Modelling Fashion Consumer Emotional and Behavioural Responses to Product Presentation Technology on Multi-Modal Mobile Devices

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Abstract

PhD in Textile Design, Fashion and Management

Due to a lack of physical interaction with products during online shopping, visual and verbal cues are essential in acquiring detailed product information. Literature demonstrates static and dynamic product presentation for online fashion goods can facilitate decision-making and mitigate perceived product risk as well as online returns (Park et al., 2005; De et al., 2013). While there is extant e-commerce research that confirms a high level of this cue positively influences consumer behaviour, there is limited research from a m-commerce perspective.

Applicability to the m-commerce platform may be unsuitable given the differences in screen size and interface (Kahn, 2017) as well as growing consumer shifts towards m-commerce (Faulds et al., 2018). As a result of these differences, understanding the impact on consumers’ cognitive processing can reveal useful insights (Kahn, 2017; Sohn, 2017b). Fluency theory has been explored in e-commerce research to determine the influence of atmospheric cues on the ease of processing stimuli (Mosteller et al., 2014; Im et al., 2010; Wu et al., 2016). To determine the influence of fashion product presentation towards m-commerce, the Stimulus-Organism-Response (SOR) framework with fluency theory was employed.

To evaluate the influence of online fashion product presentation on consumers’ cognitive, affective and behavioural outcomes when shopping on a mobile device, a two-phase mixed-methods approach was adopted. For the first phase, two online surveys were conducted with the same questions, but based on m-commerce fashion sites that differed in product presentation levels (i.e. low vs high). For the second phase, a 2 (level of product presentation) x 2 (product type) between-subject eye tracking study was employed alongside a survey and interview to understand the influence of product presentation on visual attention, perceptual fluency and purchase intentions as well as consumer perceptions and attitudes. Findings were converged to assess and explain behavioural differences towards fashion product presentation.

By analysing visualisation strategies adopted by online fashion retailers in the UK, this study has particular relevance towards the current use of static and dynamic imagery on the m-commerce platform. Findings contribute to a growing body of literature on product presentation, m-commerce atmospheric cues and perceptual processing during online shopping.
Declaration

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Candidate’s Conference Presentations

Chapter One: Introduction

1.1 Introduction

Given the exponential growth of e-commerce in the UK fashion retail sector, it is crucial for multichannel retailers to assert a strong online presence in an increasingly dynamic marketplace. However, e-commerce via a desktop or laptop computer no longer serves as a solitary online platform, as consumers can also shop via their smartphones and tablet devices. Mobile Commerce (m-commerce) is defined as the ‘use of mobile (handheld) devices to communicate and conduct transactions through public and private networks’ (Balasubramanian et al., 2002, p.349). Whilst UK online sales do not surpass in-store sales (eMarketer, 2017), smartphone purchases of consumer goods have soared in 2017 and indicate that shopping via this channel is rapidly gaining momentum (Mintel, 2017). Recent statistics reveal global retail digital payments made on a mobile device have taken over e-commerce sales and are predicted to rise further (eMarketer, 2018) as illustrated in Figure 1.1.

![Figure 1.1 Global Retail M-Commerce Sales Between 2016-2021](source: eMarketer (2018))

This effect is observed across the fashion industry with Net-a-Porter Yoox reporting more than half of its UK sales were driven by mobile sales (Fernandez, 2018), which suggests
there is huge potential for multichannel fashion retailers to maximise further revenue and profitability on the mobile platform.

Unlike brick-and-mortar retailing, consumers are unable to physically interact with products online. In comparison to other product categories such as electronics, shopping for fashion products is associated with greater perceived risk since consumers are unable to touch and feel fashion apparel (Bhatnagar et al., 2000). They are also unable to try on clothing prior to purchase. To stand out in an increasingly competitive marketplace and to mitigate perceived risk online, fashion retailers have invested and are continuing to invest in innovative technologies (Mintel, 2016a; Park et al., 2008). This includes the use of product presentation, which is commonly used by fashion retailers to display images of fashion merchandise, such as apparel, shoes and accessories, online. As a visual format, product presentation is comprised of static and dynamic product imagery (Roggeveen et al., 2015). Specifically, the use of Image Interactivity Technology (IIT) has been developed to provide greater product information (Beuckels and Hudders, 2016). An example includes image enlargement, otherwise referred to as zoom function (Fiore et al., 2005b). Research reveals the use of interactive product presentation positively influences approach behaviour when shopping online (Fiore et al., 2005b; Lee et al., 2010).

Literature has mainly focussed on examining product presentation on an online platform and less so on mobile devices. An important distinction between the online and mobile platforms is the interaction with the user interface. Unlike desktops and laptops, which usually require a mouse or touchpad, using a mobile device requires a touchscreen functionality; interaction is manipulated using a direct-touch interaction (Park et al., 2011). Another important distinction is the size; mobile devices have a smaller screen size, which may create difficulties during the evaluation of visual product information (Wang et al., 2015).

 Majority of product presentation literature has also relied on self-reported measures, i.e. verbal recall, and are mostly based on online shopping using a PC. From a m-commerce perspective, the influence of product presentation on consumer behaviour is less well understood. There is also a research gap in understanding the influence of product presentation on visual attention. Using eye tracking technology enables a greater understanding of the human-computer interaction and cognitive processing. This
technology also offers a variety of benefits that would not be captured using verbal recall (Holmqvist et al., 2011). Since product presentation is an important visual attribute of online fashion retailing, analysing the influence of this particular visual stimuli on eye movements may reveal useful insights (Kahn, 2017). As a result, eye tracking technology was utilised in this study to explore differences in visual attention towards different levels of product presentation. Interviews were also conducted alongside eye tracking experiments to clarify ambiguity of fixation data and to understand evolving m-commerce behaviours towards product presentation technology.

Recently, e-commerce literature has focussed on aspects of website design and how they contribute towards fluent processing (Mosteller et al., 2014; Wu et al., 2016; Kahn, 2017). Depending on the conditions of the stimuli, consumers may process stimuli with ease or difficulty. By increasing ease of information processing, an individual experiences higher levels of perceptual fluency (Reber et al., 2004b). Empirical research confirms high perceptual fluency can result in positive emotions and approach behaviour (Mosteller et al., 2014). There is a gap in literature in exploring the concept of perceptual fluency in relation to product presentation. This area of research is supported by literature who state the application of processing fluency as a theoretical underpinning is considered appropriate to enable greater understanding on how consumers process product presentation (Song and Kim, 2012; Kahn, 2017). Compared to complex stimuli, simple stimuli is shown to have a stronger influence on fluent processing (Hermann et al., 2013; Im et al., 2010; Wu et al., 2016). However, in terms of product presentation, a simple level implies a lower level of product imagery, which although may be easy to process, may not provide sufficient product information. Hence, greater clarification is required to assess the influence of different levels of product presentation on perceptual fluency and approach behaviour. Current image interactivity tools used by online fashion retailers, such as ASOS, Boohoo and Net-a-Porter include image enlargement i.e. zoom function, 360° product rotation and catwalk video. This study is the first to empirically confirm whether differences in product presentation technology can lead to differences in perceptual fluency and visual attention during online shopping and its impact on approach behaviour from a m-commerce perspective.
1.2 Research Context

Increase in smartphone size, such as the iPhone 8 Plus and the iPhone Xs Max, signal a trend towards ‘phablet’ devices, which are a combination of smartphones and tablets (IDC, 2014; Apple, 2018). Other developments such as iBeacon technology and QR codes are furthering consumers’ adoption towards mobile methods of shopping and payment (Shankar et al., 2016). Due to obsession with these devices, the attractiveness for mobile marketing and mobile shopping also rises (Ström et al., 2014). Compared to other age groups, users aged between 18-34, which account for 22.8% of the UK population (i.e. 12.8 million people) spend at least three hours a day on their smartphone and are more likely to engage in multiple online activities, such as listening to music, sending/receiving emails and online shopping (Ofcom, 2017; Department of Office for National Statistics, 2019). This age group, which is comprised of Millennials (i.e. born between 1980-1995) and Generation Z (i.e. born after 1995) cohorts illustrate smartphone consumption is embedded in everyday life for this generation of consumers (KPMG, 2017). As a result, mobile payments for fashion have increased. This includes purchases on apps, on a mobile optimised site, on the phone in store and mobile wallets (The Business of Fashion and McKinsey & Company, 2017). To cultivate further mobile growth, fashion retailers are exploring and developing new mobile technologies. Fashion retailers such as Tommy Hilfiger have developed “stores of the future” to further consumer engagement on mobile devices as well as providing consumers with a digital wardrobe and the ability to pay via an app (The Business of Fashion and McKinsey & Company, 2017).

Market research data reveals using a mobile device to shop for fashion clothing is popular among Millennials (eMarketer, 2016; Mintel, 2017). Almost half use their smartphone to make a fashion purchase (Mintel, 2017). While UK online sales of fashion clothing and footwear have increased by 17% since the previous year, high product returns highlight an ongoing issue. Half of all fashion clothing purchased online is returned back to the retailer (Mintel, 2017). According to Mintel (2015a), 23% of young females had returned their online clothing purchases because the items contrasted to what they had pictured online. Empirical findings by De et al. (2013) demonstrate the use of zoom function decreases the propensity of online product returns, which highlights the importance of these tools in displaying fashion merchandise. Despite screen size constraints, this study posits effective
implementation of static and dynamic product presentation should also improve product visualisation when shopping on a mobile device.

