneity concern in this study because the results duplicate the original findings.

5.8.4.2 Stability of customer interaction effect on customer experience

Alternative operationalisation of customer interaction depth

We replicated the curvilinear effect of customer interaction on customer experience using different operationalisation of Depth in order to test the stability of the effects. In Model 1, instead of using the accumulation of frequencies that carry the influence of channel variety, we tested Depth as the multiplication between a variety of activities and the average frequency of all possible activities. The regression result showed a consistent finding as the original version: a U-shaped relationship to customer experience for Breadth ($\beta_{Breadth} = -0.589$, $t = -8.910$, $p < 0.001$; $\beta_{Breadth2} = 0.291$, $t = 4.643$, $p < 0.001$) and an inverted U-shaped effect of Depth ($\beta_{Depth} = 0.821$, $t = 12.783$, $p < 0.001$; $\beta_{Depth2} = -0.280$, $t = -4.406$, $p < 0.001$). In Model 2, we calculated Depth as a function of the sum of frequency divided by the variety of channels used. This model revealed a positive linear effect of Depth on Customer Experience ($\beta_{Depth} = 0.538$, $t = 13.018$, $p < 0.001$) and a negative beta coefficient of quadratic term of $Depth^2$ ($\beta_{Depth2} = -0.032$, $t = -0.822$, $p > 0.05$) albeit a non-significant one. The last model also changed the effect of Breadth on Customer Experience, where both linear and quadratic terms were found to be nonsignificant predictors.

Table 5.15 Alternative operationalisation of customer interaction depth

DV: Customer Experience	**Model 1: Variety of activities x Average of frequency**			**Model 2: Σ frequency / Σ channel used**		
Control variables	**β**	**t**		**β**	**t**	
Spending per trip	-0.034	-0.891		-0.035	-0.907	
Length of tenure	-0.044	-1.084		-0.045	-1.098	
Income	-0.007	-0.177		-0.015	-0.393	
Age	-0.057	-1.422		-0.050	-1.241	
Gender	0.064	1.662	†	0.045	1.176	
Linear						
Breadth	-0.589	-8.910	***	0.077	1.487	
Depth	0.821	12.783	***	0.538	13.018	***
Quadratic						
Breadth	0.291	4.643	***	0.062	1.224	
Depth	-0.280	-4.406	***	-0.032	-0.822	
Model fit						
R^2		0.567			0.571	
F		24.995	***		25.571	***

Note: ***= 0.001; ** = 0.01; * = 0.05; † = 0.1

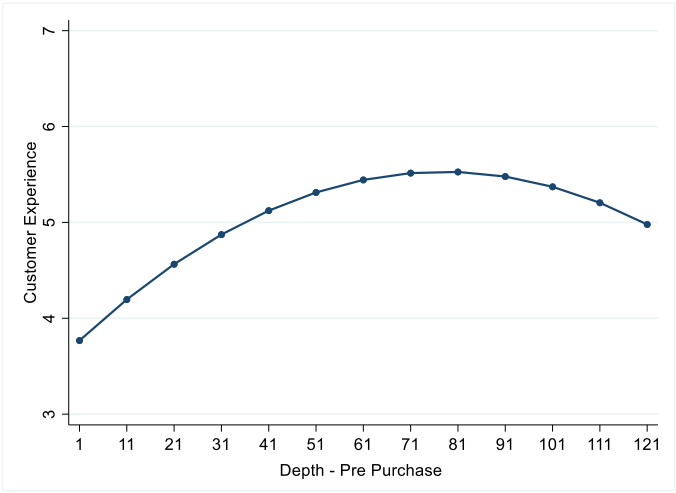
The effect of customer interaction depth on customer experience at different purchase stages

The second test to examine the stability of customer interaction effect on customer experience was done by breaking down the independent variable of customer interaction depth into three new variables based on purchase stages. Nineteen customer activities listed in Table 5.1 were classified into three purchase stages: pre-purchase, purchase, and post-purchase stages. Using the similar operationalisation as Depth, we computed the frequency of customer activities belong to each purchase stage. These three new variables acted as customer interaction depth, and together with customer interaction breadth, they became the predictors of customer experience. Hierarchical regression was conducted to test the linear and curvilinear effect of three variables of Depth (Pre-Purchase, Purchase, and Post-Purchase). Model 2 shows the curvilinear estimates from a significant model, where $F_{(13, 471)} = 19.66$, $R^2 = 0.352$, $p < 0.001$. While Breadth retained its U-shaped effect on customer experience, there was a slight variation in the

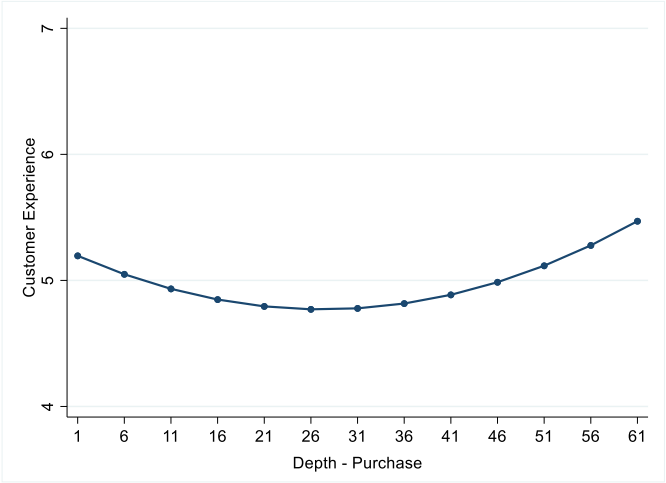
effect of Depth on customer experience, as shown in Figure 5.4. The customer interaction depth at Pre-Purchase and Post-Purchase stages have a significant inverted U-shaped relationship on customer experience ($\beta_{Pre\text{-}Purchase}$ = 0.843, t = 3.510, p < 0.001; $\beta_{Pre\text{-}Purchase2}$ = -0.572, t = -2.590, p < 0.001; $\beta_{Post\text{-}Purchase}$ = 0.814, t = 4.760, p < 0.001; $\beta_{Post\text{-}Purchase2}$ = -0.463, t = -2.680, p < 0.001). Meanwhile, customer interaction depth at Purchase stage only shows a weak significant negative linear effect on customer experience, but nonsignificant quadratic effect ($\beta_{Purchase}$ = -0.276, t = -1.660, p < 0.1; $\beta_{Purchase2}$ = 0.261, t = 1.530, p > 0.1). Details on the findings can be seen in Appendix C.4.

The results further elaborate on our initial finding regarding customer interaction depth. Frequencies and variety of activities within pre-purchase and post-purchase stages contribute to the superior customer experience at a moderate level. The key is balancing the level of depth at these stages so that customers are well informed about their purchase, confident enough to make a purchase (at the pre-purchase stage), and effective enough to resolve issues or engage in post-purchase activities. The negative linear effect of depth at the purchase stage signals the importance of the efficiency of purchase procedures. Simplification of the checkout process and product fulfilment should be the highlight within this stage. However, this perhaps has something to do with the product category or the chosen retail sector. As grocery and apparel, in this case, are quite low-involvement and low-risk, customers experience is gained from simple interaction at the purchase stage. In a different condition, such as high-involvement or high-risk product purchase, customers may be willing to engage in more activities to ensure that the purchase fulfils their expectations.

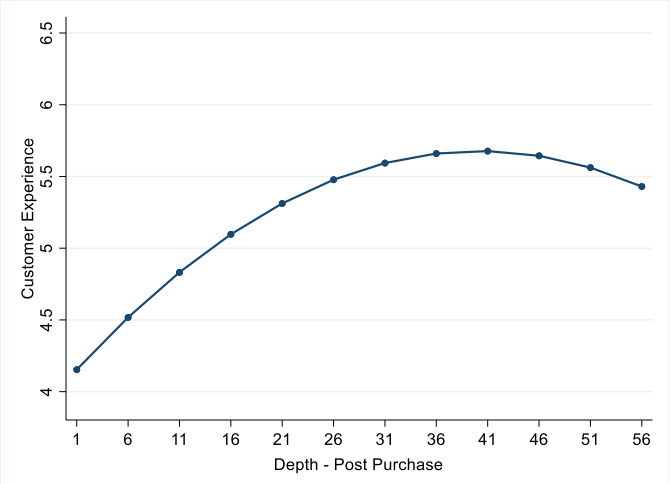
Figure 5.4 Depth on customer experience at different purchase stages: (a) pre-purchase, (b) purchase, and (c) post-purchase stage



(a)



(b)



(c)

5.8.4.3 The interaction effect of customer interaction breadth and depth on customer experience

An interaction effect was tested between two independent variables, Breadth and Depth. In the main hypothesis, we have tested the coexistence of Breadth and Depth and how individually they influence customer experience. As an additional test, we conducted a moderation test to explore the interaction effect between the two variables. We ran regression analyses and created an interaction term using mean-centred Breadth and Depth. In Model 1 at Table 5.16, a significant model was emerged, where $F_{(8,476)} = 22.33$, $R^2 = 0.273$, $p < 0.001$. The linear effects of Breadth and Depth were significant predictors ($\beta_{Breadth} = -0.446$, $t = -5.160$, $p < 0.001$; $\beta_{Depth} = 0.791$, $t = -8.180$, $p < 0.001$). However, the interaction term was found to be nonsignificant ($\beta_{Depth} = -0.149$, $t = -1.130$, $p > 0.05$).

Table 5.16 Interaction effect of Breadth and Depth

DV: Customer Experience	**Model 1: Using the original Depth**			**Model 2: Using variety of activities**		
Control variables	**β**	**t**		**β**	**T**	
Spending per trip	-0.026	-0.650		-0.013	-0.330	
Length of tenure	-0.084	-2.010	*	-0.085	-1.960	*
Income	-0.030	-0.730		-0.037	-0.880	
Age	-0.090	-2.190		-0.099	-2.320	**
Gender	0.065	1.650	†	0.093	2.290	**
Main effect						
Breadth	-0.446	-5.160	***	-0.523	-2.210	**
Depth	0.791	8.180	***	0.270	3.220	***
Interaction effect						
Breadth x Depth	-0.149	-1.130		0.501	1.890	†
Model fit						
R^2		0.273			0.225	
F		22.33	***		17.3	***

Note: ***= 0.001; ** = 0.01; * = 0.05; † = 0.1

Another regression analysis was conducted, but we employed a different operationalisation of Depth (Model 2). Instead of using the original operationalisation of Depth, we excluded the element of frequency and only used the variety of activities. The aim was to investigate whether the effect of Breadth on Customer Experience would be different depending on the variety of activities. The result suggested that the interaction term between Breadth x Variety of Activities was significant at $p < 0.1$ ($\beta_{Interaction} = 0.501$, $t = 1.890$, $p < 0.1$). The effect was weak; however, we further explore this interaction in the next section related to customer interaction typology.

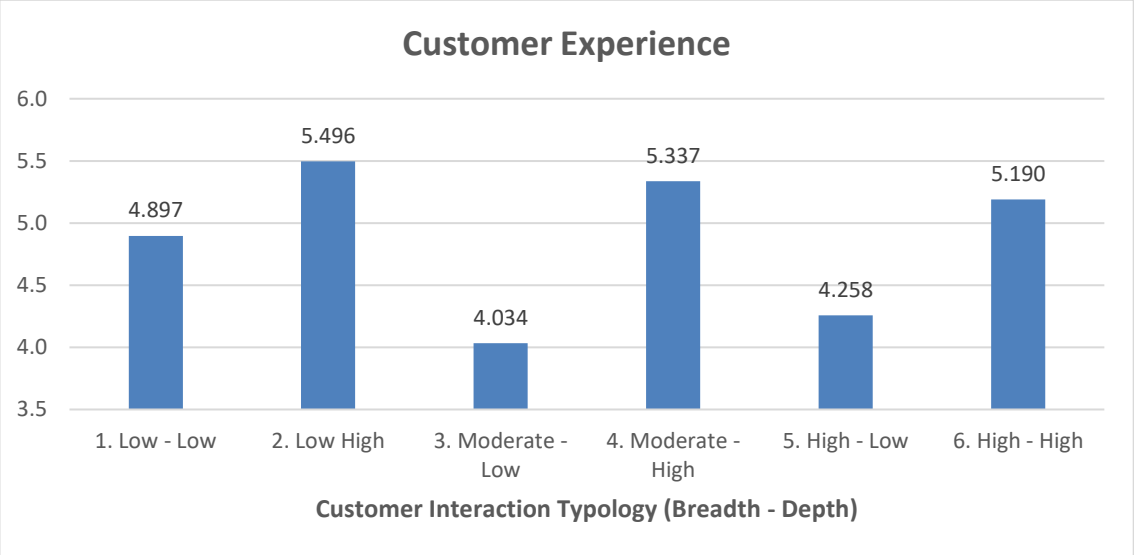
5.8.4.4 The typology of customer interaction

To follow up findings from previous moderation analyses, we further extend the interaction effect of Breadth and Variety of Activities (Depth_Alternative) by created six distinct profile constructs. Two levels of Depth_Alternative were established using the mean-split method ($\bar{x}_{Depth\_Alternative} = 16.19$). Low Depth was, therefore, consisted of a variety of activities 1 – 16. The remaining levels were, therefore, included as High Depth. In a slightly different fashion, we divided Breadth into three levels: Low, Moderate, and High. We used the $\bar{x}_{Breadth}$ (2.8) as our guide to set the cut-off point. We classified a single channel as Low Breadth, 2 – 3 channels as Moderate Breadth, and 4 – 8 channels as High Breadth. These three categories aimed to mimic the actual condition in the real world where single-channel customers were being compared to omnichannel customers. Moreover, creating three groups of Breadth enable us to retain the curvilinearity of Breadth as we suggested in the main hypotheses. As a result, six profile constructs emerged as a combination of Breadth-Depth: (1) Low-Low, (2) Low-High, (3) Moderate-Low, (4) Moderate-High, (5) High-Low, and (6) High-High.

We conducted a one-way ANOVA to determine differences between profile constructs. First, a Levene test of equality of error variance was run initially, resulting in $F_{(5, 479)} = 3.866$, $p = 0.002$, signifying that the assumption of homogeneity of variances was

violated. Hence, we were using the Welch statistic from the robust test of equality of means to determine whether there was a significant difference between profiles (Welch = 22.271, $p < 0.001$). A significant Welch statistic indicated the presence of significant differences between profiles, and the post-hoc comparison using the Games-Howell test revealed four profile constructs were significantly different. The visualisation of the result can be seen in Figure 5.5.

Figure 5.5 Customer Interaction Typology and Customer Experience



The mean score for profile 3 ($M_3 = 4.034$) were the lowest amongst all other profiles but significantly lower compared to profile 1 ($M_1 = 4.897$, $p < 0.01$), 2 ($M_2 = 5.496$, $p < 0.001$), 4 ($M_4 = 5.337$, $p < 0.001$), and 6 ($M_6 = 4.897$, $p < 0.001$). In general, the variety of activities were deemed to be the one that drives the level of customer experience because all profiles with High Depth exhibit a higher customer experience score than the Low Depth counterpart. However, it is interesting to see the difference between profile 1 versus profile 3, in which cases both Depth levels were low. In this instance, the single-channel experience was higher than the multiple-channel experience, reiterating that complex interaction is not necessarily superior. Profile 1, where both Breadth and Depth are low, can be seen as the type of customer interaction that emphasises simplicity and efficiency in the customer journey.

5.9 Discussion

Study 1 reveals the baseline relationships between dimensions of customer interaction complexity and customer experience. The regression results showed evidence on the nonlinear prediction of the relationship: a U-shaped relationship between customer interaction breadth and customer experience (H_1) and an inverted U-shaped relationship between customer interaction depth and customer experience (H_2). These results are further supported by all but one post-hoc test. The test of the significance of each point in the curvilinear (see 5.8.1.4) suggests that our dataset could not provide empirical support for the positive return (for customer interaction breadth) and the negative return (for customer interaction depth). It highlights the limitation in Study 1 that the survey dataset is skewed towards the lower level of breadth.

Additionally, this first study stipulates evidence for a prominent role of channel integration in changing the relationship between customer interaction breadth and customer experience (H_3). High channel integration gives retailers a more positive customer experience when customers deal with a low to a moderate number of channels, which is the majority of the observations. Meanwhile, at retailers who have less integrated channels, the effect of breadth on customer experience is negative when customer interaction breadth at low to moderate levels.

5.10 Summary

Study 1 investigated the influence of customer interaction complexity which has two dimensions, customer interaction breadth and customer interaction depth, on customer experience. Using grocery retail and fashion retail as the focus of data collection, Study 1 confirmed the nonlinear nature of the relationship between customer interaction complexity and customer experience (H_1 and H_2). Additionally, Study 1 provides empirical evidence on the moderating role of channel integration in changing the relationship between customer interaction breadth and customer experience (H_3). In

Study 2, the researcher aims to replicate the curvilinear relationship between customer interaction depth and customer experience. Moreover, the conditions and processes under which this curvilinear relationship occurs are examined. The hypotheses will be tested using a causal research design, implementing an experimental study design.