1.3 Research Problem

Regardless of the shopping platform, consumers rely upon certain cues in product evaluation to arrive at an informed decision (Citrin et al., 2003). Delivering detailed visual information and as well as verbal information is imperative when consumers are unable to physically examine the product (Kim and Lennon, 2010). Fundamentally, the absence of tactile input is a limitation of online shopping which can obstruct consumers’ decision making (Citrin et al., 2003; Peck and Childers, 2003b; Balaji et al., 2011). This is particularly significant for pure-play retailers, as the absence of a physical store increases the trouble of inspecting clothing items online (Citrin et al., 2003; Khakimdjanova and Park, 2005). To minimise online product returns, there is a need for fashion apparel retailers to ensure there are effective product presentation strategies in order to ascertain product characteristics, qualities and performance. As product information is an essential element for apparel webpages (Kim and Lennon, 2010), creating sensory enabling technologies could additionally facilitate positive attitudes and purchase decisions (Krishna and Shwarz, 2014; Kim and Forsythe, 2008).

While convenience and product information are often cited as the main reasons for using mobile phones during the shopping process (Wang et al, 2015), the issue of product visualisation is likely to be amplified with smartphones and tablets. Size and functionality are a problem when viewing product information (Wang et al., 2015; Shankar et al., 2010). This is important as research demonstrates that visual information, such as images, receives the most baseline attention (Pieters and Wedel, 2004). There is a preference to view visual information over textual information (Kahn, 2017). Subsequently, there is a need to understand how consumers process visual product information, and how this affects m-commerce consumer behaviour. Although a high level of product presentation stimuli provides richer and detailed product information and may ease processing for fashion consumers, a high level of product presentation viewed on smaller screens may also enhance information intensity that could result in disfluent processing (Mosteller et
Therefore, clarification is required to assess differences in product presentation and its impact on perceptual fluency.

Additionally, the nuances of touchscreen devices and the way it can be utilised, through gestural interactivity for example, reveals that smartphones are an untapped area of growth if designed effectively (Cano et al., 2017). Gestural interactivity refers to a gesture-based input on a touchscreen interactive display (LaViola, 2013; Bragdon et al., 2011), which enables individuals to interact with their fingers using gestural motions such as swiping and tapping (Billinghurst and Vu, 2015). Devising effective image interactivity strategies with the use of gestural interactivity may help to compensate the loss of tactile information (Cano et al., 2017). In this regard, interactivity is essential. If consumers are wary of not being able to visualise the product in sufficient detail on mobile devices, then existing product presentation strategies are not enough in satisfying consumers’ needs.

1.4 Research Aim

By using a multi-phase mixed-methods approach, the overall aim of this study is to analyse the influence of different conditions of product presentation technology including visualisation tools used by current online fashion retailers (i.e. zoom function, catwalk video, 360-degree rotation) when shopping on mobile devices by assessing the differences in perceptual fluency and visual attention during the shopping process and how this effect directly and indirectly contributes towards consumers’ emotional responses and purchase intentions. Perceptions and attitudes are also explored to understand usage and perceptions towards product presentation technology as well as the influence of evolving shopping behaviours from a m-commerce perspective.
1.5 Research Objectives

The research objectives of this study are:

1. To evaluate perceptual fluency as a theoretical framework for the analysis of fashion product presentation as a visual stimulus on mobile devices.
2. To construct a multi-dimensional theoretical framework from existing literature that demonstrates the relationship between product presentation conditions on mobile devices, perceptual fluency, approach responses and purchase intentions.
3. To assess whether gestural interactivity for fashion product presentation on mobile devices contributes towards positive approach responses.
4. To determine whether static and dynamic product imagery that is comprised of more detailed information leads to higher levels of perceptual fluency.
5. To assess behavioural differences in visual attention towards fashion product presentation using eye tracking technology.
6. To understand behavioural differences in visual attention towards product presentation using retrospective verbalisations.
7. To understand perceptions and attitudes towards fashion product presentation on mobile devices.

1.6 Research Outcomes

The research outcomes of this study are:

1. To demonstrate the usefulness of perceptual fluency as a theory for examining the mobile fashion shopping environment.
2. To understand consumer perceptions towards current product visualisation techniques used by fashion apparel retailers on mobile devices.
3. To determine the potential of gestural interactivity in designing effective product presentation technology for fashion m-commerce.
4. To provide recommendations on how fashion apparel retailers can improve existing product presentation on mobile devices.
5. To validate a multi-phase mixed methods approach as an appropriate methodology in studying consumer responses and visual attention towards product presentation technology.
1.8 Research Methodology

A two-phase mixed-method approach was adopted, consisting of online surveys and eye tracking with interviews. For both studies, a between-subject design was employed to compare differences between two fashion retail websites on a mobile device that either employ a high level or a low level of image interactivity. This type of experimental design is routinely applied in IIT literature as well as online shopping studies that evaluate fluency (Lee et al., 2010; Beuckels and Hudders, 2016; Im et al., 2010). The retail website tested in both studies was a UK pureplay fashion brand: ASOS. On a mobile device, ASOS can be accessed using the optimised m-commerce site or via an app, which users can download to use alternatively. Not all online fashion brands have an app (Gilliland, 2017). Thus, both formats (i.e. m-commerce site and app) were tested in phase one (i.e. online survey). For technical reasons, only the ASOS m-commerce site was considered for phase two (i.e. eye tracking and interview). For both phases, the sample criterion was 18-24-year-old females who have online shopping experience.

In the first phase, an online survey was conducted to confirm relationships proposed in the theoretical framework. Participants were asked to browse on the selected fashion retailer’s website using their smartphone and answer questions towards the product presentation and on their shopping experience. A total of 514 survey responses were collected (225 ASOS responses and 259 Amazon responses). Statistical data analysis comprised of a Cronbach’s alpha reliability analysis, Exploratory Factor Analysis (EFA) and Structural Equation Modelling (SEM).

The second phase involved field experiments using eye tracking technology followed by an interview. Participants were asked to browse fashion merchandise on a fashion mobile website using a tablet device while wearing an eye tracker (Tobii Pro Glasses 2). To compare data with ASOS, a mock website (Pretty Gal) was designed on Wix.com to manipulate product presentation for a less interactive condition. A total of 24 participants recruited from The University of Manchester were randomly assigned to either condition. As well as eye tracking data, participants also completed questions based on perceptual fluency and purchase intentions and took part in a short interview after eye tracking. Interviews were conducted to understand consumer attitudes towards product presentation as well as shopping on mobile devices. Quantitative data was analysed using a series of
independent samples $t$-tests to compare and assess significant differences between perceptual fluency, purchase intentions and eye tracking metrics, while qualitative interview data was transcribed and coded to reveal common themes in the dataset.

1.9 Chapter Summary

Multi-modal mobile devices are rapidly changing the retail landscape, and this has important implications for the fashion apparel industry. Despite the exponential rise of smartphones and tablet penetration in recent years and the body of research on the online shopping environment, mobile and tablet shopping for fashion is a growing area of research, particularly in terms of factors that influence purchase intentions (Gao et al., 2015). The importance of visual product information, including product presentation tools, for fashion apparel products is acknowledged in literature with research mostly focused from an e-commerce perspective. Given the screen size constraints and touchscreen interaction, studying the influence of these tools on consumers’ perceptions and behaviour will provide valuable insights into how fashion retailers can effectively manage these tools on a mobile platform. Fluency theory furthers understanding towards these tools by examining whether these tools contribute towards ease of processing. This study also has particular relevance to current online fashion retailing in the UK; static and dynamic product imagery analysed in this study is currently employed in the online fashion industry with differences in terms of operation, size and quality.


Chapter Two: The Online Fashion Retail Environment

2.1 Introduction

This chapter outlines the development of the online fashion retail environment. Today, fashion retailers have a variety of formats to sell fashion merchandise including bricks-and-mortar retailing, e-commerce, and more recently m-commerce. While e-commerce has grown exponentially, global market data reveals 58.9% of digital payments in 2017 were driven by m-commerce sales, with an increase of 18.7% from 2015 (eMarketer, 2018). Technology has played a key role; innovations and advanced developments, such as m-commerce, continue to disrupt the retail landscape (Treadgold and Reynolds, 2016; Grewal et al., 2017). Due to these changes, fashion retailing has experienced major shifts in the last 30 years (Guercini et al., 2018; Bhardwaj and Fairhurst, 2010).

2.2 Overview of Fashion Retailing

In contrast to other consumer products, fashion is comprised of unique characteristics. Clothing is symbolic to the individual; it enables consumers to communicate their personal style and identity (Auty and Elliot, 1998; Evans, 1989). In addition to functional requirements, fashion is considered a response that stems from social and emotional needs (Diaz Meneses and Nieves Rodriguez, 2010). O’Cass (2004, p.880) summarises this finding by stating ‘in reality, we are who our clothes allow us to be’. From a consumption perspective, fashion clothing purchases may be either goal-directed or based on pleasure-seeking behaviour (Park et al., 2012).