Chapter 6 The role of channel type in the relationship between customer interaction depth and customer experience (Study 2: H_4 – H_6)

6.1 Introduction

Study 2 closely examined the relationship between customer interaction depth and customer experience. First, this study aims to confirm the finding of an inverted U-shaped relationship between depth and customer experience (H_2), as found in Study 1. Second, it also aims to provide evidence of the causal relationship between customer interaction depth and customer experience. Third, it addresses a deeper understanding under what conditions the effect of customer interaction depth on customer experience can be strengthening or otherwise (H_4). Fourth, it seeks to explain the underlying mechanism of the inverted U-shaped relationship by testing customer effort and customer enjoyment as mediators (H_5 and H_6). A series of hierarchical regression analysis, one-way ANOVA, and the test of instantaneous indirect effect were conducted to test the hypotheses.

6.2 Overview of methodology

Taking some discussion from Chapter 4, Study 2 employed a factorial between-subject design. As mentioned previously, an independent variable was tested (Depth) together with a moderating variable (channel type), resulting in a factorial research design. Hence, this study employed a 3x 2 ([Depth: low versus moderate versus high] x [Channel type: offline versus online]) between-subject design. The sample was drawn from the same population as other studies in this research project, using the online crowdsourcing platform MTurk with an online questionnaire designed using Qualtrics. This section discusses the operationalisation of variables, data collection strategy and participants' profile, the design, and the procedure of the experiment.

6.2.1 Operationalisation of variables

The independent variable, Depth, was operationalised by manipulating the number of activities in a participant's shopping journey. Three levels of Depth representing low level, moderate level, and the high level were set at three activities, six activities, and nine activities, respectively. The activities listed in the scenario were adapted from the initial Study 1 (see 5.3.2 Customer interaction depth). The moderator, channel type, was manipulated by applying either two types of channels, offline or online.

The operationalisation of customer enjoyment and customer effort, as mediators, were adapted from Franke and Schreier (2010). In particular, customer enjoyment was also adapted from an established scale of Intrinsic Motivation Inventory (see http://www.psych.rochester.edu/SDT). To measure customer enjoyment, respondents were asked: "How much do you enjoy your interaction with Wearable Goods?". The respondents rated this question using a seven-point Likert scale, anchored from 1 = *Not at all enjoy* to 7 = *Very much enjoy*. To measure customer effort, respondents were asked "How much effort do you need to spend when interacting with Wearable Goods?". Similarly, respondents rated this question using a seven-point Likert scale, anchored from 1 = *Very little effort* to 7 = *A great deal of effort*.

Additionally, five variables were measured as control variables. Aligned with Study 1, three customer characteristics were used: age, gender, and income. All of these customer characteristics were measured using multiple-choice options similar to the type of measure used in Study 1. Two new control variables in Study 2 were online shopping frequency and an attitude toward fashion shopping. The online shopping frequency was measured using seven-point Likert scale item from 1 = *Never* to 7 = *Very Frequent*: "How frequently do you shop fashion items online?". To measure customer attitude toward fashion shopping, participants had to rate from a scale 1 to 7 a question of "In general, how much do you like shopping for fashion items?", where 1 represents

Very much like it and 7 represents *Very much dislike it.* The summary of measures used in Study 2 can be seen in Table 6.1 below.

Table 6.1 Summary of measures in Study 2

Measure	Item(s)	Type of measure and anchoring
Customer experience	Consistent with Study 1, see section 5.3.3	Likert scale
Customer enjoyment	How much do you enjoy your interaction with Wearable Goods?	Likert scale 1 = Not at all enjoy 7 = Very much enjoy
Customer Effort	How much effort do you need to spend when interacting with Wearable Goods?	Likert scale 1 = Very little effort 7 =A great deal of effort
Manipulation checks	In your interaction with Wearable Goods, how many activities do you usually perform?	Multiple choice: 1 to 9 activities
	In your interaction with Wearable Goods, what type of channel did you use?	Multiple choice: a. Online channel b. Brick-and-mortar store
Online shopping frequency	How frequent do you shop fashion items online	Likert scale 1 = Never 7 =Very Frequent
Attitude towards fashion shopping	In general, how much do you like shopping for fashion items	Likert scale 1 = Very much like it 7 = Very much dislike it
Gender	Consistent with Study 1, see section 5.3.6	Multiple choice: see section 5.3.6
Age		
Income		

Two manipulation check questions were used to measure how participants perceived the level of Depth and how well they recognise the type of channel. First, participants had to indicate an answer to question "In your interaction with Wearable Goods, how many activities do you usually perform?". To answer this, participants choose a number between 1 to 9. Second, participants had to choose between (a) *an online channel* or (b) *a brick-and-mortar store* as an answer to the question "In your interaction with Wearable Goods, what type of channel did you use?".

6.2.2 Data collection and participants

Participants were recruited using Amazon M-Turk, and they were financially compensated for participating in the study. The length of the study is less than 5 minutes, and participants received $.70 in return. The location of participants was restricted to the United States, and the minimum number of tasks were retained at 50. This number means that M-Turk worker can only participate in the study if they have completed 50 tasks in the past. Initially, 312 responses were collected, but eleven of them were excluded from the study due to failing multiple attention checks. As a result, 301 responses were used for further analyses. These responses were equally distributed across six experimental conditions, as seen in Table 6.2.

Table 6.2 Distribution of respondents on Study 2

		Depth		
		Low	*Moderate*	*High*
Channel type	*Offline*	50	50	50
	Online	50	51	50

The demographic profile of participants is similar to two previous studies. Male was a slight majority group (N = 174, 57.8%) compare to female. Two largest age groups were 25 – 34 years old (N = 108, 35.9%) and 35 – 44 years old (N=110, 36.5%). The participants were dominated by those who hold a bachelor degree; this group accounted for 48.2% of the sample, followed by some college but no degree (19.6%), and graduate

degree (11.6%). More than half of the participants identified themselves as a full-time employee (N = 233, 77.4%). The range of annual income of $50,000 - $74,999 was the largest group (23.6%) and those below $9,999 having the smallest proportion (4.7%). The summary of respondents' characteristics can be found in Table 6.3.

Table 6.3 Respondent profile in Study 2

Demographic		N	%
Gender	Male	174	57.8%
	Female	127	42.2%
Age Group	18 – 24	9	3.0%
	25 – 34	108	35.9%
	35 – 44	110	36.5%
	45 – 54	45	15.0%
	55 – 64	21	7.0%
	65 and over	8	2.7%
Education level	Less than high school degree	1	0.3%
	High school degree or equivalent (e.g., GED)	32	10.6%
	Some college but no degree	59	19.6%
	Associate degree	29	9.6%
	Bachelor degree	145	48.2%
	Graduate degree	35	11.6%
Occupation	Employed full time	233	77.4%
	Employed part-time	34	11.3%
	Unemployed looking for work	6	2.0%
	Unemployed not looking for work	15	5.0%
	Retired	11	3.7%
	Student	2	.7%
Income	Below $9,999	14	4.7%
	$10,000 to $19,999	35	11.6%
	$20,000 to $34,999	53	17.6%
	$35,000 to $49,999	56	18.6%
	$50,000 - $74,999	71	23.6%
	$75,000 to $99,999	35	11.6%
	over $100,000	37	12.3%

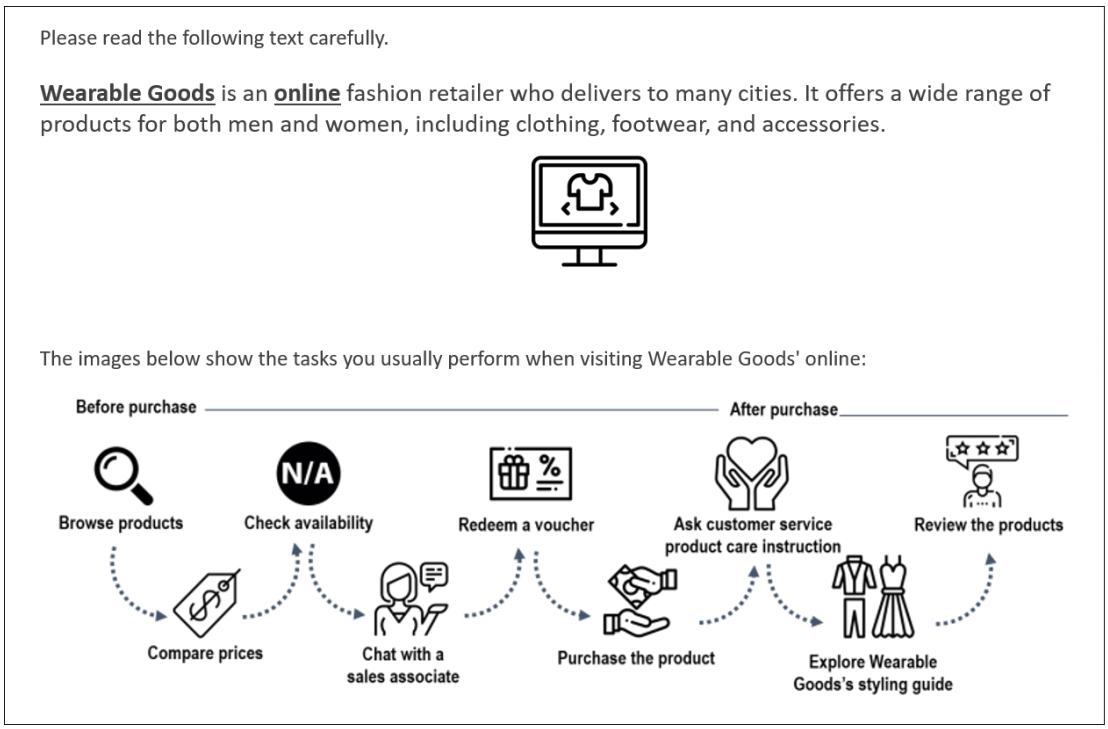
6.2.3 Design

Study 2 employed a 3 x 2 ([Depth: low versus moderate versus high] x [Channel type: offline versus online]) between-subject design. Low Depth condition consists of three activities, while moderate and high Depth consists of six and nine activities,

respectively. All activities used in the scenario had a neutral tone which means some unsatisfactory activities such as “return a product” or “complain about an issue” were excluded. Additionally, the activities described across conditions captured the essence of shopping journey that involve search, purchase, and after purchase. Hence, in no condition participant would experience an incomplete shopping journey.

Consistent with Study 2, an imaginary fashion retailer called *Wearable Goods* was used as the retailer of interest. In each condition, a participant would read a text that presented *Wearable Goods* as either an offline-only retailer or online-only retailer. This information was reinforced by an image of either a stand-alone store or a computer screen representing an online store. A breakdown of shopping activities was followed thereafter, which is explained by short sentences and images in Figure 6.1, for the full script please refer to Appendix D.

Figure 6.1 Example of a script for depth experimental study



6.2.4 Procedure

Participants started the study by reading general information about the study, contact information of the researcher, and the consent statement. The first page that followed was an attention check page, on which participants had to type-in a specific colour in a provided textbox. Next, a participant would be assigned to one out of six conditions described in the previous section. Once they had finished reading the assigned scenario, a participant had to fill out a short questionnaire about perceived effort, perceived enjoyment, customer experience, and manipulation checks. The second attention check question was put in the middle of this questionnaire. In the end, some demographic questions related to gender, income, age, education level and occupation were included.

6.3 Preliminary analysis

6.3.1 Reliability test

A reliability test was conducted on multi-items constructs of which these are cognitive experience, affective experience, behavioural experience, sensory experience, and social experience. All other constructs were single-item constructs. The minimum Cronbach α coefficient's threshold of 0.7 – 0.8 was used to signify whether a construct is reliable (Hair et al., 2014; Nunnally, 1978). The result shows that the Cronbach α coefficient range between 0.843 – 0.945 indicates that all constructs were reliable.

Once the reliability of the constructs was established, we were able to create a composite variable of customer experience. To test the reliability of customer experience, five experience constructs were treated as variable's items. The Cronbach α coefficient of customer experience was 0.869, exceeding the minimum threshold set in the beginning. This composite variable was used as a measure of customer experience throughout analyses in Study 2.

6.3.2 Descriptive statistics

A descriptive statistics analysis was conducted to obtain values of mean, standard deviation, skewness and kurtosis. The mean value provides an illustration of the central tendency of the data, while the standard deviation indicates the dispersion of the data. The summary of descriptive statistics and Cronbach's alpha is presented in Table 6.4.

Table 6.4 Descriptive statistics of variables in Study 2

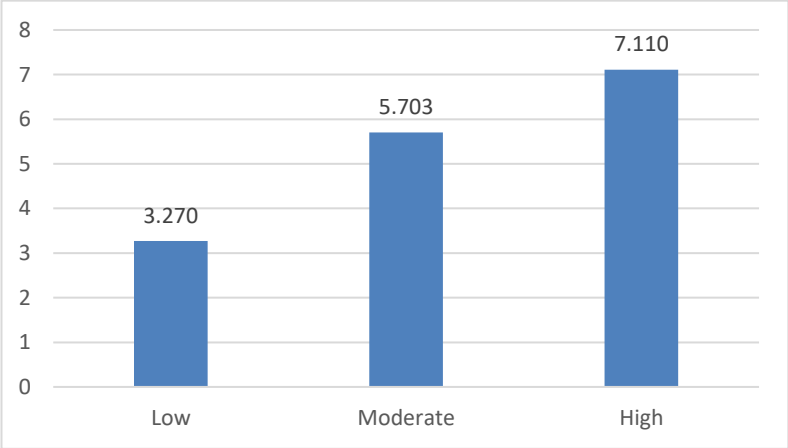
Construct	Number of items	Mean	SD	Skewness	Kurtosis	Cronbach α
Cognitive Experience	3	4.635	1.374	-0.715	-0.122	0.862
Affective Experience	3	3.902	1.558	-0.123	-0.830	0.931
Behavioural Experience	3	4.590	1.403	-0.549	-0.319	0.843
Sensory Experience	3	4.721	1.476	-0.787	-0.070	0.945
Social Experience	3	4.293	1.503	-0.418	-0.656	0.945
Customer Experience	5	4.428	1.186	-0.485	-0.056	0.869
Customer Effort	1	4.545	1.615	-0.306	-0.764	-
Customer Enjoyment	1	5.036	1.369	-0.717	0.407	-
Online Shopping Experience	1	4.694	1.641	-0.435	-0.811	-
Attitude towards fashion shopping	1	3.884	1.750	0.018	-0.957	-

From the table, it can be seen that the highest mean was found in customer enjoyment, 5.043, and the lowest mean was from the attitude toward fashion shopping, 3.884. The standard deviation of the latter variable was also found to be highest (1.750), indicating that the variation of data points was quite dispersed. However, the value was not extraordinarily high. Skewness and kurtosis provide information about the shape of the distribution of the data. It is usually utilised to signify how the data is distributed following a normal distribution. Using a maximum threshold of |2| for skewness and |7| for kurtosis (Kline, 2011; Finch et al., 1997), it can be concluded that there was no issue with the distribution of the data.

6.3.3 Manipulation checks

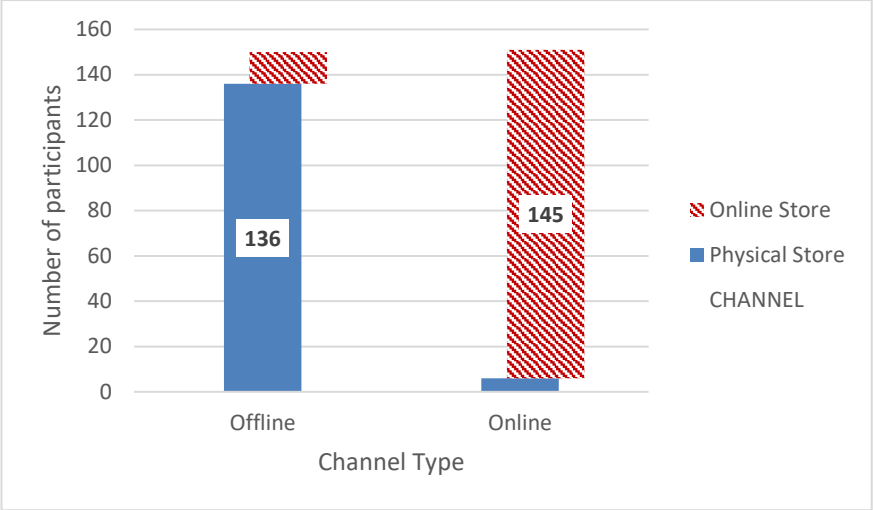
A manipulation check test was analysed using two-way ANOVA to find out whether participants' perceived level of depth was different across three levels as the researcher intended it to be. The results are shown in Figure 6.2 that participants in the low Depth condition rated their number of activities significantly the lowest among other groups (M_{Low} = 3.270, $M_{Moderate}$ = 5.703, M_{High} = 7.110, $p < 0.001$). Moreover, the difference between moderate depth and high depth was also significant ($p < 0.001$).

Figure 6.2 Manipulation check of depth experiment



A crosstab analysis was conducted to check whether participants could recall the type of channel they were assigned in the experiment. A Chi-square test indicated significant association between channel type and experiment condition, χ^2 (1, N = 301) = 226.944, $p < 0.001$, Phi coefficient = 0.868. The majority of participants were able to identify the type of channel they interacted with based on the scenario (see Figure 6.3). Lastly, we checked if participants perceived the scenario to be realistic or not. The average value for realism was 5.8704 (out of a 7-point Likert scale), and one sample t-test showed that this value was significantly different from the mid-point of 4.0 (t = 27.626, $p < 0.001$). More importantly, there were no significant differences across six conditions for realism ($p = 0.516$), indicating a uniform perception toward the realism of the scenario.

Figure 6.3 Type of channel in Study 2



6.4 Result

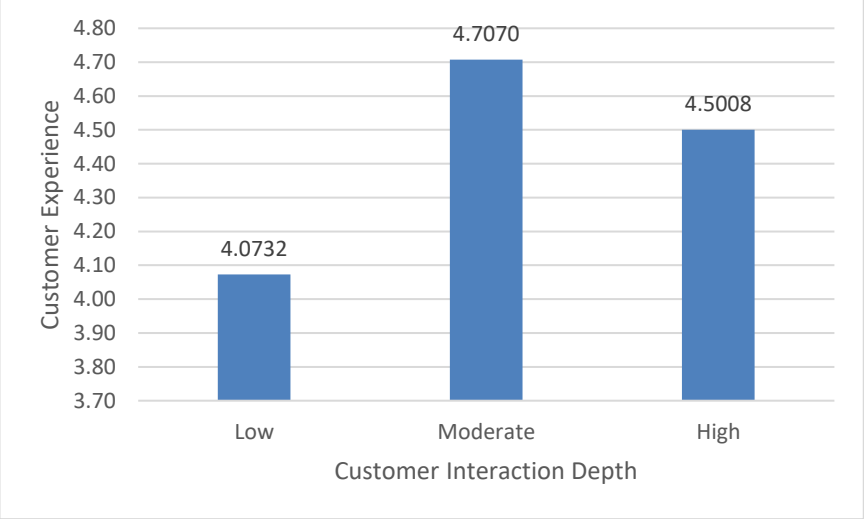
6.4.1 The relationship between depth and customer experience

A regression analysis was run to predict the relationship between Depth and Customer Experience. An inverted U-shaped relationship (H_2) was expected to be replicated, as found in Study 1. A quadratic term of depth ($Depth^2$) was created using a squared mean-centred value of depth to test the curvilinear relationship. Some control variables were added similar to Study 2, such as Gender, Income, Age, Online shopping experience, and an additional variable: Attitude toward fashion shopping. The result in Table 6.6 show that Depth affects Customer Experience positively and significantly ($\beta = 1.233$, $t = 3.205$, $p < 0.01$) while $Depth^2$ has a significant and negative effect on Customer Experience ($\beta = -1.101$, $t = -2.861$, $p < 0.01$). These were results presented by Model 3 (see Table 6.6) with the following model fit; Adjusted $R^2 = 0.103$, $F_{7,292} = 5.903$, $p < 0.001$. They imply the curvilinear relationship between constructs, specifically an inverted U-shaped.

Furthermore, a two-way ANOVA was used to test the differences between three different level of Depth, low, moderate, and high. A Levene test of equality of error variance was conducted prior to ANOVA, which showed a result of $F_{(2,306)} = 3.617$, $p =$

0.028, indicating that the assumption of homogeneity of variances was violated. Hence, further analysis was conducted using a Robust test of equality of means and utilised welch statistics to see the significant value.

Figure 6.4 Customer experience at three levels of depth



The expected result was that the moderate level would have the highest Customer Experience, which should significantly be higher than both low level and high level of Depth. An ANOVA revealed that there was a significant difference between groups ($F_{2,298} = 7.131$, $p < 0.001$). The post-hoc analysis using the Games-Howell test showed that a significant difference was found between the low and moderate group ($M_{Low} = 4.073$, $M_{Moderate} = 4.707$, $p < 0.001$). There was a marginal decrease in customer experience from the moderate to the high group, but no significant difference was found between them ($M_{Moderate} = 4.707$, $M_{High} = 4.501$, $p = 0.391$). Figure 6.4 depicts the results.

6.4.2 The moderation analysis of channel type

To test the moderating effect of channel types (H_4), two analyses were performed. Model 4 in Table 6.6 of the hierarchical regression analysis shows a significant model where $F = 6.870$, $p < 0.001$, Adjusted $R^2 = 0.640$. In this model, the interaction terms between Depth and Channel Types are significant at $p < 0.05$. First, the interaction term

of Depth x Channel Types has negative and significant value (β = -1.613, t = -2.063, $p < 0.05$) and $Depth^2$ x Channel Types has positive and significant value (β = 1.741, t = 2.331, $p < 0.05$). The significant values of both interaction terms indicates the presence of shape-flipping curves (Haans et al., 2016). However, it is necessary to follow this up further by incorporating the categorical values of offline and online channels into the model. To do this, data for the offline and online channel was split and a one-way ANOVA was performed for each group (Table 6.5). The mean plot shows a distinct shape of the curves between offline and online channel as seen in Figure 6.5. It can be inferred that the effect of Depth on Customer Experience takes an inverted-U shape for the offline channel, meanwhile it shows a positive linear effect for the online channel.

Table 6.5 One-way ANOVA result

		Customer Interaction Depth			Group Mean	F	Sig.
		Low	**Moderate**	**High**			
Offline	*Mean*	4.304	5.122	4.563	4.663	8.969	$p < 0.001$
	SD	1.150	0.846	0.939	1.038		
Online	*Mean*	3.842	4.300	4.439	4.195	3.067	$p < 0.05$
	SD	1.303	1.293	1.183	1.278		

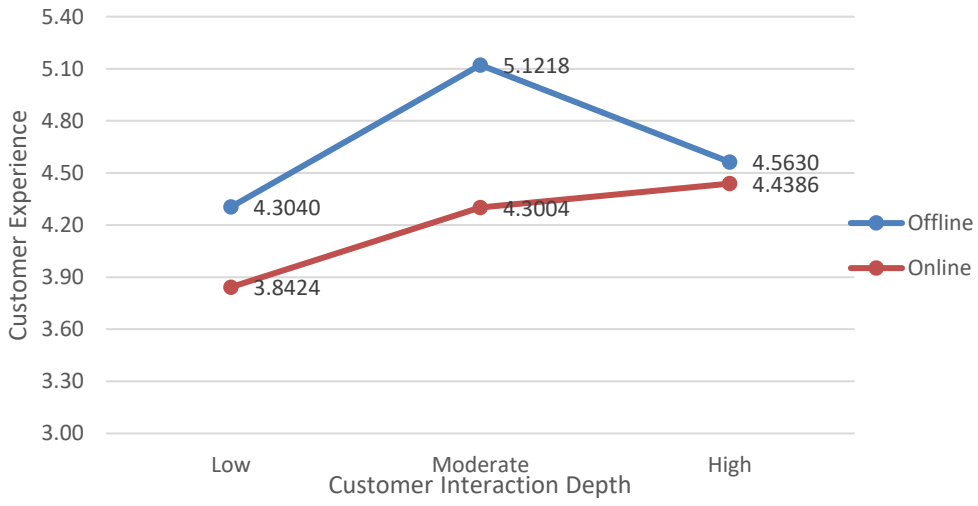
Table 6.6 Hierarchical regression results of Study 2

	DV: Customer Experience											
	Model 1			Model 2			Model 3			Model 4		
	β	t		β	T		β	t		β	t	
Online shopping frequency	0.253	4.333	***	0.247	4.259	***	0.239	4.163	***	0.269	4.823	***
Attitude fashion shop	-0.032	-0.561		-0.042	-0.741		-0.048	-0.843		-0.047	-0.859	
Gender	-0.096	-1.623		-0.098	-1.685	†	-0.104	-1.799	†	-0.096	-1.719	†
Age	-0.057	-0.970		-0.058	-0.999		-0.055	-0.960		-0.057	-1.017	
Income	0.005	0.093		0.009	0.159		0.003	0.062		-0.023	-0.428	
Depth				0.144	2.581	**	1.233	3.205	**	2.182	3.068	**
$Depth^2$							-1.101	-2.861	**	-2.237	-3.150	**
Channel type										-0.097	-0.770	
Depth x Channel type										-1.613	-2.063	*
$Depth^2$ x Channel type										1.741	2.331	*
Adjusted R^2		0.063			0.081			0.103			0.640	
Change in R^2					0.020			0.025			0.615	
F		5.039	***		5.391	***		5.903	***		6.870	***

Note: DV = dependent variable; ***= 0.001; ** = 0.01; * = 0.05; † = 0.1

To further assess each channel type, a post-hoc analysis was run to measure the significance of the differences between each level of Depth in respective channel type. This is pertinent to ensure whether the inverted-U shape curve for offline channel has a significant negative return. First, a Levene test of equality of error variance was conducted prior to ANOVA, which showed a result for Offline: $F_{(2,147)} = 2.033$, $p = 0.135$; for Online: $F_{(2,148)} = 1.271$, $p = 0.284$, indicating that the assumption of homogeneity of variances was not violated for both conditions. Table 6.5 shows that for the offline channel, there was a statistically significance difference at the $p < 0.001$ in Customer Experience scores for the three levels of Depth: $F_{2,147} = 8.969$, $p < 0.001$. Post-hoc comparisons using the Bonferroni test indicated that the mean score for moderate Depth is significantly higher in comparison to the low and the high levels of Depth ($M_{Low} = 4.3040$, $M_{Moderate} = 5.1218$, $p < 0.001$; $M_{Moderate} = 5.1218$, $M_{High} = 4.563$, $p < 0.001$). For the online channel, there was also a significant difference between groups ($F_{2,148} = 3.067$, $p < 0.05$). More specifically, a Bonferroni test revealed that a difference was found between low and high Depth ($M_{Low} = 3.8424$, $M_{High} = 4.4386$, $p = 0.058$). The results support Hypothesis 3 by confirming the presence of a curvilinear (i.e., inverted-U shape) effect in the offline channel and a rather linear effect in the online channel as seen in Figure 6.5.

Figure 6.5 The effect of Depth on Experience at different channel type



Although the regression analysis in Model 4 provided the significant moderating effect of channel type, it is useful to understand in which level of Depth the effect is significantly different. Two moderation analyses using Process Model 1 were conducted to test the moderating effect at low-moderate and moderate-high groups. At low-to-moderate levels of Depth, channel type did not significantly moderate the effect of Depth on Customer Experience as the interaction term showed a nonsignificant result ($\beta_{Interaction\_Low\text{-}Mod}$ = -1.613, t = -1.0961, p = 0.274), the relationship between Depth and Customer Experience is positive in either type of channel. However, the moderating role of channel type becomes prominent at moderate-to-high levels of Depth ($\beta_{Interaction\_Mod\text{-}High}$ = 0.234, t = 2.2843, p < 0.05). In these levels, the effect of Depth on Customer Experience was significantly different, where it presents a negative relationship in the offline channel and a positive but nonsignificant effect in the online channel (Offline: 95% CI = -0.3284, -0.0441]; Online: 95% CI = -0.0954, +0.1875]).

6.4.3 The mediation analyses in curvilinear paths

The previous analysis shows that Depth influences Customer Experience differently depending on the channel where customer interaction occurs. This current mediation analysis delves deeper into the underlying mechanisms that explain why the effect of Depth on Customer Experience varies between the offline and online channels. Two mediators were tested, Customer Effort and Customer Enjoyment, to test H_5 and H_6. We use the subgroup approach to combine moderation and mediation analysis, as Edwards and Lambert (2007) explained. Using the subgroup approach, we estimated the indirect effect separately for each dataset based on the channel type. Moreover, we also performed comparison path analyses between groups, enabling us to categorically conclude differences in mediation across channel types.

As discussed in Chapter 3, we expect that Effort and Enjoyment mediate the effect of Depth and Channel Type on Customer Experience. Chapter 4 (section 4.6.6.1)

introduced the instantaneous indirect effect as an appropriate computation to evaluate the indirect effect in the curvilinear path (Stolzenberg, 1980; Hayes and Preacher, 2010). Therefore, instead of estimating the overall mediation effect in the Depth – Customer Experience relationship, we estimated the indirect effect at three levels of Depth: Low, Moderate, and High. In this way, we are able to understand how much the Customer Experience changes indirectly through Effort and Enjoyment at different levels of Depth.

In doing so, our model specified that the effect of Depth on Customer Experience is curvilinear (modelled as quadratic), carried through the curvilinear effect (modelled as quadratic) of Depth on Effort and Enjoyment (in parallel), which in turn lead to a positive influence (modelled as linear) on Customer Experience after controlling for the direct quadratic association between Depth and Customer Experience as well as the linear effect of other control variables. The instantaneous indirect effects were estimated using 10.000 bootstrap samples with 95% bias-corrected confidence intervals and, in some cases, 90% bias-corrected confidence intervals. All of the results are documented in Table 6.7 and will be further discussed in the following subsections.

Table 6.7 Results of mediation analyses

	Instantaneous Indirect Effect (Θ)												Path b (M→Y)		
	Low Depth (X = 3)				Moderate Depth (X = 6)				High Depth (X = 9)						
	Effect	SE	95% CI[a]		Effect	SE	95% CI[a]		Effect	SE	95% CI[a]		β	SE	
	Offline														
Effort	**0.058** †	0.03	0.007	0.108	**0.033** *	0.014	0.006	0.061	0.009	0.021	-0.033	0.051	0.126	0.047	*
Enjoy	**0.17** *	0.068	0.037	0.304	-0.019	0.018	-0.054	0.017	**-0.207** *	0.069	-0.343	-0.072	0.401	0.049	***
	Online														
Effort	0.01	0.029	-0.037	0.058	**0.037** *	0.013	0.011	0.063	**0.064** †	0.034	0.008	0.12	0.157	0.045	***
Enjoy	0.024	0.091	-0.154	0.202	**0.071** *	0.026	0.021	0.122	0.119	0.091	-0.059	0.297	0.617	0.055	***
	Differences (Offline vs Online)														
Effort	0.047	0.042	-0.035	0.129	-0.004	0.019	-0.041	0.034	-0.055	0.04	-0.133	0.024			
Enjoy	0.146	0.113	-0.076	0.369	**-0.09** *	0.032	-0.152	-0.028	**-0.326** *	0.114	-0.55	-0.102			

Note: ***= 0.001; ** = 0.01; * = 0.05; † = 0.1; Θ = $(a_1 + 2a_2X)\,b$

Indirect Effects in Offline Channel

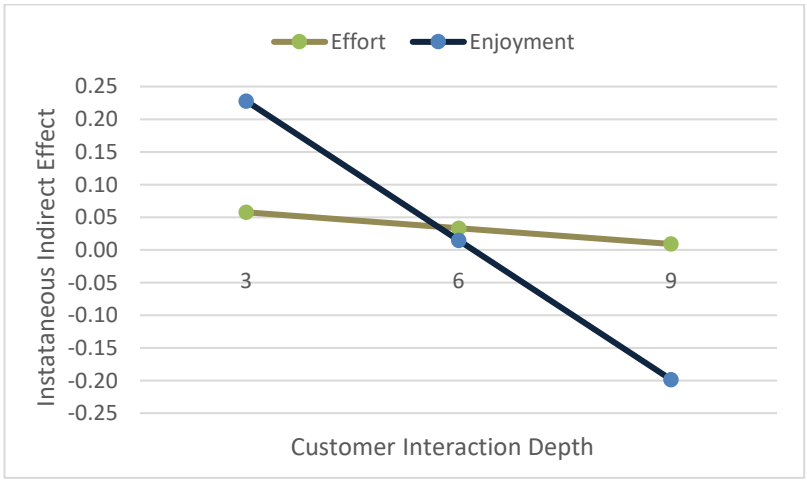
The overall mediation model in offline channel was significant ($F_{(9, 140)} = 10.7525$, $p < 0.001$, $R^2 = 0.4087$). Contrary to our assumptions, instead of curvilinear relationship, there was a linear relationship between Depth and Effort (path Depth → Effort = 0.652, SE = 0.329, $p < 0.05$; $Depth^2$ → Effort = -0.032, SE = 0.027, $p > 0.10$) and a significant positive direct linear effect of Effort on Customer Experience (path Effort → Customer Experience = 0.126, SE = 0.047, $p < 0.05$). Mediation analysis generated a significant instantaneous indirect effect $\Theta_{Depth\text{-}Low} = 0.058$, 90% CI = [+0.007, +0.108], indicating that when customers conduct low numbers of shopping-related activities at an offline channel, an increasing in customer activities leads to higher customer experience by increasing the effort consumers expend during the interaction. This positive indirect effect continues but weakens as customer interaction depth reaches a moderate level. In particular, for customers who interact through moderate numbers of shopping-related activities, further increasing numbers of activities performed during customer-retailer interaction produces a significant positive effect through customer effort $\Theta_{Depth\text{-}Moderate} = 0.033$, 95% CI = [+0.006, +0.061], while for high depth this positive indirect effect becomes nonsignificant $\Theta_{Depth\text{-}High} = 0.009$, 95% CI = [-0.033, +0.051].