While traditional fashion retailers have moved into online and mobile retailing, there are fast fashion and luxury fashion retailers, such as ASOS and Net-A-Porter, who operate solely online and on mobile, and are referred to as pure-play retailers (Rowley, 2009; Marciniak and Bruce, 2004). In some cases, a reverse strategy has been implemented; fashion retailers, such as Missguided, who were original pure-play, have also experimented with physical retailing (Mintel, 2016b).
In addition to retail changes, there have also been consumer shifts. Today’s consumers are more involved, knowledgeable, demanding and time-pressured (Treadgold and Reynolds, 2016; Labrecque et al., 2013). Traditionally, fashion consumers consume fashion products based on seven stages of the Consumer Decision Process (CPD) (Blackwell et al., 2006). Along with consumer shifts and technological developments, consumers no longer follow a traditional buying process. In addition to brick-and-mortar establishments, consumers can search for information and shop for fashion apparel anywhere, anytime online or on their mobile device (Kaplan, 2012; Grewal et al., 2017; Sands et al., 2016; Rodriguez-Torrico et al., 2017). Consumers may also choose to shop for fashion on different channels at the same or different stages of the consumer journey (Luceri and Latusi, 2015). As a result of today’s retail landscape, consumers’ decision-making process and purchasing may not occur in a linear fashion but appears to be rather more complex. With the ability to collect more data, fashion retailers can use such insights to strategically target consumers with relevant marketing messages or promotions (Bradlow et al., 2017). Such approaches typically involve the use of digital channels or digital media (Shephard, 2016).

The store environment in general has an impact on fashion consumer behaviour, which then impacts on the decision-making process (Dholakia et al., 2010). Fashion literature has evolved to focus on specific elements of the store environment (Park et al., 2015; Morrison et al., 2011; Mower et al., 2012; Doucè and Janssens, 2013; Blázquez, 2014). Consumers expect a much more sophisticated store environment (Foster and McClelland, 2015). Providing an immersive store experience can help fashion retailers to differentiate themselves and provide a competitive advantage in an already competitive environment. Evidence suggests changes in retailing are required to attract future shoppers and provide a satisfying store experience (Grewal et al., 2017; Mintel, 2018). Priporas et al. (2017) emphasise the need to innovate in attaining and improving the consumer experience for Generation Z consumers (who were born after 1994). Although this consumer group are demanding and spend a great amount of time on their smartphones, they do value and shop in physical stores due to the experiential element (Mintel, 2017). Despite the growth of online and mobile channels, findings suggest the physical channel remains a valuable channel for fashion consumers and fashion retailers, but integration with the online channel using a multichannel strategy is an important aspect (Sands et al., 2016; Blázquez, 2014).
Since the use of advanced technology is transforming retailing (Grewal et al., 2017), there is a need to understand these changes from a fashion context and how they will influence fashion consumption. Recently, Zara unveiled its new digital store in Westfield Stratford featuring interactive mirrors, staff with iPads to make payments and self-service technology that does not require scanning (Geoghegan, 2018). The store also includes designated areas for online shopping and click and collect orders. In doing so, this strategy complements Zara’s online channel in providing a more seamless and interactive experience in store (Geoghegan, 2018). Literature confirms the use of technologies such as digital screens, shopping assistant systems, Radio-Frequency Identification (RFID), Artificial Intelligence (AI), machine learning, Augmented Reality (AR), Virtual Reality (AR) can provide a personalised service, facilitate positive consumer behaviour and enhance the overall shopping experience (Blázquez, 2014; Pantano and Naccarato, 2010, Pantano and Servidio, 2012; Poushneh and Vasquez-Parraga, 2017; Roy et al., 2017; Yim et al., 2017; Javornik, 2016; Grewal et al., 2017; Watson et al., 2018).

Therefore, as an area that is continually evolving with digital advancements and changes in consumer shifts, more research is warranted to determine the overall effectiveness of these changes in fashion retail. Despite digital gains, current economic woes continue to affect the fashion industry for traditional retailers who also operate online. There is also increased competition among pure-play fashion retailers (Mintel, 2018). While the role of the physical store retailing may need to be re-evaluated in a digital age, place is an important aspect of marketing (Goworek and McGoldrick, 2015).

### 2.3 E-Commerce

The internet is a revolutionary tool that is continuing to have a colossal impact on society. Otherwise referred to as online shopping, online retailing or e-tail, Electronic Commerce (e-commerce) involves orders of goods or services purchased electronically (Turban et al., 2018). Initially, fashion retailers perceived the internet as a communication tool whereby the focus was on delivering consistent branding rather than driving sales via this channel (Siddqui et al., 2003). Rather than being considered an additional channel, Bhatnagar and Syam (2014) state the online channel should be considered complimentary to offline retailing. With the expansion of the internet in the 2000s, early predictions of e-commerce
asserted it would cannibalise offline sales (Doherty and Ellis-Chadwick, 2010; Mahadevan, 2000). While this has yet to come to fruition, data confirms retail sales are increasingly driven by online shopping (Geddes, 2018). Comparing data between 2002-2010, Falk and Hagsten (2015) demonstrate e-commerce sales across different industries and countries in Europe have increased considerably. In addition to online sales, there has been a rapid adoption of online retail technologies as a result of IT advancements (Roy et al., 2017).

Internet developments that have propelled e-commerce can be characterised as different stages of the Web, such as Web 2.0 and Web 3.0 (Turban et al., 2018; Newman et al., 2016; Wirtz, 2001). In comparison to Web 1.0, there is emphasis on social networks, collaboration, personalisation as well as providing a consumer-centric approach based on consumer information in Web 2.0. This web development has led to user-generated content whereby information is shared among individuals, consumers and retailers (Jayawardhena and Wright, 2009; Wirtz et al., 2001; Hoffman and Novak, 2009). As a result of these changes, retailing has witnessed a shift in power from marketers to consumers (Labrecque et al., 2013).

Newman et al. (2016, p. 596) acknowledge connection and the role of smartphones are key aspects of Web 3.0 that involves ‘cloud-computing, Big Data, Internet of Things, social networks, security and existing features in Web 2.0’. Although literatures detailing the overall influence of these developments appear to be limited from an e-commerce perspective, e-commerce literature has focussed on specific elements that influence characteristics defined by Web 2.0 and Web 3.0. For example, smart technologies, such as AR, can provide a more personalised experience and greater interaction with e-commerce (Roy et al., 2017; Yim et al., 2017), while Big Data can be analysed to provide useful insights to improve consumer experience as well as nuanced marketing approaches (Bradlow et al., 2017). As well as using technology in physical stores, the above findings suggest implementation of smart technologies for online fashion retail has huge potential.
2.3.1 Drivers and Motivations of E-Commerce

In comparison to the offline channel, e-commerce offers several distinctions (Chaparro-Peláez et al., 2016; Häubl and Trifts, 2000; Bhatnager and Syam, 2014; Ganesh et al., 2010), which highlights the importance of re-evaluating this dynamic landscape. E-commerce frameworks appear to be varied, with different dimensions, moderators and mediators as well as interrelations between various dimensions and/or factors studied. Benefits and drivers of online shopping have been extensively discussed and evaluated in literature and can be considered from a retailer or consumer perspective, as shown in Table 2.1.

<table>
<thead>
<tr>
<th>Table 2.1 Examples of E-Shopping Drivers from Literature</th>
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<tbody>
<tr>
<td><strong>Factor(s)</strong></td>
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<td>--------------</td>
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<tr>
<td>Lower cost structures</td>
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<tr>
<td></td>
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<tr>
<td>Maintenance, innovation &amp; flexibility</td>
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<tr>
<td></td>
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<tr>
<td>Merchandise assortment</td>
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<td></td>
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<tr>
<td>Domestic and global reach</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Accessibility (i.e. convenience)</td>
</tr>
<tr>
<td>Customised search tools</td>
</tr>
<tr>
<td>Customer communication and feedback</td>
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<tr>
<td></td>
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<tr>
<td>Consumer engagement</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Personalisation &amp; product recommendations</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Search alternatives</td>
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<tr>
<td>Product &amp; retailer information</td>
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</table>
One way to categorise antecedents of online shopping adoption is to study shopping motivations, which can provide further insight in online consumers’ buying behaviour (Dholakia and Zhao, 2009). Shopping motivations encompass utilitarian or hedonic dimensions (Babin et al., 1994; Hirschman and Holbrook, 1982; Arnold and Reynolds, 2003; Wolfinbarger and Gilly, 2001). Babin et al. (1994) describe utilitarian consumption as goal-oriented behaviour. Hedonic consumption is described as a pleasure-seeking shopping experience (Babin et al., 1994). Due to differences between online and physical retail formats, it is important to acknowledge shopping motivations may vary accordingly (Arnold and Reynolds, 2003).

While utilitarianism and hedonism constructs are distinct, effects are not always isolated; empirical data confirms there is no effect on price consciousness, which suggests consumers behaving hedonically have some levels of price consciousness and vice versa (Scarpi, 2006; Scarpi, 2012). Similarly, utilitarian values may also result in a more hedonic experience, and therefore more positive behaviour; Jayawardhena and Wright (2009) found online websites that provide convenience, can also positively influence excitement, which can lead to re-visit intentions and positive WOM. There are greater preferences and positive intentions towards websites that satisfy both shopping motivations (To et al., 2007; Overby and Lee, 2006; Scarpi, 2012), which reinforces the need to provide an experience that caters for both shopping motivations.