As for Enjoyment, there was a significant curvilinear effect of Depth on Enjoyment (path Depth → Enjoyment = 0.895, SE = 0.314, $p < 0.01$; $Depth^2$ → Enjoyment = -0.078, SE = 0.026, $p < 0.001$) as well as a significant positive direct linear relationship between Enjoyment and Customer Experience (Enjoyment → Customer Experience = 0.401, SE = 0.049, $p < 0.001$) in offline channel. Mediation analysis resulted in a significant instantaneous indirect effect $\Theta_{Depth\text{-}Low} = 0.170$, 95% CI = [+0.037, +0.304], signifying that when customers conduct a low number of activities, an incremental interaction enhances the customer experience by generating customer enjoyment. However, this positive indirect effect has diminishing returns as customer interaction

depth moves up to a moderate level, above which any additional shopping-related activities performed during interaction creates negative consequences. More specifically, for customers with high interaction depth, conducting more shopping-related activities reduces the evaluation of customer experience through diminishing customer enjoyment which is indicated by the significant negative instantaneous indirect effect $\Theta_{Depth\text{-}High}$ = -0.207, 95% CI = [-0.343, -0.072]. Therefore, consistent with our assumptions, customer interaction depth in an offline channel environment creates a higher customer experience via its effect on customer enjoyment at low levels of depth. However, additional activities and incremental frequency to customers who already possess a high interaction depth can produce detrimental effects to the overall customer experience since it suffers from enjoyment diminution.

Figure 6.6 sums up the underlying process behind the inverted U-shape of the Depth-Customer Experience link in the offline channel, which arises due to the contribution of both customer effort and customer enjoyment. Both instantaneous indirect effects have a negative slope indicating weakening effects. Nevertheless, the indirect effect of customer interaction depth on customer experience via customer enjoyment decreases to a point where it is no longer positive.

Figure 6.6 The instantaneous indirect effect of customer enjoyment and customer effort for offline channel



Indirect Effects in Online Channel

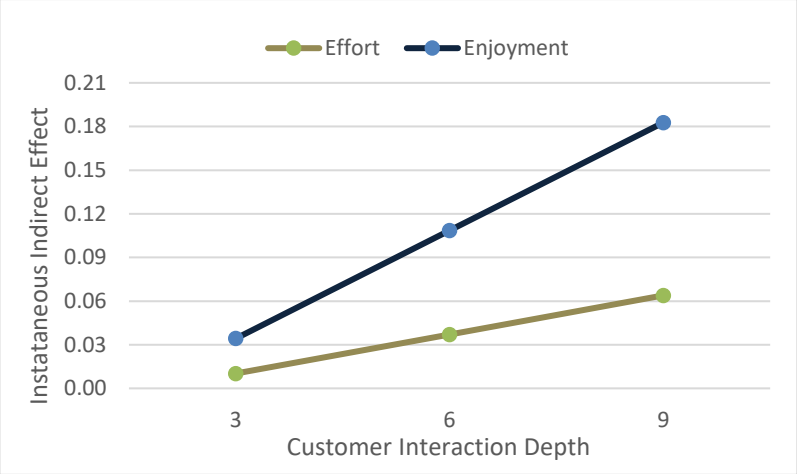
For the online channel dataset, the mediation analysis shows a significant mediation model, where $F_{(9, 141)} = 22.1076$, $R^2 = 0.5455$, $p < 0.001$. The results in Table 6.7 shows that the quadratic effect of Depth on Customer Experience in online channel is non-significant (path Depth → Effort = -0.105, SE = 0.353, $p > 0.10$; $Depth^2$ → Effort = 0.028, SE = 0.029, $p > 0.10$), but there was a significant positive linear relationship between Effort and Customer Experience (path Effort → Customer Experience = 0.157, SE = 0.045, $p < 0.001$). The mediation analysis showed a non-significant instantaneous indirect effect at low levels of Depth; however, the results were significant for moderate and high levels of Depth. A significant instantaneous indirect effect at moderate Depth $\Theta_{Moderate} = 0.037$, 95% CI = [+0.011, +0.063] suggesting that when customers interact through moderate numbers of activities and frequency, increasing interaction influences higher customer experience via its positive effect on customer effort. This positive indirect effect carries through to high levels of Depth, where $\Theta_{High} = 0.064$, 90% CI = [+0.008, +0.120]. Similar to the findings in the offline channel, the indirect effect of Depth on Customer Experience through Customer Effort in the online channel consistently shows a positive indirect effect, although the level of depth in which the indirect effect is significant does vary. This result implies that an incremental interaction depth for customers with moderate and high interaction depth can enhance their overall customer experience in an online channel through an increasing level of customer effort.

In terms of customer enjoyment in online channel, the quadratic relationship between Depth and Customer Experience also showed a non-significant effect (path Depth → Enjoyment = -0.038, SE = 0.285, $p > 0.10$; $Depth^2$ → Enjoyment = 0.013, SE = 0.023, $p > 0.10$). The linear relationship between Enjoyment and Customer Experience in an online channel, however, was significant and positive (Enjoyment → Customer

Experience = 0.617, SE = 0.055, $p < 0.001$). Further mediation analysis was conducted to reveal the instantaneous indirect effect, which appears to be significant at moderate levels of depth ($\Theta_{Depth\text{-}Moderate}$ = 0.071, 95% CI = [+0.026, +0.021]). The result indicates that for customers who are moderately involved in their interaction, more substantial participation with retailers' online touchpoints can create a superior customer experience via its effect on customer enjoyment. For other levels of customer interaction depth, increasing involvement in customer activities leads to the overall experience assessment but not necessarily occurs through increasing enjoyment.

In combination, the dynamic of the indirect effect of Depth on Customer Experience through Effort and Enjoyment can be seen in Figure 6.7.

Figure 6.7 The instantaneous indirect effect of customer enjoyment and customer effort for an online channel



Differences of Indirect Effects between Channel Type

From the results above, the difference between indirect effects under two conditions can be computed and tested using 10.000 samples with 95% bias-corrected confidence intervals. There were no significant differences for the instantaneous indirect effect of Depth on Customer Experience through Customer Effort. Although some significant indirect effects were found in both offline and online channels, the differences between indirect effects in the offline and online channels were not significant. In regard to

Customer Enjoyment, the differences for instantaneous indirect effect of Depth on Customer Experience through Customer Enjoyment were significant at all but low levels of Depth ($\Delta\Theta_{Moderate}$ = -0.090, 95% CI = [-0.152, -0.028]; $\Delta\Theta_{High}$ = -0.326, 95% CI = [-0.550, -0.102]).

6.5 Discussion

Study 2 provided empirical evidence of the causal effect of customer interaction depth on customer experience. The inverted U-shape was once again found as a result of a regression analysis using a quadratic term of depth, confirming H_2. The ANOVA analysis could not provide evidence on the turning point of the inverted U-shape, as the difference between moderate level of depth and high level of depth was not significant. However, there was a diminishing positive effect on the high level, which contributed to the regression analysis' result of an inverted U-shaped relationship, confirming the acceptance of H_2.

Pertaining to the moderating effect of channel type on the relationship of customer interaction depth and customer experience, the findings presented in this chapter lend their support to accept H_4. Aligned with the prediction for the offline channel, the effect of customer interaction depth on customer experience is curvilinear, taking an inverted-U shape. In contrast, customer interaction depth influences customer experience linearly and positively in the online channel. For offline customers, engaging in a high level of customer interaction depth results in a poorer customer experience. Meanwhile, for online customers, as customer interaction depth increases, customer experience also increases.

The mediation analysis was conducted to understand the underlying processes effect of customer interaction depth on customer experience. In this instance, customer effort and customer enjoyment were tested. The examination was done for separate conditions,

offline and online. The analysis of the instantaneous indirect effect was used to identify the indirect effect at three different levels of depth, low, moderate, and high. Findings show that both customer enjoyment and customer effort mediate the effect of customer interaction depth and channel type on customer experience, at some levels of customer interaction depth. For the offline channel, both customer effort and customer enjoyment mediate the positive effect of customer interaction depth on customer experience, at the low level. At the high level, increasing customer interaction depth costs customers their enjoyment, hence creating a negative return of customer experience. For the online channel, the indirect effect of customer interaction depth on customer experience through customer effort and customer enjoyment are consistently positive across all levels of customer interaction depth. The results support H_5 and H_6.

Although the results provided from the mediation analysis did confirm the mediating effect of both customer effort and customer enjoyment, some findings deviate from our initial assumptions. First, the indirect effect that customer interaction depth has on customer experience via customer effort was not curvilinear but instead linear. Furthermore, the relationship between customer effort and customer experience was positive. This finding can be perceived as counterintuitive. The customer effort, which is categorised as an element of cost, is frequently seen as a factor that supposedly decreases customer experience; and we hypothesised so to happen at a moderate to a high level of depth. This view is rooted in a perspective that customers constantly aim to keep their effort to a minimum in order to maximise convenience (Berry et al., 2002) and enjoyment subsequently (Garbarino and Edell, 1997). Instead, our mediation findings support the notion that effort is a signal of perceived value (Hult et al., 2019). The variety of activities performed and the increasing frequency of those activities suggest the importance of a journey. More activities and more repetitions grant control to customers over the journey and stimulate customer confidence regarding the outcome

of their journey (Dabholkar and Bagozzi, 2002), hence indirectly benefit the customer experience enhancement.

6.6 Summary

Chapter 6 focused on the analysis of Study 2, which further examined the dynamic relationship between depth and customer experience. An overview of methods, the design of the experiment, and the data analysis were discussed in this chapter prior to hypotheses testing. Study 2 supported some findings that were found in Study 1 (H_2) but also offered a new understanding of the condition (H_4) and the underlying mechanism of such a relationship (H_5 and H_6). The following chapter is the final chapter of this thesis which discusses all results and implications across two studies. Several limitations will also be explained, and a recommendation for future research will be summarised.

Chapter 7 General Discussion and Conclusion

7.1 Introduction

This chapter summarises and brings together result from three studies presented in chapter 5 and 6. It provides a more comprehensive and overall discussion that links back the research findings to the objectives and the relevant theories. Furthermore, it discusses the implications of the studies, which are twofold: the theoretical contribution and managerial implication. Finally, at the end of this chapter, there will be suggestions for improvement and recommendations for future studies.

7.2 General discussion

Table 7.1 below recapitulates the results of the series of hypotheses testing from H_1 to H_6. The following sections will discuss these results in three different parts: (1) the effect of omnichannel customer interaction on customer experience, (2) the role of channel integration, (3) the role of channel type and the mediating effect of customer effort and customer enjoyment.

Table 7.1 Summary of hypotheses testing results

	Hypothesis statement	Result
H_1	Breadth – Customer Experience (∪)	Supported
H_2	Depth – Customer Experience (∩)	Supported
H_3	Channel Integration moderates Breadth – Customer Experience	Supported
H_4	Channel Type moderates Depth – Customer Experience	Supported
H_5	Customer effort mediates Depth x Channel Type – Customer Experience	Supported
H_6	Customer Enjoyment mediates Depth x Channel Type – Customer Experience	Supported

7.2.1 Customer interaction complexity in the creation of omnichannel customer experience

In the era of omnichannel retailing, customers have multiple ways to interact with a retailer. Channel multiplicity—where customers rely on multiple channels, multiple touchpoints, multiple devices—has become more common to occur across purchase stages. To deepen our knowledge about how the complexity of customer interaction has an impact on a customer experience, this thesis introduced *customer interaction breadth* and *customer interaction depth* representing *customer interaction complexity*.

This research critically questioned the optimum levels of customer interaction complexity that could potentially lead to a superior customer experience. First, from the analysis, it can be gathered that customer interaction breadth is curvilinearly related to the customer experience, taking a U-shape. It indicates that both low and high levels of customer interaction breadth contribute positively to customer experience. A cross-section survey was conducted to see how customer interaction breadth influences the customer experience. The hierarchical regression analysis found supporting evidence to accept H_1. It shows that the relationship between customer interaction breadth resembles a U-shaped curve in which customer experience decreases as customers interact with more channels and it picks up at the high level of interaction breadth. The empirical results suggest that the negative effect of customer interaction breadth on customer experience diminishes as customers interact with more channels. Hence, the H_1 is supported.

The results lend support to the notion that customers value simplicity (Spenner and Freeman, 2012) and yet benefit from omnichannel behaviour (Sopadjieva et al., 2017). Nonetheless, customers have a stronger propensity to get a better customer experience with a simpler interaction by using minimal channels. In the beginning, customers may be more occupied with cognitive tasks as they interact with more channels. The high

interaction with channels creates an overwhelming feeling, but as customers are used to the variety of channels, the feeling eventually disappears and is replaced with more encouraging effect. Therefore, there are moments, or tipping points, where the interaction with additional channels is no longer detrimental and instead positively affects customer experience.

Different to customer interaction breadth, customer interaction depth has been found to have a curvilinear effect on the customer experience that bears a resemblance to an inverted U-shaped. Parallel to the argument in the hypothesis formulation, as customers perform numerous activities with a retailer, they received multiple service outputs to help their decision-making process. At the same time, customers also gain value from repeatedly interacting with a retailer. Repeated interaction can stimulate trust-building and provide a stronger foundation to build a relationship (Morgan and Hunt, 1994; Nicholson et al., 2001). Repetition reinforces a positive belief about the retailer and subsequently forms a positive attitude (Hawkins et al., 2001). From these interactions, customers feel a more superior customer experience.

Customer interaction depth is, however, not costless. Performing a wide range of activities can be time-consuming, laborious, and effortful, which could damage customer evaluations towards the efficiency of the customer journey. Consequently, a high level of customer interaction depth raises expectation on the output, and over interacting may instead obstruct customer experience. Hawkins et al. (2001) noted the marginal diminishing return of repeated interaction on the positive brand attitude. It echoes the negative return that has been found previously in the studies pertaining to the frequency of interaction (Venkatesan and Kumar, 2004; Venkatesan et al., 2007). It also suggests that a positive effect lasts up to a point where it becomes harmful to the overall customer experience. The optimum level of customer interaction depth would be at the

moderate levels where customers obtain both efficiency and effectiveness of their interaction; this results in the highest customer experience.

7.2.2 The role of channel integration

The previous section discussed how customer interaction complexity shapes the customer experience. This section further explains the conditions that change the effect of customer interaction on customer experience. This thesis shows how channel integration plays an important role in flipping the effect of customer interaction breadth on the customer experience. Channel integration is commonly positioned as the differential factor of omnichannel retailers. Without one, retailers are merely seen as multichannel retailers (Beck and Rygl, 2015; Picot-Coupey et al., 2016).

In a seamless omnichannel environment in which channel integration is high, interacting with multiple channels and touchpoints provides a favourable customer experience. The highest customer experience is not gained by customers who use minimal or all channels, but instead comes from a moderate number of channels. This indicates that customer interaction breadth has a positive effect to a point where it diminishes and becomes negative. This thesis argues that customers in a highly integrated omnichannel environment feel higher perceived fluency (Shen et al., 2018) and therefore process abundant information from different channels easily. They can see and embrace the benefit of interacting with multiple channels (Balasubramanian et al., 2005). Nevertheless, since benefit increases as they interact with more channels, they do not necessarily have to interact with all channels to get the same level of benefits. At a high level, additional interaction with channels will no longer deliver additional customer experience.

In a non-integrated multichannel environment, the effects of customer interaction breadth on customer experience are completely different from those in a nearly perfect

omnichannel environment. The U-shaped relationship is retained and even more prominent. The decreasing customer experience is stronger between low levels of breadth and moderate levels of breadth. However, it bounces back from moderate levels to high levels of breadth. In a low integration condition, customers receive no support in their journey and rely on themselves to be familiar and knowledgeable about different channels. There are still benefits they can reap from interacting with more channels, but there is a higher cost in turning the experience from negative to positive. Without channels being integrated, customers expend more cognitive effort to interchangeably use multiple channels (Shen et al., 2018).

Our results show that there is no significant moderation effect of channel integration on the relationship between customer interaction depth and customer experience. This result is perhaps due to the customer interaction depth being less directly related to channels. Unlike customer interaction breadth that directly measures customer interaction with channels, customer interaction depth focuses on the other dimensions of interaction: activities and frequencies. The influence of customer activities and frequencies on customer experience is apparently isolated from the level of channel integration.

7.2.3 The moderating role of channel type and its underlying mechanisms on customer interaction depth – customer experience link

This thesis delves deeper into the differences between online and offline channels when it comes to facilitating interaction depth. While a significant negative return of customer experience was found in the offline channel, the effect of customer interaction depth on customer experience was positive and linear in the online channel. This thesis further investigated the underlying mechanism behind the moderated relationship between customer interaction depth and customer experience. Two variables were tested, namely, customer effort and customer enjoyment.

From the mediation analysis, it was discovered that both customer effort and customer enjoyment play a role in shaping an inverted-U shaped effect of customer interaction depth on customer experience in the offline channel. On average, the offline channel offers a higher customer experience than the online channel, but the pattern fluctuates more, hence facilitating a curvilinear effect on depth-customer experience link. In the offline channel, the indirect effect of customer interaction depth on customer experience through customer effort was found to be positive but diminishing as customer experience depth increased. At the high level of depth, the indirect effect was still positive but weaker compared to the low depth condition. At the same time, in the offline channel the indirect effect of customer interaction depth on customer experience through customer enjoyment is negative. The combination of the diminishing positive indirect effect of depth via effort and the negative indirect effect of depth via customer enjoyment reduce customer experience at high level of customer interaction depth.

Findings from the study also support the notion that the online environment does indeed mitigate a negative return of interaction depth (Shankar et al., 2003) and proves to be a more stable retail environment that stimulates enjoyment at high levels of customer interaction depth. Customer interaction depth in the online channel has a positive influence on customer experience via its positive effect on both customer effort and customer enjoyment.

In sum, the mediation effect of customer effort and customer enjoyment was found at some levels of customer interaction depth in both the offline channel and online channels. These results are consistent with the study regarding customer participation in personalised service (Franke and Schreier, 2010) and suggest that interaction depth can be seen as part of customer participation that promotes a positive customer experience. What is surprising is that the indirect effect of customers interaction depth on customer experience via customer effort was positive at any levels of depth. Regardless of the

nature of the channel, customers identify the level of effort spent in their interaction with a retailer to be similar. This does not support previous research that argued that customers perceive the amount of effort they expend in the online channel to be lower than in the offline channel for the same set of activities (Bechwati and Xia, 2003; Chiu et al., 2019). As customer interaction depth increases, customer effort rises, even at the high levels. This indicates that customers measure effort objectively, and that the negative return of customer experience was mostly contributed by customer enjoyment.

7.3 Theoretical contributions: Understanding customer interaction complexity

This thesis makes a vital contribution to the omnichannel research opportunity of customers behaviour and retail mix across channels (Verhoef et al., 2015). It is the first to empirically examine the role of customer interaction complexity on the creation of customer experience and offer new insights into the moderating effects of the channel integration and channel type. In particular, this thesis introduced two new concepts – customer interaction breadth and customer interaction depth – to depict the complexity of customer behaviour when interacting with an omnichannel retailer. By doing so, it extends the application of complexity theory (Wang and Von Tunzelmann, 2000) as well as social penetration theory (Taylor et al., 1969; Altman and Taylor, 1973). It supports the notion that the omnichannel retail environment is indeed a complex system (Saghiri et al., 2017), signifying that the relationship between a customer and a retailer is increasingly personal nowadays (Cao and Li, 2015). A retailer's capability to create, along with a customer's ability to choose a personalised service transforms the relationship view to be interpersonal-oriented.

Second, studies in this research project collectively extend the findings from past multichannel research (Kushwaha and Shankar, 2013; Cambra-Fierro et al., 2016). The linkages between omnichannel customer interaction and customer experience are rather

nonlinear. The omnichannel customers are not necessarily the customer segment with the highest customer experience. The results demonstrate that customers have the highest customer experience when interacting with a moderate number of channels within omnichannel retailers. Meanwhile, within multichannel retailers (i.e., retailers without channel integration), the level of customer experience is similar between customers who interact with few or a very high number of channels. To some extent, these findings answered the research opportunity about shape-flipping curves that seldom explored (Haans et al., 2016).

Third, the studies in this research illustrate the optimum level of customer interaction depth that creates the highest customer experience. As the nature of the relationship resembles a U-shaped curve, the combination of frequency and variety of customer activity produces the highest customer experience when it occurs at a moderate level. On one side, the results lend their support to prior research regarding the effect of frequency that seems to be similar to a double-edged sword. However, beyond confirming past findings, this study offers a new conceptualisation of interaction depth that is distinctly useful to improve future studies pertaining to the customer journey. The current application of customer journey's studies usually focusses on three main stages of the purchase process. However, it overlooks the intricate details of activities within each stage. For that reason, the operationalisation of customer interaction depth is able to tackle this limitation and still, at the same time, give other researchers room for flexibility to adapt the operationalisation for different service environments.

Fourth, this thesis extends prior research on the importance of channel integration in creating a superior customer experience. Prior research has examined the significance of channel integration on variables such as organisation performance (Cao and Li, 2015), patronage intention (Emrich et al., 2015), perceived service quality (Herhausen et al., 2015), omnichannel service usage (Shen et al., 2018), and customer engagement (Lee et

al., 2019). This thesis extends this area of research by showing the moderating effect of channel integration on the relationship between customer interaction and customer experience.

Finally, the findings pointed out under what conditions and why the effect of customer interaction depth on customer experience differs. The offline and online channels provide a unique environment to facilitate customer interaction, and each channel contributes differently to the creation of customer experience. The findings accumulatively enrich the conversation about similarities and differences between physical and digital channels from customers' perspective and adds to the current knowledge about offline-online comparison in loyalty (Danaher et al., 2003; Shankar et al., 2003) and shopping time (Chiu et al., 2019).

Existing research has discussed the motivation behind customer interaction choice (Balasubramanian et al., 2005; Barwitz and Maas, 2018), but this current research expands the understanding of customer interaction by demonstrating that customer experience is driven by the accumulation of effort and enjoyment resulting from customer interaction depth. The results confirm that customers are involved in the analysis of cost and benefit when evaluating their interaction with the retailer. In a way, this study offers an empirical progression to the interpersonal relationship development between a customer and a retailer in an omnichannel retail environment context.

7.4 Managerial implications: Formulating effective channel design

Adopting omnichannel strategies is a transformation that not every retailer can afford. It requires a high level of investment for a retailer to introduce new channels and touchpoints. The investment needed is not limited to the amount of capital needed to develop a new supply chain and a back-end system for new channels and touchpoints but also the amount of investment to train and manage people to provide the service.

Thus, it is pertinent to understand how to design and use channels and touchpoints that optimise the customer experience.

7.4.1 Defining the level of channel integration

This research shows how crucial it is to define the desired level of channel integration because it will determine the complexity of customer interaction that benefits the retailer. Managers may implement several tactics to increase customer perception of channel integration. There are three major streams of integration: information management, product flow, and customer support. First of all, customers should be well informed about the existence of other modes of purchase. This can be done by placing an advertisement for one channel in another channel. Moreover, both product and non-product information specific to one channel should be readily available on other available channels. For example, a retailer enables customers to check in-store stock online and vice versa. The key is being transparent and increasing the accessibility of customers to move across channels.

Second, managers need to ensure that products flow between channels. This includes executing initiatives such as BOPIS or in-store orders with a delivery service to customers' addresses. Furthermore, customers should also be allowed to return products through many channels they prefer. The takeaway from these strategies is to provide flexibility and promote convenience for customers. The strategy gives customers a seamless shopping experience, something they expect to receive from an omnichannel retailer. To achieve the seamless state, managers have to consider several aspects regarding how the products move around storage, stores, and customers, concerning the purchase and return processes.

Finally, there should be support from knowledgeable salespeople to assist customers in navigating their journey across various channels and touchpoints. Customers appraise

channel integration quality based on the consistent service level received in every channel. They expect a uniform response to an inquiry, whether it involves a complaint or an order, in every channel within their journey (Lee et al., 2019). More importantly, salespeople who is in charge of a particular channel should understand how things work on other channels. For example, an offline salesperson is expected to be able to explain the order process from a mobile channel. On the other hand, a social media customer advisor should be able to advise on the return procedure at an offline store. This collective knowledge of the overall omnichannel operation must be maintained by retailers' employee throughout the organisations.

7.4.2 Balancing customer interaction complexity

The following step after deciding the level of channel integration is to design the number of channels, variety of activities, and frequency of interaction. Matrix 7.1 summarises the strategies for managers regarding customer interaction breadth and customer interaction depth, considering the channel integration level. Under low channel integration conditions, the results show how customers achieved the highest customer experience when interacting with few or a very high number of channels. Retail managers with none to low channel integration could consider encouraging customers to use very few channels. The findings from Study 1 demonstrate that customer experience is at the highest at one channel, two channels, or eight channels. Managing interaction at eight channels requires more effort, and therefore managers could focus on the single or two-channel interaction. This finding by no means suggests any elimination to retailer's channels. The emphasis is on the recommendation to keep customer interaction limited to no more than two channels. Managers should avoid enabling certain activities only in a particular channel because this might disrupt customers' current channel combinations and lower their customer experience. For instance, some retailers have a policy where customer inquiries can only be solved

through a call centre. For customers whose channel repertoire only includes an offline channel and an online channel, having to expand it to a call centre can cause a dysfunctional consequence.

Matrix 7.1 Strategies for customer interaction breadth and depth versus channel integration

Customer Interaction		*Channel Integration*	
		Low Integration	**High Integration**
	Breadth	• Encourage customers to use fewer channels (e.g., one or two channels). • Prioritise channels that facilitate most customer interaction. • Invest in selected channels and touchpoints, based on channel prioritisation.	• Encourage customers to use more channels (e.g., three up to five channels). • Spread the investment on all channels and touchpoints to ensure a consistent service level. • Maintain channel integration throughout key purchase stages.
	Depth	• Be conscious of the frequency of retailer-initiated interaction. Managers can control several areas, including (1) promotional newsletter/firm-initiated interaction, (2) customer inquiry completion period, (3) customer inquiry simplification process. • Introduce express checkout, single-click purchase, or "items bought last time" to simplify basic activities, especially for habitual purchase. • Facilitate more detailed and elaborate customer activities within the online channel.	

Under high channel integration conditions, our findings suggest that managers could be more creative and encourage customers to interact with multiple channels (e.g., three or up to five channels). These numbers are found to stimulate the highest customer experience (Study 1). The findings do not imply that customers have to be encouraged to use all channels since the highest customer experience resulted from a moderate level of customer interaction breadth. Nonetheless, compared to low integration conditions, customer experience in highly integrated omnichannel retailers is higher. As a consequence, managers could spend the investment on many or even all channels and touchpoints. Nevertheless, more attention should be given to managing the high level of

channel integration throughout key purchase stages. Consistent integration quality ensures a seamless experience across channels and touchpoints, which is the hallmark of true omnichannel retailing.

The implication of designing customer interaction depth is somewhat similar in both low and high channel integration conditions. However, slight differences occur between the offline and online channels. In general, the inverted U-shaped relationship indicates customer experience is optimised at a moderate level of interaction breadth. Managers need to be conscious of the frequency of retailer-initiated interaction. This is due to the decreasing customer experience at high levels of depth. Hence, managers need to pay attention to the areas that they can control, such as (1) frequency of outgoing promotional mail to customers, (2) time spent solving a customer inquiry, (3) the number of steps customers have to take to search, purchase, and deal with the after-purchase inquiries. Customers have to be kept long enough in the retailer but not too long that it deters their enjoyment. Overall, an interaction that is too complicated should be avoided in terms of a very high customer interaction depth. Apart from controlling the frequency, managers could also implement strategies that ease a customer journey, such as express checkout in-store or single-click online purchase.

Our experimental studies found that customers could tolerate a deeper online interaction without costing their enjoyment as much as in the offline channel. The idea is to encourage more interaction in the online channel. Managers, therefore, could achieve this by enhancing the information content of the online channel and designing a more sophisticated online channel that facilitates all customer activities. Managers should enable customers to place a product review online even if customers purchased a product from other channels. Bleier et al. (2019) gave detailed insights on building a comprehensive online channel such as providing a comparison matrix, descriptive

details, other product recommendations, a particular style of images, avoiding a content filter, and providing videos on how products are used in real life.

7.5 Limitation and future recommendation

This research has contributed significantly to the progression of literature and strategic managerial approaches for omnichannel retailers. Nevertheless, there are several limitations centred around this research. The following sections will discuss those issues and the subsequent suggestions for future research.

7.5.1 The mediating variables in the customer interaction breadth – customer experience relationship

Our research has not analysed the underlying mechanism of the relationship between customer interaction breadth and customer experience. Future studies could address this to complete the overall picture of how a variety of channels leads to customer experience. Using an experimental study, future research could test the interplay between customer interaction breadth and channel integration and explore the mediation effect. Some potential variables include customer effort and customer enjoyment as tested and suggested by this thesis. Alternatively, other variables such as customer convenience potentially reveal why breadth causes a curvilinear effect on customer experience. The evaluation of customer convenience involves a more subjective perspective. It includes the ease of use, time and effort during an interaction (Berry et al., 2002; Collier and Kimes, 2013) and the timing when the interaction occurs (Meuter et al., 2000). For a retailer with relatively low integration levels, a low level of customer interaction breadth can be seen as a convenient interaction because it involves a few channels. But at the same time, high levels of customer interaction breadth can also be viewed as a convenient interaction because each channel and touchpoint can serve customers just right *when they need it*.

7.5.2 The methodological issues and future advancement

From a methodological perspective, this research provides no objective data. In particular, there were no actual responses of customer behaviour within an omnichannel retailer. It does, however, deploy experimental studies to confirm the results. Nevertheless, historical data about customer transactions from omnichannel retailers with different levels of channel integration will increase the research validity and enrich the research findings. Therefore, future research would benefit from the analysis of such data. The use of MTurk sampling also possesses inherent issues, which have been discussed in Chapter 4.

Nevertheless, the characteristics of MTurk workers create an unbalanced proportion of the participants' demographic profile. Most participants fall in the group of 25 – 44 years old with a higher education degree. This sample represented the proportion of omnichannel customers who are commonly affiliated with smartphone users. However, it does alienate responses from other demographic categories such as senior citizens and teenagers. Furthermore, responses from our cross-sectional survey lean towards a low channel interaction breadth. More specifically, more than half participants mentioned that they have interacted with either two or three channels.

Meanwhile, less than seven per cent of them have interacted with six or more channels. This might have impacted our result, especially related to the significance of the customer experience curve at moderate to high levels of channel interaction breadth; especially, concerning the moderating effect of channel integration. Future research will benefit from an experimental research design in which researchers can conduct a study in a controlled environment with an equal number of observations between low, moderate, and high channel interaction breadth. Moreover, the low interaction breadth, consisting of single-channel interaction, can be split into offline and online. In this way,

the experimental study can enrich our understanding of the offline-online dynamics and whether the channel type itself contributes to a different level of customer experience.

The experimental studies used in this research examined the effects of customer interaction depth on customer experience. Customer interaction depth was measured using a set of activities that were seen as appropriate for fashion shopping. This does mean, however, that other customer activities were excluded from the study. Some adjustments are needed to replicate this research in a different context, such as financial service, public service, or other retail sector environments. For example, in a private healthcare provider, appropriate activities would be: seek for information, browse for specialists, compare treatment packages, check insurance compatibility, book an appointment, register as a patient, consult with physicians, and follow up treatment.

Accordingly, future research could apply a longitudinal approach to provide empirical evidence on the iterative process within a customer journey (Lemon and Verhoef, 2016; Grewal and Roggeveen, 2020). This will answer the question of whether the present customer experience will influence future customer interaction. Moreover, longitudinal studies would reveal the strength of customer experience in influencing future customer interaction from time to time. Edelman and Singer (2015) presented the double loops customer journey, which suggests that customers go through two different processes: (1) the classic journey consisting of extended consideration and evaluation and (2) the loyalty loop where interactions are shorter and simpler. The impact of customer experience on the complexity of customer interaction may appear stronger in the classic journey and become less prominent in the loyalty loop.

7.5.3 Future theoretical development in omnichannel research

From the theoretical perspective, the present research includes limited customer characteristics as factors that could potentially change the shape of the relationship.

Aligned with social penetration theory, personal characteristics and the level of self-disclosure are named as factors that influence relationship development. Hence, the current research framework can be improved for future research application by adding personal characteristics such as the Big Five personality traits and self-disclosure construct into the framework. It will be insightful to understand how personality traits and self-disclosure can influence the relationship between customer interaction and customer experience. Customers with high openness to experience, characterised as creative, bold-mindedness, and adventure seekers (LePine, 2003), may bode well with a high level of interactions. Differently, customers associated with high conscientiousness are task-oriented and motivated to get things done (Barrick and Mount, 1991). With this in their mind, the complexity of interaction will not have much influence on the affective states produced, and therefore differences in customer experience will be less pronounced. Furthermore, the personality traits can be utilised to collectively explain the typology of customer interaction complexity. In reality, the personality of most individuals falls in between the extreme points of the traits. For instance, an individual might be both extrovert and open, or both high in agreeableness and conscientiousness. Therefore, rather than examining the personality traits individually, it is more appropriate to assess the combination of personality traits consumers may possess.