Initially, there was focus on online shopping adoption with many papers empirically testing variables that influence adoption and acceptance. Thus, usage of the Technology Acceptance Model (TAM) framework proposed by Davis (1989) was widespread in e-commerce literature in determining behavioural intentions towards technology with original constructs perceived usefulness and perceived ease of use. An example is displayed in Figure 2.1. Empirical research confirms an increase in these variables positively influence attitudes and purchase intentions online (van der Heijden et al., 2003; Fenech and O’Cass, 2001; Chang et al., 2005; Childers et al., 2001).
This is consistent with literature evaluating online shopping motivations with such factors associated with utilitarianism (Ha and Stoel, 2009). Older e-commerce literature demonstrates preference for utilitarian value. This includes aspects such as ease of navigation, delivery, convenience and providing information (To et al., 2007; Overby and Lee, 2006; Bridges and Florsheim, 2008). To et al. (2007) explain there is less preference on hedonic value by suggesting the indirect effect on purchase intentions is due to lack of proving a full multi-sensorial experience online, and that consumers with a hedonic shopping orientation are more likely to shop in a physical store than online. Empirical results corroborate convenience as the most influential driver of e-commerce (Chaparro-Peláez et al., 2016; Mee and Huei, 2015; Rohm and Swaminathan, 2004; Childers et al., 2001).

As e-commerce has evolved, more research is warranted to determine if this is still the case as Scarpi (2012) argues causal relationships are stronger for hedonism experienced online; satisfying hedonic needs is likely to yield more items purchased, higher sales and higher levels of loyalty for online retailers. Despite drivers of e-commerce stating convenience as the main reason, research demonstrates consumers enjoy shopping online (Childers et al., 2001; Pappas et al., 2017). Providing an enjoyable online experience is shown to facilitate trust (Oliveira et al., 2017). In comparison to general online shopping studies, Ha and Stoel (2012) particularly emphasise the importance of the experiential dimension, such as try-it-on and a live chat mechanism, for online fashion apparel. Unlike other product categories, fashion elicits emotion as well as cognition (Scarpi et al., 2014). Table 2.2 indicates that
although hedonic consumption has greater relevance for fashion products, utilitarian consumption is also an important aspect in online fashion research.

Table 2.2 Differences in Online Fashion Hedonic and Utilitarian Consumption

<table>
<thead>
<tr>
<th>Author(s) and Context</th>
<th>Antecedents</th>
<th>Outcome(s)</th>
<th>Main findings</th>
<th>Shopping Channel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ha and Stoel (2012)</td>
<td>Atmospheric/experiential</td>
<td>Satisfaction, shopping</td>
<td>Experiential motives are positively associated with satisfaction and indirectly influences shopping intentions, which is mediated by satisfaction</td>
<td>Online</td>
</tr>
<tr>
<td>Online shopping quality</td>
<td>Privacy/security</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Content/functionality</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>Customer service</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Park et al. (2012)</td>
<td>Product attributes</td>
<td>E-impulse buying</td>
<td>Hedonic browsing drives impulse purchases. Product selection positively influences utilitarian browsing which does not lead to impulse buying. Price is positively associated with hedonic browsing,</td>
<td>Online</td>
</tr>
<tr>
<td>Online impulse buying</td>
<td>(selection, price, sensory), utilitarian</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>browsing</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scarpi et al. (2014)</td>
<td>Hedonism, utilitarianism, price</td>
<td>Intentional loyalty, Word</td>
<td>Price consciousness mediates the positive relationships between both shopping motivations and intentional loyalty online and offline. Utilitarianism leads to WOM offline, whereas hedonism is more likely to result in WOM online.</td>
<td>Online and offline</td>
</tr>
<tr>
<td>Comparing shopping environments</td>
<td>consciousness</td>
<td>of Mouth (WOM)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In line with above research that confirms that importance of utilitarian consumption driving hedonism, fashion consumers enjoy shopping for bargains online, which is value driven, and is associated with hedonic browsing (Park et al., 2012). Due to lack of touch online, fashion product attributes are essential stimuli in facilitating browsing behaviour online that can propel impulse purchases. Therefore, Park et al. (2012) recommend fashion apparel retailers to invest in technology to help improve utilitarian and hedonic browsing on fashion apparel websites.

Newer research emphasises the importance of personalisation that can result in enjoyment, higher click-through rates and higher purchase intentions (Kaptein and Parvinven, 2015; Pappas et al., 2017). This type of shopping experience is also deemed important for online fashion apparel (Hwangbo et al., 2018). Similarly, recent findings demonstrate the influence of online promotional and selling cues. Such cues are confirmed to have a greater impact on hedonic consumption than utilitarian consumption (Kivetz and Zheng, 2017). In contrast, Das et al. (2018) state selling cues, such as best seller and limited-edition cues, can lead to a positive evaluation and purchase intentions, but that this dependent on whether the product is hedonic or utilitarian.
Research also demonstrates consumers increasingly turn to e-commerce to search and look for information i.e. to compare products and prices (Dutta and Das, 2017; Dörnyei et al., 2017). Kukar-Kinney and Close (2010) observe consumers use shopping baskets as a source of information rather than using it for purchases. Online product reviews also provide information, which can be influential in decision-making and purchase intentions (Jiménez and Mendoza, 2013). It is also important to note that the size of merchandise assortment can influence consumers’ information search and that online search is less likely to be the case for low cost everyday goods (Dörnyei et al., 2017).

Currently, e-commerce alone may not be adequate enough to drive sales and revenue (Faulds et al., 2018; Macchion et al., 2017). However, this channel can help fashion retailers to innovate; to decrease their lead times and deliver fashion goods to the market more quickly (Macchion et al., 2017). Overall, studying e-commerce adoption appears to be less relevant with focus shifting to newer aspects of online shopping and consumer behaviour, such as personalisation (Pappas et al., 2017).

### 2.3.2 Barriers of E-Commerce

In comparison to the offline channel, it is difficult to interact with human senses online that same way that brick-and-mortar environment can do (Turley and Chebat, 2002; Soars, 2009). Reasons for slow uptake of e-commerce was attributed to perceived risk in shopping and purchasing goods and services online (Bhatnagar et al., 2000; Forsythe and Shi, 2003; Laroche et al., 2005). E-commerce literature describes perceived risk as a complex, multidimensional construct that is comprised of different types of risks, which include product risk, financial risk, psychological and time/convenience loss risk (Bhatnagar et al., 2000; Forsythe and Shi, 2003; Chang and Tseng, 2013; Pappas, 2016; Nepomuceno et al., 2016; Turban et al., 2018). Perceived risk can negatively influence online purchase intentions (Chang and Tseng, 2013; Pappas, 2016). While, e-commerce is no longer a new platform in developed countries, perceived risk continues to be studied in current literature (Pappas, 2016; Chaparro-Peláez et al., 2016).

Earlier studies on financial risk emphasised the risk of entering card details online where it may not be secure to do so while time/convenience risk was associated with download
speeds and internet connection that affected online transactions (Forsythe and Shi, 2003; Bhatnager et al., 2000). Despite security improvements over the years, e-commerce is still perceived to be risky even for consumers with purchasing experience (Chaparro-Peláez et al., 2016). Reducing security and privacy concerns is important in facilitating consumer trust, which positively influence purchase intentions towards online shopping (Oliveira et al., 2017).

Empirical research demonstrates mixed results in depicting the influence of variables such as age, gender, experience, brand familiarity and product knowledge towards perceived risk, which can have a negative effect on online patronage behaviour (Forsythe and Shi, 2003; Bhatnagar et al., 2000; Koganonkar et al., 2006; Pappas, 2016). This may be due to differences in evaluation of product type or type of retailer. For example, Pappas (2016) analyses responses towards a holiday booking website. Generally, perceived risk is less likely to be a determinant for consumers who have experience of purchasing online (Forsythe and Shi, 2003). Security and privacy concerns are also likely to vary according to the type of retailer, type of product as well as the price (Lian and Lin, 2008; Koganonkar et al., 2006).

Whilst e-commerce offers certain benefits, these benefits could also be considered as a barrier from a retailer or consumer perspective. This includes a large merchandise assortment and internationalisation. A larger merchandise assortment can lead to higher levels of complexity and choice overload (Townsend and Kahn, 2014). This is consistent with findings from Häubl and Trifts (2000) and Dörnyei et al. (2017); browsing a large product selection online requires more cognitive effort, which can affect decision-making as consumers are less likely to make an informed decision. This may be a greater issue for online fashion retailers, such as ASOS, that offer a huge variety of fashion brands and products. Internationalisation may have a negative effect on fashion retail’s operations if the fashion retailer does not properly evaluate the global market and could lead to a reduction in operational performance ‘to meet a more volatile international demand, weakening companies’ ability to respond quickly to customers’ requirements and thus penalising market flexibility’ (Macchion et al., 2017, p.1025). Of the barriers to e-commerce from a consumer perspective, Chaparro-Peláez et al. (2016) argue risk is found to be the only barrier of purchasing experience of online shopping.
2.3.3 Product Risk

Unlike brick-and-mortar retailing, there are restrictions in providing a tactile and tangible experience online as consumers are unable to physically interact with goods (Peck and Childers, 2003b; Bhatnagar et al., 2000; Forsythe and Shi, 2003; Turley and Chebat, 2002). Thus, intangibility is often studied in e-commerce studies that evaluate product risk. Nepomuceno et al. (2016, p.620) describe intangibility as ‘one that is hard to be imagined, remembered or simply mentally grasped’. Product risk refers to a fear of receiving a product that does not match an individual’s expectations, whereby factors such as product complexity, quality and price of products can have an impact (Bhatnagar et al., 2000; Laroche et al., 2005). In comparison to price, product quality is found to have more of an influence on perceived risk (Pappas, 2016). In terms of fashion apparel, consumers are unable to physically touch and feel the material that can otherwise help to determine product quality; there isn’t an opportunity to touch and try on fashion apparel products prior to purchase when shopping online (Bhatnagar et al., 2000; Forsythe and Shi, 2003; de Klerk et al., 2015). For pure-play fashion retailers, this is an even greater issue (Aghekyan-Simonian et al., 2012).