Meanwhile, self-disclosure refers to any information one may communicate verbally to another individual (Cozby, 1973). It signals how open customers are when interacting with a retailer. Interaction breadth and interaction depth have implied self-disclosure on their own; however, researchers may utilise more objective data in the future. To do so, researchers may consider using information regarding the number of retailer's programs that a customer opts in or whether customers allow a retailer to track cookies on their website.

The future direction to move this forward is to explore the cross-country analysis. Channel combinations for omnichannel retailers around the world would be different across countries due to the variety of customers preferences and the strengths of technological infrastructure in each country. The plethora of digital and social media channels call for further research into channel compatibility for each market across countries. For instance, O'Sullivan and Carr (2018) investigated perceived accessibility and message personalisation. They used them to conceptualise profile construct with orthogonal dimensions leading to four distinct quadrants of masspersonal communication channels. This approach can be applied in creating clusters of channel combinations in omnichannel retailers. In particular, investigating how customer interaction in each channel profile may lead to a different set of engagement will further extend the study conducted by Polo and Sese (2016). Culture, in this case, can be one of the key elements to understand customer preferences across nations. Certain nations may be prone to use a highly personal channel for purchase. Still, others prefer a more formal option to conduct business with a retailer. Understanding which channel should be included in a retailer's channel repertoire can benefit retailers who want to expand internationally.

7.6 Chapter summary and concluding remark

This chapter discussed the results found in the main research regarding the role of omnichannel customer interaction complexity, channel integration, customer enjoyment, and customer effort in creating a customer experience. It further highlights this thesis's contributions to the various bodies of research, including omnichannel retailing, social penetration theory, and theory of complexity. Managerial implications were discussed as suggested strategies for retail managers who want to improve their customer experience. Last but not least, there is a summary of research limitations and future research recommendations.

Omnichannel retail strategies have brought new challenges for retailers but have offered new opportunities at the same time. They have changed the way customers do business with retailers. The interconnectedness between channels and touchpoints determines the optimum level of customer interaction. Balancing customer interaction breadth and customer interaction depth becomes key in creating a superior customer experience. It is achieved through managing customer enjoyment and customer effort throughout the customer journey. Managers need to understand when to promote a simple journey and when to encourage a more complex one. Finally, it is important to understand how the complexity of customer interaction affects customer experience because it eventually leads to all dimensions of future customer engagement. There is a significant positive influence from customer experience to the likelihood of how customers purchase products, give feedback to the retailer, refer a retailer to their friends, and provide positive word-of-mouth in social media. Overall, the results provide empirical evidence that could enrich the literature on omnichannel retailing. However, it also postulates further research to strengthen the conceptualisation of customer interaction as a critical construct in the customer journey.

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Appendix A Overview of Omnichannel Literature Review

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Beck and Rygl (2015)	Conceptual	Typology	None	None	None	None	Multichannel retail management	Typology of multiple channels retailers
Saghiri et al. (2017)	Case studies and expert interviews	Typology	None	None	None	None	Complex adaptive system	Three-dimensional framework based on (1) Channel stage, (2) channel type, and (3) channel agent.
Picot-Coupey et al. (2015)	Conceptual	Typology	None	None	None	None	Channel integration	Differentiation between multi-, cross-, and omnichannel based on the intensity of of integration.
Hosseini et al. (2018)	Econometric modelling and customer scanner data	Omnichannel strategy	Channel combination	None	None	Firm value	Customer journey and investment analysis	The optimum omnichannel strategy depends on customer preferences and channel attributes.
Brynjolfsson et al. (2013)	Customer transaction data	Omnichannel strategy	Channel type	Product characteristics	None	Cross-channel ompetition	IT-mediated retail environment	There is a strong competition from offline retailer when online retailers sell mainstream products. However, the same competition was not found when it comes to niche products.
Bijmolt et al. (2019)	Conceptual	Omnichannel strategy	Customer journey	None	Marketing-operation strategies	Product flow	Flow model	The framework assesses strategies to use in omnichannel retail environment that consider both customers and product flow.

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Bell et al. (2017)	Quasi experiment	Omnichannel strategy	New channel introduction	None	Showroom behaviour	Demand, operational efficiency	Customer uncertainty	The introduction of showroom increases overall demand as well as on online channel. Showroom also improve operational efficiency and provide space for customers that are otherwise costly to serve.
Rigby (2011)	Conceptual	Omnichannel strategy	None	None	None	None	IT-mediated retail environment	The ability of one retailer to survive and adapt in omnichannel environment can extend the business sustainability in the future. The challenge is delivering customer expectation and experience and create synergies between virtual and physical channels.
Ailawadi and Farris (2017)	Conceptual	Omnichannel strategy	None	None	None	None	Distribution intensity	Creating metrics for managing an omnichannel distribution based on the convenience of finding a stockist and in-store attractiveness.
Piotrowicz and Cuthbertson (2014)	Focus group	Omnichannel research area	None	None	None	None	IT-mediated retail environment	Lay down the concept of omnichannel retailing and important research areas based on the role of IT in changing the nature of retail environment.
Verhoef et al. (2015)	Conceptual	Omnichannel research area	None	None	None	None	Multichannel retail environment and management	There are three major streams in the area of omni-channel retailing: - Impact of channels on performance - Shopper behaviour across channels - Retail mix across channels
Neslin et al. (2006)	Conceptual	Multichannel research area	None	None	None	None	Decision making process	The challenges of multichannel management are related to data integration, customer behaviour, channel strategy, and channel management.

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Neslin and Shankar (2009)	Conceptual	Multichannel research area	None	None	None	None	Customer management	Channel-based segment is relevant as long as each channel attract a significant customer base. Enabling multichannel shopping may increase customer loyalty.
Bell et al. (2014)	Customer transaction data and field experiment	Cross-channel strategy	BOPS initiative	None	None	Customer purchase	Customer-focused framework	Assessing how retailers can effectively adapt to an omnichannel environment with strategy such as BOPS, which implement a hybrid online-offline approach for information provision and product fulfilment.
Gao and Su (2017)	Econometric modelling	Cross-channel strategy	BOPS initiative	None	None	Profitability	Newsvendor model	The success of BOPS initiative depends on the product-channel congruity. It helps retailer reaching new customer but may decrease profit for existing customer that usually go fully online (order-fulfilment).
Zeng et al. (2016)	Field experiment	Cross-channel strategy	Cross-channel promotion	None	None	Customer purchase	Offline-online competition	Cross channel promotion only works to promote online customer to shop offline but not the other way around.
Gu and Tayi (2017)	Econometric modelling	Cross-channel strategy	Omnichannel product placement strategies/ assortment	None	Pseudo-showrooming behaviour	Profitability	Showrooming behaviour	Pseudo-showrooming behaviour can be induced by offering only one product at two different channel and the other different but related product exclusively on online channel. This strategy is more profitable than enabling both products at both channels.

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Zhang et al. (2010)	Conceptual	Cross-channel strategy	None	None	None	Channel synergy	Multichannel retail management	Channel strategy is one of the source of competitive advantage, the challenges is to improve firm's capability in data analytics. Cross-channel strategies related to retail mix are perceived as opportunity to utilise the multichannel environment.
Lee et al. (2019)	Customer survey	Channel integration	Channel integration quality	None	None	Customer engagement	Social exchange theory	Dimensions of channel integration quality influence positive customer engagement. There are variety of the strength of the influence between low vs high involvement product, where integrated interaction is stronger at high-involvement product, but the influence of breadth of channel-service choice is stronger for low-involvement product.
Zhang et al. (2018)	Customer survey	Channel integration	Channel integration	None	Consumer empowerment	Purchase intention	Stimulus-organism-response (SOR)	Channel integration positively influence trust, satisfaction, and purchase intention. Moreover, such relationships are mediated through consumer empowerment due to the incremental control over shopping process.
Shen et al. (2018)	Customer survey	Channel integration	Channel and service integration quality	Usage experience	Perceived fluency	Omnichannel service usage	Wixom and Todd model: object-based belief vs behavioural belief	Channel and service integration quality brought positive impacts on perceived fluency which eventually promote omnichannel usage experience. Moreover, channel usage experience significantly moderates the effect of perceived fluency on omnichannel service usage: internal usage experience attenuates while external usage experience enhance the effect.

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Herhausen et al. (2015)	Experiment and field experiment	Channel integration	Channel integration	Online experience	Perceived service quality	Channel outcomes	Technology adoption and diffusion theory	Channel integration increases perceived service quality of the online store and perceived service quality of online store increases overall online channel outcomes. Chanel integration does not promote channel canibalism and does not harm offline channel. The mediation effects of perceived service quality were stronger for low online shopping experience
Emrich et al. (2015)	Experiment	Channel integration	Channel structure	Assortment structure	Shopping benefits	Patronage intention	Customer perceived benefits	Compare to no integration, full integration provides a better outcome across all assortment structures. Assymetrical integration for substitutive relation is worse than no integration. However, it can be superior if it is applied on independent relation.
Cao and Li (2015)	Content analysis of firm's annual reports	Channel integration	Channel integration	Online experience & offline presence	Trust, loyalty, cross sell	Firm performance	Multichannel retail management	Channel integration influence sales growth positively, but firm's online experience and the presence of offline stores exacerbates the effect. Being strong in one specific channel diminishes the positive impact of integration.
Oh et al. (2012)	Retailer survey	Channel integration	Channel integration capability	Cross-channel HR capability & environmental dynamism	Explorative and exploitative competence	Firm performance	The resource-based view	The interaction of IT-enabled channel integration capability and cross-channel capability builds firm competence and eventually affect firm performance positively. It helps firm to meet demand of existing customers and attract new customers at the same time. Moreover, the positive effect of innovation ability on performance is positively moderated by environmental dynamism.

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Yan et al. (2010)	Mathematical modelling	Channel integration	Channel integration	Profit sharing	None	Firm performance	Game theory	This study provides mathematical evidence that channel integration can benefit both online and offline channels via using profit sharing mechanism. Profit sharing is able to strengthen collaboration and diminish channel competition.
Sousa and Voss (2006)	Conceptual	Channel integration	None	None	None	Service quality	SERVQUAL	Framework on channel integration quality that comprises channel-service configuration and integrated interaction.
Bendoly et al. (2005)	Customer survey	Channel integration	Channel integration	None	None	Channel choice and customer loyalty	Risk aversion perspective	Channel integration alleviate the negative impact of product availability failure. Furthermore, it improves customer loyalty, because customers tend to stick with the same retailers if such integration is sufficiently transparent.
Payne and Frow (2004)	Conceptual	Channel integration	Channel integration	None	None	Firm performance	Customer relationship management	Channel integration significantly contribute to customer value creation. As cost to serve offline increases, it is pertinent for firms to adopt multichannel strategies. This is to manage cost-efficiency while providing a superior customer experience at the same time. The challenge is how to achieve consistency in communication and collaboration from people within the firm.
Thomas and Sullivan (2005)	Customer transaction data	Customer segmentation	Customer purchase characteristic	None	Channel choice and marketing expenditure	Marketing communi-cation channel	Customer relationship management	Two major segments emerged consisted of catalogue-prone and offline-focused customers. Depending on the first channel choice, customer segments were encouraged to migrate to another channel, to stay where they are, or to become a dual-channel segment.

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Konus et al. (2008)	Customer survey panel data	Customer segmentation	Psychographic	None	Perceived benefit and cost	Channel choice	Customer journey and perceived utility	Considering two stages of purchase, three segments of multichannel customers emerged: uninvolved shoppers, multichannel enthusiasts, and offline-prone customers. Multichannel enthusiasts are more innovative and have higher shopping enjoyment but offline-prone customers are more loyal.
De Keyser et al. (2015)	Customer survey	Customer segmentation	Psychographic	None	Perceived benefit and cost	Channel choice	Customer journey and perceived utility	Using three stages of purchase, six segments emerged: online-prone, offline prone, call centre prone, and research shoppers (after sales channel: offline/ online/ call centre). Call centre-prone and offline-prone customers are more loyan than others.
Herhausen et al. (2019)	Customer survey	Customer segmentation	Satisfaction	Segment	None	Loyalty	Customer journey	Five segments emerged: offline-focused, pragmatic online, extensive online, multichannel shopper, & online-offline shopper.
Kumar and Venkatesan (2005)	Customer database	Customer value	Customer characteristics and supplier-related factors	None	None	Multichannel shopping	Customer lifetime value	B2B multichannel customers provide higher revenues, higher share of wallet, have higher past customer value, and have a higher likelihood of being active than other customers. Customer propensity to use multiple touchpoints align with the use of multiple channels too.
Kushwaha and Shankar (2013)	Customer transaction data and profiles	Customer value	Channel usage	Product characteristics	None	Monetary value	Role of product category	Multichannel customers are profitable for large mass-merchanidise retailers. For specialty retailers, multichannel customers only profitable for hedonic products (both high and low risk), and traditional channel customers are more lucrative for utilitarian one (esp. low risk products).

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Cambra-Fierro et al (2016)	Customer transaction panel data	Customer value	Channel usage	None	None	Gross margin	Multichannel retailer customers value	Multichannel customers are not the most profitable segment in banking industry. Gross margin is recorded high when customer interaction was concentrated on some single channels of combination of two channels.
Wallace et al. (2004)	Customer interview and survey	Channel choice	Channel usage	None	Satisfaction	Loyalty	None	The use of multiple channels by customers increased their exposure to higher service outputs and therefore increased satisfaction which lead to loyalty.
Balasubramanian et al. (2005)	Customers interview	Channel choice	Shopping goals	None	Utility	Channel choice	Purchase process	Customers choose a specific channel at a specific phase of their journey based on shopping motivation, which is identified as: economic, self-affirmation, symbolic, social influence, and invocation of schema.
Venkatesan et al. (2007)	Customer transaction data	Channel choice	Customer interaction characteristics	None	None	New channel adoption duration	Social exchange theory	Second channel adoption largely influenced by frequency-related interaction characteristics. Third channel adoption was mainly driven by purchase-related interaction.
Polo and Sese (2016)	Longitudinal data of customer interaction	Channel choice	Channel preference, prior experience, marketing effort, customer attitude	Nature of interaction (high-risk vs low-risk)	None	Channel choice	Perceived risk	There are differences in how customers choose a channel between for purchase (high-risk) and for communication (low-risk). The effect of attitude is more pronounce when choosing a purchase channel, while the effect of personal touch is stronger when it comes to communication channel.

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Rodríguez-Torrico et al. (2017)	Customer survey	Channel choice	Personality traits	None	None	Channel usage	Impulse and contemplative behavior	Impulsive shoppers use of mobile devices more often whereas individuals with high need for touch are more likely to use online devices in their omnichannel process.
Rapp et al. (2013)	Three-level dataset (supplier salespeople, retail store managers, and customers)	Specific channel strategy	Social media usage	Customer interaction, reputation, service ambidex-terity	None	Loyalty and performance	Contagion theory	Social media usage by supplier, retailer, and customer influence brand performance, retail performance, and customer loyalty. All moderators except customer interaction has found to enhance the likelihood of social media use.
Rippé et al. (2017)	Scenario methodology	Specific channel strategy	Mobile channel usage	Adaptive selling	Perceived control	Purchase intention	Media dependence theory	Salesperson can use adaptive selling technique to influence purchase intention and promote positive interaction with customers.
Kohler et al. (2011)	Dyadic agent and customer survey	Virtual employee interaction	Interaction style and content	Interaction style	Newcomer adjustment	Employees' performance	Buyer-seller interaction	Virtual employees' interaction style and content significantly influence the newcomer adjustment, and in turn, influences their performance. Specifically, there is an inverted U-shaped effect between social content interaction on newcomer adjustment.
Sopadjieva et al. (2017)	Customer scanner data and survey	Customer interaction	Channel usage	None	None	Customer purchase	None	Positive correlational result between omnichannel behaviour and loyalty, customer purchase, and positive word-of-mouth.

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Nambisan and Baron (2007)	Customer survey	Customer interaction	Interaction benefits and affective evaluation	Product involvement, community identification	Customer attitude	Customer participation	Uses and gratification perspective	Customer beliefs regarding virtual interaction benefits influence the continuity of customer participation. Also, that customer attitude is shaped by customers' affective response and affect customer participation positively. The effect is especially higher within high-involvement product and high-identification relation.
Dholakia et al. (2010)	Conceptual	Customer interaction	None	None	None	None	Customer-focused framework	Three areas that define customer behaviour in multichannel and multimedia environment are (1) what they bring, (2) what they encounter, and (3) what they strive for and do.
Yadav and Pavlou (2014)	Conceptual	Customer interaction	None	None	None	None	IT-mediated environment	Two areas related to this thesis are (1) Firm-customer interaction and (2) customer-firm interaction. There is a need to develop typology based on customer-firm interaction and a structured version of shopping funnels.
Hudson et al. (2016)	Experimental studies	Customer interaction	Customer interaction in social media	Anthropo-morphism perception & uncertainty avoidance	None	Brand relationship quality, WOM, brand loyalty	Consumer-brand relationship	Customer interaction on social media is highly related with brand relationship quality. Moreover, the effect is stronger with high anthropomorphism perception. The effect also different across culture. Within high uncertainty avoidance, increased interaction on social media is related to stronger brand relationship quality and WOM.

Authors (year)	Type of data	Area of interest	Key antecedents	Moderator	Mechanism	Outcome	Theoretical perspective	Key finding(s)
Barwitz and Maas (2018)	Expert interview and focus group	Customer interaction	Value-in-use	None	None	Interaction choice	Channel choice, journey choice, and segmentation	A hierarchical value map was created to understand how customer interaction choice is defined by the value they are looking for and the inter-connection of customer attributes in one's journey. It unravels the inertia and customer journey patterns within omnichannel interaction.
Cambra-Fierro et al. (2020)	Customer transaction data and customer survey	Customer interaction	Customer interaction - channel habit	None	Switching cost and loyalty	Cross buy and service usage	Theory of planned behaviour	Offline channel habit increases perceived switching cost and contribute positively to attitudinal loyalty. Online and self-service kiosk habits negatively impact service usage.
This research	**Customer survey and experiment**	**Customer interaction**	**Customer interaction complexities**	**Channel integration**	**Customer enjoyment and effort**	**Customer experience**	**Social penetration theory**	**Nonlinear relationship between dimensions of customer interaction and customer experience, in which the effect is flipped considering the level of channel integration (for interaction breadth). Customer enjoyment and customer effort mediates the relationship between customer interaction depth (and not on interaction breadth), differently between online and offline channel.**

Appendix B Cross-sectional customer survey (Study 1)

Survey Flow

Standard: Introduction (2 Questions)
BlockRandomizer: 1 - Evenly Present Elements
Standard: Grocery Shopper (6 Questions)
Standard: Touchpoints Interaction (9 Questions) **Standard: Value, Experience, Engagement (6 Questions)** **Standard: Demographic (6 Questions)**
WebService: GET - http://reporting.qualtrics.com/projects/randomNumGen.php - Fire and Forget

Start of Block: Introduction

Q2 **Welcome to the Omnichannel Customer Journey survey!**

Thank you for participating in this survey.

This survey is a part of the research project about understanding the omnichannel customer journey and specifically aims to understand the implication of different levels of interaction between a customer and a retailer. Omnichannel environment is marked by the presence of multiple contact points or channels provided by the retailer to communicate or to facilitate transaction. This can be both online and offline contact points. The questions in this survey will include the frequency of your interaction using different types of retailer's contact point as well as demographic questions. There are no right or wrong answer, we would like to know your true experiences and opinions.

If you have any question prior to taking part in this survey,

Please contact Triana (Yana) Hadiprawoto

Email: t.r.hadiprawoto1@leeds.ac.uk

This survey will take around 20 minutes of your time.

By continuing this survey, you are giving your consent.

More about the consent form, please visit: Informed Consent

Q55 Before you proceed to the survey, please complete the captcha below.

End of Block: Introduction

Start of Block: Grocery Shopper

Q9 Introduction

In the next section, we would like you to recall the shopping experience you had over the past one year. Specifically, we would like to ask your interactions with **a grocery retailer** for which you are the **main shopper and from which you shop frequently.** More specifically, we are interested in a particular retailer from which you frequently buy and operates using **more than two channels** (e.g. online store, call centre, mobile, brick-and-mortar shop, in-store tablet/ technology, mobile store, catalogue, newsletter).

Q10 Could you please mention the grocery retailer's name? (For the rest of the survey, the word "retailer" will refer to this specific retailer's name)

_____

Q11 How much in average do you usually spend per shopping trip? Please enter a number in US Dollar, if you do not remember the exact amount, please give your best estimate. _____
_



Q63 Approximately what percentage of all of your purchased grocery goods came from this retailer?_____

Q12 How long have you been a customer of this retailer? (please specify either in number of years or months)_____

Q46 How frequently do you buy products from this retailer?

- More than once a week (1)
- Once a week (2)
- 2-3 times a month (3)
- Once a month (4)
- Once every two months (5)
- Once every three months (6)

End of Block: Grocery Shopper

Start of Block: Touchpoints Interaction

Q34
Retailer's channels

The options below represent the type of channel that are usually owned and used by a retailer to interact with customers. Based on your interaction **in the last one year**, could

you please select all touchpoints/channels from the retailer that you have ever used? (Select all that applies, can be more than one)

- [ ] Physical store (1)
- [ ] Online store (2)
- [ ] Mobile app store (3)
- [ ] Catalogue or Newsletter (4)
- [ ] Call centre (5)
- [ ] The retailer's social media account (6)
- [ ] In-store technology (such as tablet, kiosk, or interactive pod in the store) (8)
- [ ] External (such as third-party delivery/pick-up counter) (7)

Page Break

Display This Question:

If Retailer's channels The options below represent the type of channel that are usually owned and us... = Physical store

Q36 Based on your interaction with this retailer, how frequently do you perform the following activities in the **Physical store** of this retailer?

Please indicate your answer with the value in between 0 - 3, where
0 = Never
1 = Rarely
2 = Occasionally
3 = Frequently

	Frequency (1)
Browse	
Receive/seek offers/coupon	
Consult with a staff	
Check for availability	
Compare price & payment methods	
See product visualisation & how that product works	
Look for social interaction	
Find product reviews	
Get a product trial	
Place an order	
Redeem a coupon	
Complete a payment	
Track an order	
Receive a product	
Share an experience	
Review a product	
Report an issue/ a complaint	
Identify know-how (installation)	
Exchange/return	

Page Break

Display This Question:

If Retailer's channels The options below represent the type of channel that are usually owned and us... = Online store

Q37 Please rate how frequently do you perform the following activities in the **Online store** of this retailer?

Please indicate your answer with the value in between 0 - 3, where
0 = Never
1 = Rarely
2 = Occasionally
3 = Frequently

	Frequency (1)
Browse	
Receive/seek offers/coupon	
Consult with a staff	
Check for availability	
Compare price & payment methods	
See product visualisation & how that product works	
Look for social interaction	
Find product reviews	
Get a product trial	
Place an order	
Redeem a coupon	
Complete a payment	
Track an order	
Share an experience	
Review a product	
Report an issue/ a complaint	
Identify know-how (installation)	
Arrange an exchange/return	

Page Break

Display This Question:

If Retailer's channels The options below represent the type of channel that are usually owned and us... = Mobile app store

Q38 Please rate how frequently do you perform the following activities in the **Mobile app store** of this retailer?

Please indicate your answer with the value in between 0 - 3, where
0 = Never
1 = Rarely
2 = Occasionally
3 = Frequently

	Frequency (1)
Browse	
Receive/seek offers/coupon	
Consult with a staff	
Check for availability	
Compare price & payment methods	
See product visualisation & how that product works	
Look for social interaction	
Find product reviews	
Get a product trial	
Place an order	
Redeem a coupon	
Complete a payment	
Track an order	
Share an experience	
Review a product	
Report an issue/ a complaint	
Identify know-how (installation)	
Arrange an exchange/return	

Page Break

Display This Question:

If Retailer's channels The options below represent the type of channel that are usually owned and us... = Catalogue or Newsletter

Q39 Please rate how frequently do you perform the following activities in the **Catalogue/Newsletter** of this retailer?

Please indicate your answer with the value in between 0 - 3, where
0 = Never
1 = Rarely
2 = Occasionally
3 = Frequently

	Frequency (1)
Browse	
Receive/seek offers/coupon	
Compare price & payment methods	
See product visualisation & how that product works	
Find product reviews	
Get a product trial (sample)	
Place an order	
Share an experience	
Report an issue/ a complaint	
Identify know-how (installation)	

Page Break

Display This Question:

If Retailer's channels The options below represent the type of channel that are usually owned and us... = Call centre



Q40 Please rate how frequently do you perform the following activities in the **Call Centre** of this retailer?

Please indicate your answer with the value in between 0 - 3, where
0 = Never
1 = Rarely
2 = Occasionally
3 = Frequently

	Frequency (1)
Browse	
Receive/seek offers/coupon	
Consult with a staff	
Check for availability	
Compare price & payment methods	
Look for social interaction	
Get a product trial	
Place an order	
Redeem a coupon	
Complete a payment	
Track an order	
Share an experience	
Report an issue/ a complaint	
Identify know-how (installation)	
Arrange an exchange/return	

Page Break

Display This Question:

If Retailer's channels The options below represent the type of channel that are usually owned and us... = The retailer's social media account

Q41 Please rate how frequently do you perform the following activities in the **Social Media page** of this retailer?

Please indicate your answer with the value in between 0 - 3, where
0 = Never
1 = Rarely
2 = Occasionally
3 = Frequently

	Frequency (1)
Browse	
Receive/seek offers/coupon	
Consult with a staff	
Check for availability	
Compare price & payment methods	
See how a product works & visualisation	
Look for social interaction	
Find product reviews	
Get a product trial	
Share an experience	
Review a product	
Report an issue/ a complaint	
Identify know-how (installation)	

Page Break

Display This Question:

If Retailer's channels The options below represent the type of channel that are usually owned and us... = In-store technology (such as tablet, kiosk, or interactive pod in the store)

Q42 Please rate how frequently do you perform the following activities in the **In-Store Technology (e.g. tablet, kiosk, interactive pod)** of this retailer?

Please indicate your answer with the value in between 0 - 3, where
0 = Never
1 = Rarely
2 = Occasionally
3 = Frequently

	Frequency (1)
Browse	
Receive/seek offers/coupon	
Check for availability	
Compare price & payment methods	
See how a product works & visualisation	
Find product reviews	
Place an order	
Redeem a coupon	
Complete a payment	
Track an order	
Identify know-how (installation)	

Page Break

Display This Question:

If Retailer's channels The options below represent the type of channel that are usually owned and us... = External (such as third-party delivery/pick-up counter)

Q43 Please rate how frequently do you perform the following activities in the **External touchpoints/channel (e.g. third party delivery/pick-up store)** of this retailer?
Please indicate your answer with the value in between 0 - 3, where 0 = Never, 1 = Rarely, 2 = Occasionally, 3 = Frequently

	Frequency (1)
Complete a payment	
Track an order	
Receive a product	

End of Block: Touchpoints Interaction

Start of Block: Experience

Q53 Please indicate to what extend do you agree or disagree with the following statements.

	Strongly disagree (1)	(2)	(3)	Neither agree nor disagree (4)	(5)	(6)	Strongly agree (7)
I engage in a lot of thinking when I shop from this retailer.	○	○	○	○	○	○	○
This retailer makes me think.	○	○	○	○	○	○	○
This retailer awakens my curiosity.	○	○	○	○	○	○	○
This retailer stimulates my problem-solving skill.	○	○	○	○	○	○	○

Q23 Please indicate to what extend do you agree or disagree with the following statements.

	Strongly disagree (1)	(2)	(3)	Neither agree nor disagree (4)	(5)	(6)	Strongly agree (7)
This retailer induces my feelings and sentiments.	○	○	○	○	○	○	○
I have strong emotions for this retailer.	○	○	○	○	○	○	○
For me, this retailer is an emotional brand.	○	○	○	○	○	○	○

Q54 Please indicate to what extend do you agree or disagree with the following statements.

	Strongly disagree (1)	(2)	(3)	Neither agree nor disagree (4)	(5)	(6)	Strongly agree (7)
I engage in physical actions and behaviours when I shop from this retailer.	○	○	○	○	○	○	○
Interacting with this retailer results in bodily experiences (e.g. becomes well, hungry, talkative)	○	○	○	○	○	○	○
This retailer is action-oriented.	○	○	○	○	○	○	○

Q65 Please indicate to what extend do you agree or disagree with the following statements.

	Strongly disagree (1)	(2)	(3)	Neither agree nor disagree (4)	(5)	(6)	Strongly agree (7)
This retailer makes a strong impression on my visual sense or other senses.	○	○	○	○	○	○	○
I find this retailer interesting in a sensory way	○	○	○	○	○	○	○
This retailer appeals in my senses.	○	○	○	○	○	○	○

Q66 Please indicate to what extend do you agree or disagree with the following statements.

	Strongly disagree (1)	(2)	(3)	Neither agree nor disagree (4)	(5)	(6)	Strongly agree (7)
This retailer helps me feel socially accepted.	○	○	○	○	○	○	○
Shopping from this retailer makes a good impression on other people.	○	○	○	○	○	○	○
This retailer improves the way I am perceived.	○	○	○	○	○	○	○

Page Break

Q49 Please indicate to what extent does this retailer practice the following statements?

	Extremely unlikely (1)	(2)	(3)	Neither likely nor unlikely (4)	(5)	(6)	Extremely likely (7)
Accept returns, repair, or exchange at their physical store for the purchases made through their online or mobile store.	○	○	○	○	○	○	○
Advertise its online or mobile store at its physical stores.	○	○	○	○	○	○	○
Provide access to their online store within its physical stores (e.g., through kiosk or tablet).	○	○	○	○	○	○	○
Provide information regarding the availability of specific products at specific stores through their online or mobile store.	○	○	○	○	○	○	○
Advertise its physical stores through its online or mobile store.	○	○	○	○	○	○	○
Have employees at its physical stores knowledgeable and helpful regarding the use of its online or mobile store.	○	○	○	○	○	○	○
Allow customers to purchase items through its online or mobile store and pick them up in one of its stores.	○	○	○	○	○	○	○
Allow consumer to receive non-product information on its stores (e.g., driving direction, opening hours) via email contact or other electronic communication made available through their online channel.	○	○	○	○	○	○	○

End of Block: Experience

Start of Block: Demographic

Q46 **About You**

We would like to ask some questions about you. This information important because these will give a better understanding of our data analysis and interpretation. This will be kept entirely confidential and will never be traced back to you as an individual. It will only be used for statistical and research purposes only and will be stored securely. If you wish not to answer a question, please move on to the next one.

Q47 What gender identity do you identify the most?

_____

Q48 Which category below includes your age?

- 18 or younger (1)
- 18 - 24 (2)
- 25 - 34 (3)
- 35 - 44 (4)
- 45 - 54 (5)
- 55 - 64 (6)
- 66 and over (7)

Q49 What is the highest level of school you have completed?

- Less than high school degree (1)
- High school degree or equivalent (e.g., GED) (2)
- Some college but no degree (3)
- Associate degree (4)
- Bachelor degree (5)
- Graduate degree (6)

Q50 Which of the following categories best describes your current employment?

- Employed full time (1)
- Employed part time (2)
- Unemployed looking for work (3)
- Unemployed not looking for work (4)
- Retired (5)
- Student (6)

Q51 Please tell us the total annual income of your household (before tax and deductions, but including benefits/allowances)?