Of the different types of perceived risks, Aghekyan-Simonian et al. (2012) conclude reducing product risk to be the most important and that brand image is regarded as a vital cue in purchase decisions that can act as a proxy to mitigate unknown product attributes including product quality. Consumers may rely on additional aspects, other than price or product, in their purchase decision making from an online apparel website. This may include easy return policies (Saarijärvi et al., 2017). Rather than just delivery policies, there is a preference for online retailers who offer a convenience experience in aiding consumers to save time and effort (Duarte et al., 2018). Laroche et al. (2005) and Nepomuceno et al. (2016) acknowledge that the level of product risk is dependent on moderating factors including consumers’ shopping experience, brand familiarity and product knowledge. Overall, this suggests product risk is less of an issue today for online fashion apparel consumers shopping on familiar and well-branded websites that provide convenience and easy returns.
However, it is important to not overlook product evaluation in relation to product risk. Duarte et al. (2018) conclude evaluation convenience as an important factor, which includes being able to access clear product details. Laroche et al. (2005) stress the importance of providing product information that can help lower mental intangibility, and therefore mitigate perceived risk and evaluation difficulty when shopping online. This is also echoed by Nepomuceno et al. (2016). A lower mental intangibility has a negative influence on perceived risk. Thus, Nepomuceno et al. (2016) recommend providing detailed product information, including attributes, as well as tools to help aid comparisons with alternatives in addition to product pictures. De Klerk et al. (2015, p.122) emphasise the importance of intrinsic aspects of fashion apparel online, in helping fashion consumers to arrive at a more informed decision. This includes information such as ‘textile, construction, design and finish’ of fashion items. As well as textual information, product risk has also been studied in relation to product visualisation tools (Park et al., 2005, Yang and Wu, 2009; Lee et al., 2010). This section confirms that while product visualisation is not the only factor that can help fashion retailers and fashion consumers to reduce product risk, it remains an essential consideration. It is also important to note that alongside product performance risk, fashion apparel consumers may also encounter other types of risk online, which can otherwise augment perceived risk for this product category.

2.3.4 Online Consumer Behaviour

It is important to understand how and why consumer behave in a certain why. Research is required to enhance understanding towards the online shopping experience and how this influences consumer behaviour. Examination of online consumer responses has become a burgeoning area of research in order to assess the importance of particular retailing strategies and its impact on e-shopping behaviours. This is useful in determining successful retailing or how retailers can improve their online proposition, which can help retailers to achieve a competitive advantage online (Zhang et al., 2018; Goworek and McGoldrick, 2015). Consequently, online consumer behaviour has been explored from a variety of perspectives.

Extant literature has focussed on a variety of consumer behaviour factors that influences shopper behaviour online. This includes external influences, such as website atmospherics,
as well as internal influences. It is important to understand these influences on consumer behaviour, which impacts the decision-making process (Blackwell et al., 2006). In terms of understanding consumer influences, academic research on online shopping has tested a variety of consumer characteristics including socio-demographic variables, such as gender, age, education, internet experience, situational factors as well as intrinsic dimensions (Bilgihan, 2016; Dutta and Das, 2017; Dennis et al., 2009; Koo and Ju, 2010; Garbarino and Strahilevitz, 2004). Intrinsic dimensions are comprised of ‘goals, schema, information processing, memory, involvement, attitudes, affective processing, atmospherics, and consumer attributions and choices’, which can ultimately affect different stages of the decision-making process (Puccinelli et al., 2009, p.15).

Many papers state caution should be exercised when generalising findings, as results may differ and therefore may not be applicable across all e-commerce markets (Chang et al., 2005). Results may differ if tested in a difficult country, where cultural differences exist, or if the same experiment is applied on a different age group or gender. For example, Clemons et al. (2016) state Chinese consumers are uniquely different in their attitude towards online shopping and perceived risk. Davis et al. (2017) highlight differences between male and female online and offline utilitarian behaviour, which can influence purchase intentions. A limitation of many e-commerce papers is often a student sample is used, which is not representative of all online shoppers (Bilgihan, 2016). Hence, there is a need to evaluate different types of online consumers to ensure their needs are being met when shopping online (Soopramanien and Robertson, 2007).

Using external and internal dimensions, it is possible to segment consumers using a shopper typology (Ganesh et al., 2010; Rohm and Swaminathan, 2004). For retailers, consumer segmentation is useful in understanding how to strategically target particular consumer groups (Goworek and McGoldrick, 2015). Previous e-commerce studies confirm the influence of age, gender and education and income level on consumer behaviour (Chang et al., 2005). These variables are also influential for shoppers using different retail formats to purchase fashion apparel (Luceri and Latusi, 2015; Boardman and McCormick, 2018).

Initially, there were significant differences in attitudes between consumers who purchase fashion apparel online and consumers who browse or who do not shop for fashion apparel
online (Lee and Johnson, 2002). However, this is inconsistent with newer findings that reveal consumers treat online shopping as the same as offline shopping (Clemons et al., 2017) and that shoppers who shop offline or online are not hugely different (Ganesh et al., 2010). With online fashion sales growing, this appears to be the case for fashion consumers (Mintel, 2017). Experience also appears to be a key factor. Once consumers are accustomed to purchasing items online, the likelihood of choosing the online store also increases (Melis et al., 2015).

In terms of online shopping consumer groups, much research has focussed on Generation Y or Millennial consumers (Djamasbi et al., 2010; Djamasbi et al., 2011; San-Martin et al., 2015). Literature also predominantly utilise undergraduate students for data collection (Ogonowski et al., 2014; Richard and Chebat, 2016). While this cohort process online information quickly and expect a high level of user experience when shopping online (Bilgihan, 2016), Lissita and Kol (2016) emphasise the importance of marketing for Generation X as these consumers have greater spending power. Although e-commerce literature concerning Generation Z consumers is limited, findings suggest this consumer group are likely to be more demanding with greater expectations from technology to help them with their decision-making process (Priporas et al., 2017). While there is a wealth of consumer-focussed e-commerce studies, Doherty and Ellis-Chadwick (2010) argue retailer behaviour is an essential aspect in understanding factors that influence retailing.

A plethora of cognitive, affective or behavioural responses have been examined in e-commerce research, including satisfaction, trust, loyalty, excitement and purchase intentions in relation to online shopping (Nisar and Prabhakar, 2016; Szymanski and Hise, 2000; Dholakia and Zhao, 2009; Jayawardhena and Wright 2009; Kim and Peterson, 2017; Oliveira et al., 2017). Due to complexity, these outcomes are often described as multi-dimensional (Kim and Peterson, 2017). Constructs studied are often interrelated and studied in combination to appreciate the overall impact in a real e-commerce setting. Hence, studying the influence of one factor is regarded as a limitation. While this may be useful to help control variables, which is important in an experimental setting, consumers perceive variables in a holistic manner. Subsequently, there is a need to understand the overall influence of environmental cues using a more holistic approach (Kawaf and Tagg, 2017; Demangeot and Broderick, 2007).
It is also important to note outcome variables, such as trust, may be considered an antecedent that influences other outcomes, such as purchase intentions, (Oliveira et al., 2017) or as a mediator or moderator (Weiseberg et al., 2011). In considering the relationship between an independent variable and a dependent variable, a mediator is described as a variable that ‘accounts for the relation’ (Baron and Kenny, 1986, p.1176) between these two variables, while a moderator ‘affects the direction and/or strength of the relation’ (Baron and Kenny, 1986, p.1174). Table 2.3 illustrates the complexity with the following constructs studied as behavioural responses. It shows online shopping has been studied from a variety of perspectives, and that behavioural constructs can also be studied as an antecedent that may have a mediating or moderating role.
Table 2.3 Behavioural Outcomes Examined in E-Commerce Research

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Reference</th>
<th>Method</th>
<th>Antecedents</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfaction</td>
<td>Szymanski and Hise (2000)</td>
<td>Focus groups, online survey,</td>
<td>Convenience, product information, site design,</td>
<td>All four antecedents were positively associated on satisfaction. Convenience had the strongest influence.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>N = 1,007</td>
<td>financial security</td>
<td></td>
</tr>
<tr>
<td>E-WOM</td>
<td>Mosteller et al. (2014)</td>
<td>Online survey, N = 299</td>
<td>Perceptual fluency, cognitive effort, positive affect</td>
<td>Fluent stimulus is positively associated with positive affect, which directly and indirectly influences satisfaction.</td>
</tr>
<tr>
<td>Flow</td>
<td>Guo and Poole (2009)</td>
<td>Online survey, N = 354</td>
<td>Perceived complexity, clear goal, feedback mechanism, perceived balance of challenge and skill</td>
<td>Complexity negative influenced the other three constructs. While feedback mechanism and perceived balance of challenge and skill influenced flow, clear goal did not.</td>
</tr>
<tr>
<td>Involvement</td>
<td>Demangeot and Broderick (2007)</td>
<td>Online survey, N = 301</td>
<td>Exploratory potential, sense-making potential</td>
<td>Exploratory potential positively mediates the relationship between sense-making potential and involvement.</td>
</tr>
<tr>
<td>Excitement</td>
<td>Jayawardhena and Wright (2009)</td>
<td>Online survey, N = 626</td>
<td>Involvement, merchandising, convenience and attributes of the web</td>
<td>All four constructs are positively associated with excitement, of which involvement is the most influential.</td>
</tr>
<tr>
<td>Trust</td>
<td>Oliveira et al. (2017)</td>
<td>Online survey, N = 365</td>
<td>Consumer characteristics, firm characteristics, interactions, web infrastructure</td>
<td>Overall, all relationships were supported demonstrating contribution of dependent variables competence, benevolence and integrity.</td>
</tr>
<tr>
<td>Purchase intention</td>
<td>van der Heijden et al. (2003)</td>
<td>Survey, N = 228</td>
<td>Trust, perceived risk, perceived usefulness, perceived ease of use, attitude towards online retailer</td>
<td>Trust had a negative influence on perceived risk, which negatively influenced attitude. Perceived ease of use positively influenced attitude, which mediated the relationship with purchase intentions.</td>
</tr>
<tr>
<td></td>
<td>Yoo et al. (2013)</td>
<td>Online survey, N = 257</td>
<td>Intrinsic motives, extrinsic motives, e-WOM, social site and personal site identification</td>
<td>Both motives positively influence e-WOM, which is positively associated with social and personal site identifications that facilitates positive e-loyalty.</td>
</tr>
<tr>
<td>Online repurchase</td>
<td>Martin et al. (2015)</td>
<td>Online survey, N = 555</td>
<td>Cognitive experiential state, affective experiential state, trust, perceived control, perceived risk</td>
<td>Two models are generated to compare frequent and infrequent online shoppers. Perceived risk influences re-purchase intentions. However, satisfaction partially influences this relationship.</td>
</tr>
</tbody>
</table>

Table 2.3 demonstrates online surveys are often deployed to enhance understanding of online consumer behaviour. However, more novel measures are also being applied to online consumer behaviour research such as fMRI, eye tracking and EEG technology to collect objective data to enhance understanding (Jai et al., 2014; Djamsbi et al., 2010; Luan et al., 2016; Huang et al., 2015).
2.4 M-Commerce

Since the proliferation of mobile devices and developments in smartphone technology over the last 10 years, m-commerce has received a great deal of attention and is continuing to grow in popularity. This includes a variety of mobile contexts including mobile marketing, which is defined as ‘any marketing activity conducted through a ubiquitous network to which consumers are constantly connected using a personal mobile device’ (Kaplan, 2012, p.130), as well as m-commerce, which is described as the ‘use of mobile (handheld) devices to communicate and conduct transactions through public and private networks’ (Balasubramanian et al., 2002, p.349).

For marketers, mobile devices are considered an important outlet for digital marketing where there is greater emphasis on newer pull marketing strategies that employ a consumer-centric approach (Yadav et al., 2015; Kaplan, 2012). In terms of m-commerce, consumers can use their smartphone to pay for goods and services in a number of ways, which also includes mobile-payment applications (Leavitt, 2010). In addition to being recognised as a viable alternative to shopping via desktop or laptops (Brynjolfsson et al., 2013), m-commerce has earmarked a new era for retail in that traditional shopping behaviour is changing to shopping constantly and occurs on the go (Pantano and Priporas, 2016; Chou et al., 2016; Fuentes and Svingstedt, 2017; Kourouthanassis and Giaglis, 2012). Whilst Faulds et al. (2018) assert mobile shopping as a development is still in its infancy, the development of mobile technology including the growing levels of smartphone ownership has led to new opportunities for retailers and marketers.

2.4.1 Characteristics of Mobile Devices

Otherwise referred to as personal computers, mobile devices include smartphones and tablets (Müller et al., 2015). A smartphone is defined as a ‘product of convergence of regular mobile phone and PDA (personal digital assistant), which can store critical information via personal computer or notebook computer’ (Chang et al., 2009, p.740). In comparison to the previous generations of mobile phones, smartphone devices enable individuals to direct web access as well as access to third-party "apps" (Arthur, 2012). Although tablets also feature the same offering, there are several differences. Namely, tablets are less likely to be carried everywhere, and they are less likely to be personal with
consumption based on content rather than personal communication (Müller et al., 2015). In contrast to smartphones, access to the internet on a tablet is determined by the user (Yadav et al., 2015). This suggests users are more likely to casually browse using a smartphone than a tablet. Overall, marketing literature has repeatedly highlighted the importance of smartphones and tablet devices in facilitating m-commerce usage and sales (Shankar et al., 2016; Balasubramanian et al., 2002). Although there are similarities with online shopping via PCs, there are also notable differences (Raphaeli et al., 2017; Chou et al., 2016).

Smartphones in particular are personal handheld devices that are part of everyday life. Effectively, this has led to mobile devices being used for convenience purposes, whereby consumers fit purchasing habitual products into their everyday routine. Consumers can search for information and shop for goods and services instantaneously provided they have mobile data or Wi-Fi. Unlike e-commerce and in-store shopping, there are no location restrictions in mobile shopping, enabling consumers to shop anywhere, anytime. Specifically, smartphones and tablets are small and portable enough to facilitate shopping on the move. For today’s consumers, such features complement busy lifestyles (Wang et al., 2015; Raphaeli et al., 2017; Shankar and Balasubramanian, 2009; Fuentes and Svingstedt, 2017; Chou et al., 2016; Yadav et al. 2015; Kourouthanassis and Giaglis, 2012).

Smartphones are used more often as findings confirm users routinely display checking behaviours on their smartphone. In comparison to laptops, smartphone usage occurs more frequently (Faulds et al., 2018; Oulasvirta et al., 2012). These devices also supplement the traditional retail environment as consumers can shop from their mobile whilst shopping in-store (Raphaeli et al., 2017). The use of free Wi-Fi in store can further this effect (Pantano and Viassone, 2015). While literature indicates these devices are mainly used on the go and for convenience reasons, findings reveal young consumers often use these devices to shop from at home (Fuentes and Svingstedt, 2017). This may be unsurprising given that consumers can do a variety of m-commerce related activities on their mobile device in addition to making purchases; ‘equipped with mobile phones consumers can check prices, ask friends for advice, read product reviews online, consult blogs, make shopping lists, photograph products, and read up on materials, stores, and brands and much more’ (Fuentes and Svingstedt, 2017, p.144). Consumers may also interact with a virtual shopping assistant as well as exhibit post-purchase behaviours (Pantano and Priporas,
Similarly, Oulasvirta et al. (2012) outline various mobile activities that can be categorised into informational, interactional and awareness behaviours.

Table 2.4 outlines various characteristics examined in literature. By adapting these characteristics in line with their offering, Shankar and Balasubramanian (2009) posit there is huge potential for firms to enhance interaction with an individual. While there is conceptual research into mobile devices of the future and how this may affect consumer behaviour (Faulds et al., 2018), more empirical research is required to understand the general impact of new mobile technology and how firms are adapting their mobile offering accordingly.

Table 2.4 General Characteristics of Mobile Devices Listed in Literature

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Reference</th>
<th>Type of Paper</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location-specificity, portability, wireless</td>
<td>Shankar and Balasubramanian</td>
<td>Conceptual</td>
<td>Firms can target consumers anywhere, anytime. Due to portability and wireless connection, usage is higher. Location-specificity is considered to have the most potential for mobile marketing.</td>
</tr>
<tr>
<td>device, customer adoption, small screen size</td>
<td>(2009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Convenience, instant notification, ease of use</td>
<td>Chang et al.</td>
<td>Conceptual</td>
<td>Users can receive notifications, such as emails, on the go. Using mobile devices is easier than computers. These characteristics are considered important drivers of m-commerce adoption.</td>
</tr>
<tr>
<td>and costs involved</td>
<td>(2009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time convenience, interactivity, compatibility, and</td>
<td>Kang et al.</td>
<td>Empirical</td>
<td>These characteristics influence involvement. However, unlike emotional involvement, cognitive involvement does not influence app usage intention.</td>
</tr>
<tr>
<td>effort expectancy</td>
<td>(2015)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A major difference between mobile devices and PCs is the interface. Unlike desktops and laptops, mobile devices do not have a mouse or touchpad interface. Instead, users interact via a touchscreen interface, which requires the use of hand gestures (Billinghurst and Vu, 2015; Huff, 2015). Raphaeli et al. (2017) evaluate differences between shopping on a mobile device and PC. Results confirm mobile shoppers spend less time shopping on a page via a mobile device than compared to a PC. Raphaeli et al. (2017) suggest this is due to usability issues of a mobile device, i.e. small screen size.
In general, usability is a key issue in human computer interaction literature. Lee et al. (2015, p.259) define usability ‘as the notion of ease of using a target object’. Due to smaller screen displays, mobile devices are considered more challenging to shop from (Wang et al., 2015; Raphaeli et al., 2017). The fat-finger problem is also a well-known issue of mobile interfaces (Baudisch and Chu, 2009). Shankar and Balasubramanian (2009) argue the small screen size prevent marketers delivering long messages and notifications that may require too much effort for the user. To overcome these issues, Lee et al. (2015) establish simplicity and interactivity as essential antecedents of smartphone usability. Hence, it is important to maintain a user-friendly interface, otherwise consumers may not engage in m-commerce activities (Groß, 2015). This explains the need to optimise the mobile interface for m-commerce, rather than replicating the user interface of a laptop or desktop device (Groß, 2015; Gao et al., 2015; Kourouthanassis and Giaglis, 2012; Magarath and McCormick, 2013).