- Below $9,999 (1)
- $10,000 to $19,999 (2)
- $20,000 to $34,999 (3)
- $35,000 to $49,999 (4)
- $50,000 to $74,999 (5)
- $75,000 to $99,999 (6)
- Over $100,000 (7)

End of Block: Demographic

Appendix C Supplement analysis of Study 1

C.1 Hypothesis testing with randomised sample

Table C.1 Regression Analysis with Subsample

DV: Customer experience	**90%**		**80%**		**70%**	
Control variables	**β**	**t**	**β**	**t**	**β**	**t**
Spending per trip	-0.038	-0.963	-0.042	-0.964	0.017	0.387
Length of tenure	-0.037	-0.864	-0.019	-0.407	-0.045	-0.955
Income	-0.009	-0.231	-0.014	-0.324	-0.024	-0.527
Age	-0.088	-2.119	-0.033	-0.732	-0.049	-1.059
Gender	0.072	1.814	0.036	0.834	0.001	0.019
Linear effect						
Breadth	-0.719	-9.555 ***	-0.728	-8.532 ***	-0.748	-9.022 ***
Depth	0.944	12.402 ***	0.959	11.384 ***	0.949	11.819 ***
Quadratic effect						
Breadth^2	0.284	4.137 ***	0.330	4.320 ***	0.311	4.086 ***
Depth^2	-0.308	-4.423 ***	-0.344	-4.458 ***	-0.308	-4.123 ***
Highest VIF		3.767		3.937		3.667
Adjusted R^2		0.329		0.287		0.326
F		24.730 ***		18.240 ***		20.347 ***

C.2 Test of the alternative specifications

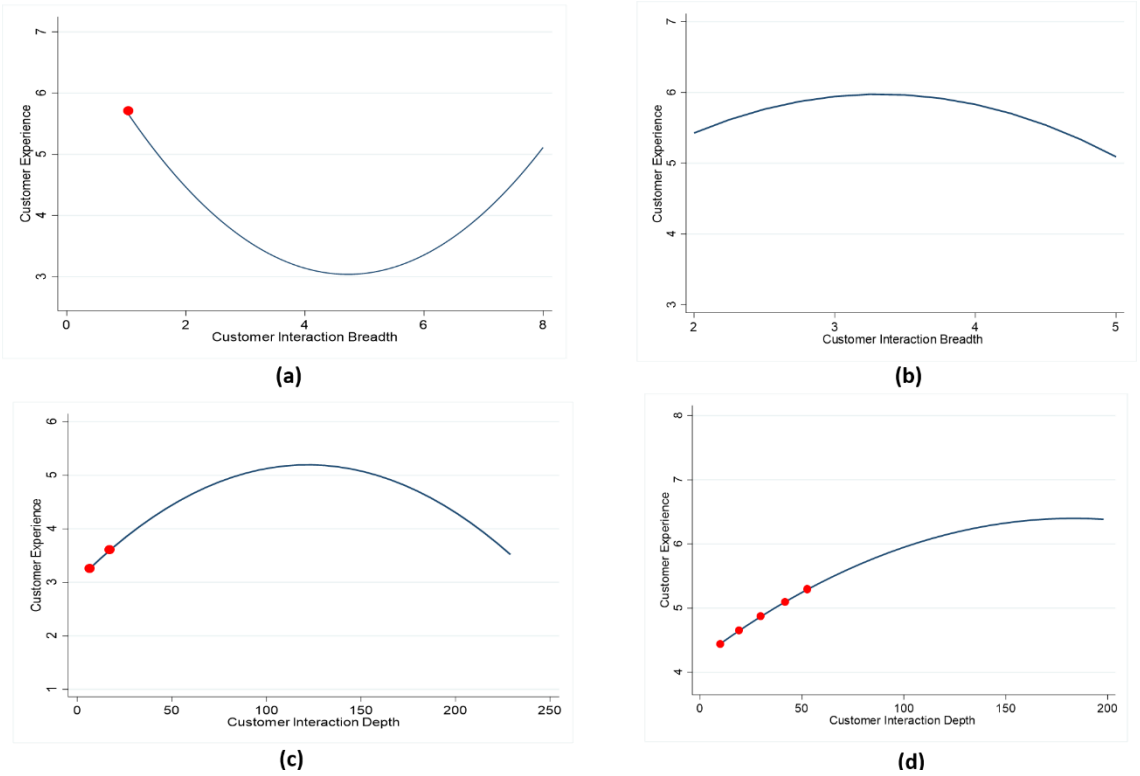
Table C.2 Regression Result Using Different Specification

DV: Customer experience	**Linear**		**Quadratic**		**Cubic**		**Log**	
Control variables	**β**	**t**	**β**	**t**	**β**	**t**	**β**	**t**
Spending per trip	-0.031	-0.784	-0.037	-0.957	-0.032	-0.840	-0.028	-0.730
Length of tenure	-0.070	-1.695†	-0.044	-1.070	-0.045	-1.090	-0.047	-1.140
Income	-0.022	-0.561	-0.009	-0.234	-0.007	-0.170	-0.012	-0.300
Age	-0.076	-1.854†	-0.056	-1.383	-0.055	-1.350	-0.061	-1.500
Gender	0.052	1.329	0.045	1.176	0.056	1.450	0.058	1.490
Linear								
Breadth	-0.591	-9.276***	-0.702	-9.918***	-0.644	-7.940***	-0.635	-5.330***
Depth	0.780	12.005***	0.922	12.954***	0.896	11.600***	-0.224	-0.590
Quadratic								
Breadth^2			0.282	4.328***	0.462	3.290***	0.112	0.910
Depth^2			-0.297	-4.469***	-0.311	-2.590**	0.940	2.390**
Cubic								
Breadth^3					-0.147	-0.970		
Depth^3					-0.036	-0.280		
Adjusted R^2		0.278		0.309		0.299		0.307
F		27.451***		24.961***		19.760***		23.480***
AIC		1434.134		1406.917		1409.481		1410.378
Δ AIC_{min}		27.217				2.564		3.461
BIC		1467.607		1448.758		1459.691		1452.219

† = 0.1; * = 0.05; ** = 0.01; ***= 0.001

C.3 Breadth and Depth at different level of channel integration

Figure C.1 The significant points of Breadth and Depth at Low and High Integration group



Note: (a) Breadth curve at Low Integration group, (b) Breadth curve at High Integration group, (c) Depth curve at Low Integration group, (d) Depth curve at High Integration group.

C.4 Stability of effect at different stages of Depth

DV: Customer Experience	**Model 1**			**Model 2**		
Control variables	**β**	**t**		**β**	**t**	
Spending per trip	-0.028	-0.730		-0.038	-1.000	
Length of tenure	-0.059	-1.270		-0.018	-0.450	
Income	-0.010	-0.260		0.011	0.300	
Age	-0.058	-1.410		-0.031	-0.780	
Gender	0.068	1.760	†	0.055	1.470	
Main effect						
Breadth	-0.402	-5.920	***	-1.005	-5.530	***
Depth - pre purchase	0.239	2.060	*	0.843	3.510	***
Depth - purchase	-0.063	-0.890		-0.276	-1.660	†
Depth - post purchase	0.488	5.430	***	0.814	4.760	***
Quadratic effect						
Breadth				0.682	3.950	***
Depth - pre purchase^2				-0.572	-2.590	***
Depth - purchase^2				0.261	1.530	
Depth - post purchase^2				-0.463	-2.680	***
Model fit						
R^2		0.298			0.352	
ΔR^2					0.053	
F	(9, 475)	22.44	***	(13, 471)	19.66	***
Δ F			***		9.687	***

Note: ***= 0.001; ** = 0.01; * = 0.05; † = 0.1

Appendix D Experimental study (Study 2)

Survey Flow

Standard: Introduction (3 Questions)

BlockRandomizer: 1 - Evenly Present Elements

- Block: Offline-Low (2 Questions)
- Block: Offline-Moderate (2 Questions)
- Block: Offline-High (2 Questions)
- Block: Online-Low (2 Questions)
- Block: Online-Moderate (2 Questions)
- Block: Online-High (2 Questions)

Block: Survey and Depth Check (8 Questions)
Standard: Confounding (4 Questions)
Standard: Demographic (6 Questions)

WebService: GET - http://reporting.qualtrics.com/projects/randomNumGen.php - Fire and Forget

EndSurvey: Advanced

Page Break

Start of Block: Introduction

Q2 **Experiencing The Omnichannel Customer Journey**
This task would require you to read paragraphs and seeing images, and answer short survey afterward.

Total duration will be less than 5 minutes. We will only accept participants who clearly demonstrate that they have read and understood the survey. Hence, there will be two attention checks.

For more info, please contact Triana. Email: t.r.hadiprawoto1@leeds.ac.uk
By continuing this survey, you are giving your consent: Informed Consent

Q3 Before you proceed to the survey, please complete the captcha below.

Q4 The colour test is simple, when asked for your favourite colour you must enter the word 'cerise' in the text box below. Based on the text you read above, what is your favourite colour?_____

End of Block: Introduction

Start of Block: Offline-Low

Q5 Please read the following text carefully.

Wearable Goods is a fashion retailer with many stores in different cities. It offers a wide range of products for both men and women, including clothing, footwear, and accessories.



Q6 The images below show the tasks you usually perform when visiting Wearable Goods' store :



All icons are from www.flaticon.com, made by Freepik, surang, Wichai.wi, monkik, smashicon, catcuro, Eucalup.

End of Block: Offline-Low

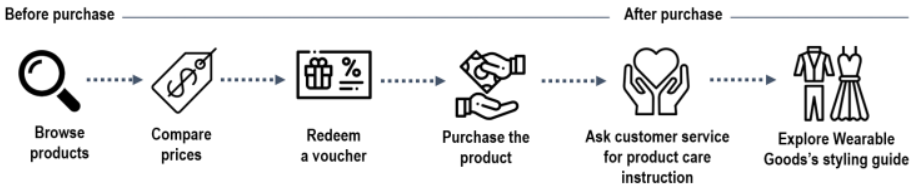
Start of Block: Offline-Moderate

Q7 Please read the following text carefully.

Wearable Goods is a fashion retailer with many stores in different cities. It offers a side range of products for both men and women, including clothing, footwear, and accessories.



Q8 The images below show the tasks you usually perform when visiting Wearable Goods' store :



All icons are from www.flaticon.com, made by Freepik, surang, Wichai.wi, monkik, smashicon, catcuro, Eucalup.

End of Block: Offline-Moderate

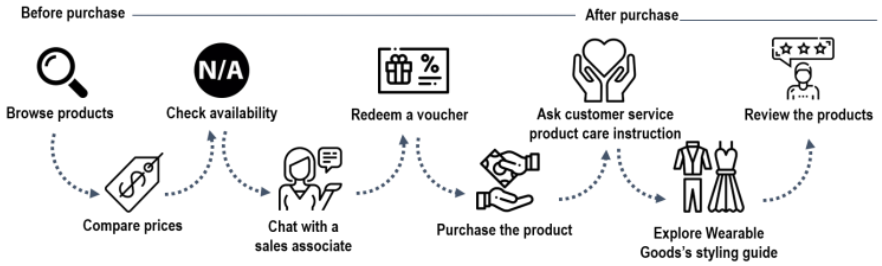
Start of Block: Offline-High

Q9 Please read the following text carefully.

Wearable Goods is a fashion retailer with many stores in different cities. It offers a wide range of products for both men and women, including clothing, footwear, and accessories.



Q10 The images below show the tasks you usually perform when visiting Wearable Goods' store :



All icons are from www.flaticon.com, made by Freepik, surang, Wichai.wi, monkik, smashicon, catcuro, Eucalup.

End of Block: Offline-High

Start of Block: Online-Low

Q11 Please read the following text carefully.

Wearable Goods is an **online** fashion retailer who delivers to many cities. It offers a

wide range of products for both men and women, including clothing, footwear, and accessories.



Q12 The images below show the steps you usually do when interacting with **Wearable Goods'** store:



All icons are from www.flaticon.com, made by Freepik, surang, Wichai.wi, monkik, smashicon, catcuro, Eucalup.

End of Block: Online-Low

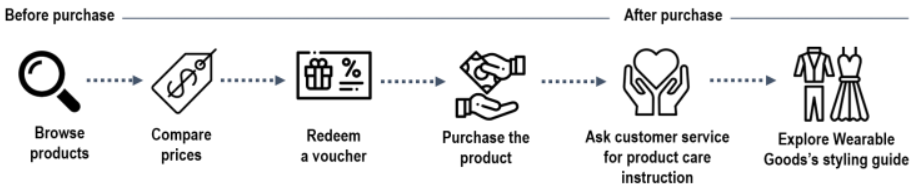
Start of Block: Online-Moderate

Q13 Please read the following text carefully.

Wearable Goods is an **online** fashion retailer who delivers to many cities. It offers a wide range of products for both men and women, including clothing, footwear, and accessories.



Q14 The images below show the tasks you usually perform when visiting Wearable Goods' online store:



All icons are from www.flaticon.com, made by Freepik, surang, Wichai.wi, monkik, smashicon, catcuro, Eucalup.

End of Block: Online-Moderate

Start of Block: Online-High

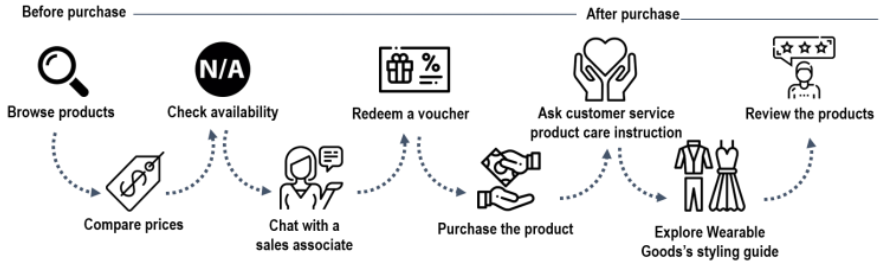
Q15 Please read the following text carefully.

Wearable Goods is an **online** fashion retailer who delivers to many cities. It offers a

wide range of products for both men and women, including clothing, footwear, and accessories.



Q16 The images below show the tasks you usually perform when visiting Wearable Goods' online store:



All icons are from www.flaticon.com*, made by Freepik, surang, Wichai.wi, monkik, smashicon, catcuro, Eucalup.*

End of Block: Online-High

Start of Block: Survey and Depth Check

Q47 1. In your interaction with Wearable Goods, how many activities do you usually perform?

0 1 2 3 4 5 6 7 8 9

Number of activities ()	

Q48 2. In your interaction with **Wearable Goods,** what type of channel did you use?

- ○ Online channel (1)
- ○ Brick and mortar store (2)

Page Break

Q23 The following statements should be answered based on your interaction with **Wearable Goods** in the beginning. Please indicate the extent to which you agree with the statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I engage in a lot of thinking when I shop from Wearable Goods.	○	○	○	○	○	○	○
Wearable Goods makes me think.	○	○	○	○	○	○	○
Wearable Goods awaken my curiosity.	○	○	○	○	○	○	○
Wearable Goods stimulates my problem solving skill.	○	○	○	○	○	○	○

Q24 .

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Wearable Goods induces my feelings and sentiments.	○	○	○	○	○	○	○
I have strong emotions for Wearable Goods.	○	○	○	○	○	○	○
For me, Wearable Goods is an emotional brand.	○	○	○	○	○	○	○

Q25 .

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I engage in physical actions and behaviours when I shop from Wearable Goods.	○	○	○	○	○	○	○
Interacting with Wearable Goods results in bodily experiences (e.g. becomes well, hungry, relief, energised, talkative, or strong).	○	○	○	○	○	○	○
Wearable Goods is action oriented.	○	○	○	○	○	○	○

Q26 .

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Wearable Goods makes a strong impression on my visual sense or other senses.	○	○	○	○	○	○	○
I find Wearable Goods interesting in a sensory way	○	○	○	○	○	○	○
Wearable Goods appeals in my senses.	○	○	○	○	○	○	○
Please check Neither agree nor disagree.	○	○	○	○	○	○	○

Q27 .

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Wearable Goods helps me feel socially accepted.	○	○	○	○	○	○	○
Shopping from Wearable Goods makes a good impression on other people.	○	○	○	○	○	○	○
Wearable Goods improves the way I am perceived.	○	○	○	○	○	○	○

Page Break

Q28 How realistic was the scenario you read in the beginning?

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Very Unrealistic	○	○	○	○	○	○	○	Very Realistic

Page Break

End of Block: Survey and Depth Check

Start of Block: Confounding

Q40 1. How much do you enjoy your interaction with **Wearable Goods**?

	(1)	(2)	(3)	4 (4)	5 (5)	6 (6)	7 (7)	
Not at all enjoy	○	○	○	○	○	○	○	Very much enjoy

Q46 3. How much effort do you need to spend when interacting with **Wearable Goods**?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Very little effort	○	○	○	○	○	○	○	A great deal of effort

Q39 4. In general, how frequent do you shop fashion items online?

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Never	○	○	○	○	○	○	○	Very Frequent

Q50 5. In general, how much do you like shopping for fashion items?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Very much like it	○	○	○	○	○	○	○	Very much dislike it

End of Block: Confounding

Start of Block: Demographic

Q29 **About You**

We would like to ask some questions about you. This information important because these will give a better understanding of our data analysis and interpretation. This will be kept entirely confidential and will never be traced back to you as an individual. It will only be used for statistical and research purposes only and will be stored securely. If you wish not to answer a question, please move on to the next one.

Q30 What gender identity do you identify the most?

_____

Q31 Which category below includes your age?

- ○ 18 or younger (1)
- ○ 18 - 24 (2)
- ○ 25 - 34 (3)
- ○ 35 - 44 (4)
- ○ 45 - 54 (5)
- ○ 55 - 64 (6)
- ○ 66 and over (7)

Q32 What is the highest level of school you have completed?

- ○ Less than high school degree (1)
- ○ High school degree or equivalent (e.g., GED) (2)
- ○ Some college but no degree (3)
- ○ Associate degree (4)
- ○ Bachelor degree (5)
- ○ Graduate degree (6)

Q33 Which of the following categories best describes your current employment?

- Employed full time (1)
- Employed part time (2)
- Unemployed looking for work (3)
- Unemployed not looking for work (4)
- Retired (5)
- Student (6)

Q34 Please tell us the total annual income of your household (before tax and deductions, but including benefits/allowances)?

- Below $9,999 (1)
- $10,000 to $19,999 (2)
- $20,000 to $34,999 (3)
- $35,000 to $49,999 (4)
- $50,000 to $74,999 (5)
- $75,000 to $99,999 (6)
- Over $100,000 (7)

End of Block: Demographic