In terms of m-commerce, consumers may use mobile optimised websites or apps. According to Zhao and Balagué (2015), the purpose of m-commerce apps is to promote the brand and generate interest as well as driving transactions and sales. It also enables the retailer to collect consumer information about behaviours etc. (Zhao and Balagué, 2015). Although apps and optimised mobile websites appear similar, they vary in usability, functionality and design (Wagner et al., 2017). While websites are adapted and optimised for m-commerce (Magrath and McCormick, 2013), apps require installation (Sohn, 2017a).

Experience appears to be positively associated with app usage (Ramirez-Correa et al., 2015; Wanger et al., 2017). Results indicate individuals with online experience and mobile experience are more likely to purchase items from a m-commerce app, but that this does not necessarily translate to purchasing behaviour (Kim et al., 2017). Findings from Bellman et al. (2011) reveal branded apps can change perceptions, positively influence attitudes and purchase intentions. In terms of aesthetic quality and perceived usefulness, apps perform better than mobile optimised websites (Sohn, 2017a). When considering consumer touchpoints, Sohn (2017a) advises security and aesthetic quality should be enhanced for mobile apps, while the information quality should be enhanced for mobile websites.
Another characteristic of mobile devices is the way they make users feel. Due to instant access to the internet and social media, mobile devices can satisfy instant gratification (Wilmer and Chein, 2016). Mobile devices are also regarded as status symbols and may be paraded as fashion statements (Hahn and Kim, 2013). Similarly, research by Nysveen et al. (2005, p.343) confirm positive perceived expressiveness on mobile service that ‘enable users to express their personal and social identity’. Increasing perceived expressiveness is shown to positively influence intention to use.

2.4.2 Drivers and Motivations of M-Commerce

M-commerce factors that influence usage and purchasing are well documented in marketing literature. The arrival of m-commerce and development in smartphones sparked a huge interest in understanding consumer acceptance and usage towards m-commerce with many studies adopting the TAM framework (Table 2.5). However, Gao et al. (2015) also point out the need to study continuance purchase intention on mobile devices due to initial lack of literature evaluating consumers’ continued usage. Rather than studying intentions and attitudes, Fuentes and Svingstedt (2017) emphasise the value of capturing how consumer behaviour is actually changing in regard to mobile shopping.

Table 2.5 demonstrates other behavioural frameworks employed, such as Unified Theory of Acceptance and Use of Technology (UTAUT) (Verkasolo et al., 2009). A number of studies have also combined different frameworks or theories together. Although Theory of Reasoned Action (TRA) is useful in understanding attitudes towards mobile technology, Shankar and Balasubramanian (2009) assert TAM uses better indicators, such as perceived usefulness that are positively associated with mobile adoption. As shown below, research has modified or extended TAM in line with advanced IT systems to understand various mobile contexts on consumer behaviour. Nysveen et al. (2005) acknowledge the percentage of variance explained in intention to use mobile services was found to be higher in the extended model than the original TAM model.
Despite its popularity and usefulness in evaluating environmental stimuli in e-commerce research, Table 2.5 demonstrates the use of SOR framework in m-commerce research appears to be less widespread, particularly on specific contexts such as AR (Watson et al., 2018). It is also important to note that while some models are specific, others adopt a holistic approach to m-commerce (Lee et al., 2015).

**Table 2.5 Models Applied in M-Commerce Literature**

<table>
<thead>
<tr>
<th>Study and Sample Frame</th>
<th>Research Context</th>
<th>Model</th>
<th>Antecedent(s)</th>
<th>Mediator(s)/Moderator(s)</th>
<th>Behavioural Construct(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wu and Wang (2005) N=310</td>
<td>M-commerce intention</td>
<td>Modified TAM with Diffusion of Innovation theory</td>
<td>Perceived risk, cost, compatibility, perceived ease of use, perceived usefulness</td>
<td>Perceived usefulness</td>
<td>Intention to use, actual usage</td>
</tr>
<tr>
<td>Nysveen et al. (2005) N=201</td>
<td>Intention to use mobile services</td>
<td>Modified TAM</td>
<td>Perceived usefulness, perceived ease of use, perceived enjoyment, Perceived expressiveness, Perceived control, normative pressure</td>
<td>Experiential and goal-directed mobile services, age, gender, attitudes towards use</td>
<td>Intention to use</td>
</tr>
<tr>
<td>Dickinger and Kleijnen (2008) N=370</td>
<td>Mobile coupons</td>
<td>Conceptual model</td>
<td>Fear of spamming, perceived control, redemption effort, economic benefit, attitude</td>
<td>Value seekers</td>
<td>Intention to redeem mobile coupons</td>
</tr>
<tr>
<td>Verkasolo et al. (2009) N=579</td>
<td>Adoption of new mobile apps</td>
<td>Modified TAM with Diffusion of Innovation theory</td>
<td>Technical barriers, social norm, behavioural control, perceived enjoyment, perceived usefulness</td>
<td>Purchasing experience</td>
<td>Intention to use</td>
</tr>
<tr>
<td>Lu and Su (2009) N=369</td>
<td>Mobile shopping services</td>
<td>Modified TAM</td>
<td>Mobile skillfulness, anxiety, ease of access, compatibility,</td>
<td>Enjoyment, usefulness</td>
<td>Mobile shopping intention</td>
</tr>
<tr>
<td>Kim et al. (2009a) N=341</td>
<td>M-commerce intention to shop for fashion</td>
<td>Modified TAM with TRA</td>
<td>Perceived ease of use, subjective norms, perceived enjoyment, perceived usefulness</td>
<td>Attitude towards communication, attitude towards m-commerce</td>
<td>Mobile usage intention</td>
</tr>
<tr>
<td>Li and Yeh (2010) N=200</td>
<td>Design aesthetics on m-commerce trust</td>
<td>Modified TAM</td>
<td>Design aesthetics</td>
<td>ease of use, customisation, usefulness</td>
<td>M-trust</td>
</tr>
<tr>
<td>Groth (2015) N=128</td>
<td>Smartphone shopping acceptance</td>
<td>Modified TAM</td>
<td>Perceived usefulness, perceived ease of use, perceived enjoyment, attitudes towards mobile shopping, trust, usage</td>
<td>Attitudes towards mobile shopping (moderator)</td>
<td>Behavioural intention</td>
</tr>
<tr>
<td>Li et al. (2012) N=90</td>
<td>Consumption experience</td>
<td>SOR framework</td>
<td>Convenience, media richness, subjective norms, self-efficacy</td>
<td>Emotion (mediator)</td>
<td>Consumption experience</td>
</tr>
<tr>
<td>Agrebi and Jallais (2015) N=90</td>
<td>M-commerce intention</td>
<td>Modified TAM</td>
<td>Perceived ease of use, perceived usefulness, perceived enjoyment</td>
<td>Satisfaction (moderator)</td>
<td>Intention to use</td>
</tr>
<tr>
<td>Lu et al. (2017) N=1,522</td>
<td>Continuance intentions in different cultures</td>
<td>Modified ATAUT</td>
<td>Perceived effort expectancy, perceived performance expectancy, perceived mobile social influence, perceived privacy protection</td>
<td>Espoused cultural values</td>
<td>Continuence intentions</td>
</tr>
<tr>
<td>McLean et al. (2018) N=1,024</td>
<td>Experience with mobile apps</td>
<td>Customer experience model</td>
<td>Ease of use, convenience, customisation, customer experience</td>
<td>Gender, screen size, timeliness, enjoyment</td>
<td>Frequency of use</td>
</tr>
</tbody>
</table>

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outcomes, such as intention to use, via mediators that may include attitude, satisfaction, trust or flow, which play mediating roles (Groß, 2015, Nysveen et al., 2005; Agrebi and Jallais, 2015; Gao et al., 2015). If a mobile device is easy to use, it is more likely to be considered useful and entertaining, which facilitate positive attitudes toward m-shopping. As well as quantitative measures (Table 2.5), this finding is also corroborated using qualitative measures (Pantano and Priporas, 2016) and has been confirmed from a fashion apparel context (Kim et al., 2009a). However, this may be dependent on purchasing experience. Although non-purchasers might be satisfied when shopping on a mobile, it is not strong enough to facilitate m-commerce usage (Agrebi and Jallais, 2015). It is important to note earlier findings may not be applicable as shopping on mobile devices appears to be driving a change in consumers’ behaviour (Faulds et al., 2018; Pantano and Priporas, 2016).

Like e-commerce, consumers’ motivation may also vary towards m-commerce. Using SEM, results from Ono et al. (2012) confirm different types of shopping motivations, such as adventure motivation, can influence mobile browsing intention. Unlike physical shopping, mobile shopping requires less organisation (Fuentes and Svingstedt, 2017). Fundamentally, recent findings corroborate utilitarian attributes of mobile devices have a stronger influence on m-shopping attitudes than hedonic attributes (McClean et al., 2018; Raphaeli et al., 2017; Singh and Swait, 2017; Gao et al., 2015; Pantano and Priporas, 2016). While findings by Nysveen et al. (2005) reveal perceived enjoyment has a positive effect on intention to use goal-directed mobile services, McClean et al. (2018) observe the opposite, i.e. utilitarian factors precede enjoyment, which mediates the relationship with intention to use. Generally, mobile shoppers are more time-conscious (McClean et al., 2018). By assessing differences between shopping on mobile devices and PCs, the former is associated with goal-directed behaviours, while the latter is exploratory and hedonic in nature (Raphaeli et al., 2017). Hence, the type of device chosen to shop may be indicative of the way consumers browse shopping websites.

If shopping on the go, the mobile experience should be effective in providing utilitarian attributes (McClean et al., 2018; Wang et al., 2015). This is particularly important for devices with very small screen sizes, which indicate utilitarian factors may be less of an issue for tablet devices (McClean et al., 2018). Further research is required to warrant this. This highlights the importance of understanding extrinsic factors, whether it is experiential
or goal-directed, on behavioural outcomes (Nysveen et al., 2005; Ono et al., 2012; Gao et al., 2015; Lu et al., 2017).

Comparing trust and perceived risk, Marriott and Williams, (2018) observe trust had a greater influence on mobile shopping adoption. By increasing trust, retailers can facilitate higher levels of flow on mobile sites (Gao et al., 2015). Although these devices are used as part of a daily lifestyle, findings from Marriott and Williams (2018) still find purchasing goods via a mobile device to be associated with risk. However, depending on the retail offering, perceived risk may be mitigated by incorporating quality aspects, such as system quality, information quality and service quality. Not only does this facilitate satisfaction and lower effort, a high-quality interface design positively influences m-commerce trust and m-commerce payments (Huang et al., 2018; Gao et al., 2015; Ko et al., 2009; Li and Yeh, 2010). Despite privacy concerns, such as sharing geographical information, consumers are prepared to share locations provided apps are able to offer personalised information and recommendations (Pantano and Priporas, 2016).

Other factors that affect mobile shopping that have been studied include age and mobile illiteracy (McCLean et al., 2017; Shankar et al., 2010). M-commerce is deemed more attractive for young consumers with busy lifestyles and higher levels of mobile usage (Pantano and Priporas, 2016; Boardman and McCormick, 2018). By analysing the transition between PC and mobile shopping, Wang et al. (2015) describe mobile adoption as a cumulative process, and thus label mobile shoppers as habitual consumers. Familiarity is an important variable in driving consumers to embrace m-shopping; consumers are more likely to purchase products from apps and mobile websites they have bought from before (Wang et al., 2015; Kim et al., 2017).

Recent papers suggest mobile devices will continue to be used at various stages of the consumers decision making process and various retail touchpoints including when searching for information (Singh and Swait, 2017; Faulds et al., 2018; Rodriguez-Torrico et al., 2017). Thus, interface recommendations include personalising content to ease the browsing experience (Huang et al., 2018), as well as up to date information that is consistent with other retail channels (Gao et al., 2015; Wang et al., 2015).
Consumers also use their smartphone in a number of ways to complement their offline shopping experience. With location-based capabilities, consumers may use their smartphone as an additional tool to help them shop in-store (Kang et al., 2015; Kowatsch and Maass, 2010). M-commerce may also help with curating a shopping list to receiving reminders and promotions to assisting with a digital check-out, thereby streamlining the entire shopping experience (Faulds et al., 2018). Bryjolfsson et al. (2013) explain that unlike mobile channel, consumers can touch and feel product in a store environment that can result instant gratification. With continual developments in m-commerce, Ono et al. (2012) posit technologies such as AR on mobile devices can propel gratification motivation, while newer findings confirm smart retail technologies can provide a more satisfying mobile experience, which may encourage a greater shift towards mobile shopping behaviours (Dacko, 2017).

Shopping and searching for information has greater meaning and relevance (Faulds et al., 2018; Fuentes and Svingstedt, 2017). As a result of shifts towards consumers empowerment and correspondence between the retailer and consumer, Faulds et al. (2018) assert online retailers should modify their goal in influencing consumer behavioural outcomes and instead focus on implementing a more practical and holistic approach in driving interaction and engagement at the various consumer touchpoints. As a result of m-commerce, findings from Fuentes and Svingstedt (2017) illustrate consumers’ appetite for information is empowering consumers to believe they know more than the in-store sales assistant. This suggests there may be greater reliance on retailer and product information displayed on mobile apps and optimised mobile websites. More research is required to identify the extent of this perception and how it influences overall shopping behaviours.

### 2.4.3 Fashion M-Commerce

There is growing academic research of m-commerce from a fashion retail perspective. Earlier m-commerce research based on a fashion retail context adopted Davis et al. (1992) modified TAM framework, which also includes perceived enjoyment, to explore usage and intention (Kim et al., 2009a; Ko et al., 2009). Findings support all three variables in facilitating positive consumer attitudes and m-commerce behavioural intentions. Although perceived enjoyment was found to be less influential than perceived ease of use and
perceived usefulness, Ko et al. (2009, p.684) acknowledge the importance of driving perceived enjoyment that ‘should make it worthwhile for customers in terms of monetary and non-monetary value’. However, both papers demonstrate a greater preference for online fashion retailers to focus on utilitarian aspects of m-commerce (Kim et al., 2009a; Ko et al., 2009). This is consistent with qualitative findings from Parker and Huang (2016); efficiency was found to be the predominant shopping motivation to shop on a mobile device. However, shopping for fashion apparel today also appears to be a hedonic activity with the likes of social media and opinion leaders (Lin et al., 2018).

Results by McClean et al. (2018) reveal fashion m-commerce shopping motivations vary according to gender. Unlike male counterparts, utilitarian aspects on mobile shopping apps were found to be significantly related to a positive mobile experience for female consumers, enjoyment did not have a significant impact. Interestingly, this is the opposite for male consumers, of which enjoyment is a significant driver of a positive mobile experience. This highlights the need in delivering a customer experience that is mainly focussed on utilitarian factors, but that also delivers hedonic factors to cater to both male and female consumers for fashion retail apps. This is particularly important for fashion retailers who sell fashion merchandise to both male and female consumers (McClean et al., 2018).

Generational differences are found to be more influential than gender differences as younger consumers demonstrate higher levels of proficiency and awareness when shopping for fashion on mobile devices (Chou et al., 2016; Boardman and McCormick, 2018). Therefore, online retailers who target this consumer market are likely to benefit from implementing m-commerce services. For example, consumers who shop for fashion apparel at American Eagle, which is popular with US Millennials, are more likely to have a compelling shopping experience using mobile devices and are therefore more likely to exhibit higher usage levels (Chou et al., 2016).

Based on the capabilities and the unique characteristics of mobile devices, there are opportunities to further enhance the fashion retail experience by implementing a highly interactive interface (Pantano and Priporas, 2016). For fashion apps, the use of particular characteristics such as smartphone cameras, virtual mirror, voice sensors, AR and VR can increase interaction and engagement. With virtual mirrors, consumers can upload an image
of themselves and virtually experiment with various fashion apparel items (Zhao and Balagué, 2015; Magrath and McCormick, 2013).

Although multi-touch gestures are typically regarded a characteristic of gaming apps (Zhao and Balagué, 2015), research indicates touch gestures can enhance the experience of shopping for fashion on a mobile device (Cano et al., 2017). Incorporating such functions would create a more compelling shopping experience providing both hedonic and utilitarian value (Pantano and Priporas, 2016). However, preference to shop for fashion via a mobile device can also depend on an individual’s need for touch. Findings by Rodríguez-Torrico et al. (2017) reveal fashion consumers with high Need for Touch (NFT) favour computers more than mobile devices when shopping for fashion apparel.

According to Magrath and McCormick (2013, p.118), fashion design elements can be grouped into ‘multimedia product viewing, informative content, product promotions and consumer-led interactions’. Results by Sohn (2017a) imply fashion design elements on mobile apps are considered to have greater aesthetic quality than information quality, which was found to be stronger for purchasing tickets that is considered a search good. E-commerce literature highlights the need of providing adequate information quality that includes both visual and textual elements for online fashion apparel in reducing product risk (Kim and Lennon, 2008; de Klerk et al., 2015).

As there are screen size constraints, evaluating visual product information via images or multimedia product viewing may become more challenging. Boardman and McCormick (2018) reveal this is more of an issue for older consumers. Kahn (2017, p.40) explains attention and perception towards mobile design elements occurs ‘almost automatically without cognitive intervention’. Essentially, stimuli can affect the perceptual ease of how consumers process information, which can impact behavioural outcomes (Mosteller et al., 2014; Reber et al., 2004b). Despite these issues, there is a dearth of literature analysing the influence of specific design elements concerning fashion apparel products or fashion product information, and how this influences consumers’ information processing towards m-commerce. For optimised mobile fashion websites, there is also a need to address information quality aspects that would positively influence information search and purchasing.
2.5 Multichannel Retailing and Omnichannel Retailing

Due to multichannel and omnichannel retailing, divisions between physical and digital retailing channels are becoming less obvious and blend into one (Piotrowicz and Cuthbertson, 2014). Multichannel retailing refers to retailers operating on more than one channel (Lewis et al., 2014), whereas omnichannel retailing is defined as a ‘set of activities involved in selling merchandise or services through all widespread channels, whereby the customer can trigger full channel interaction, and/or the retailer controls full channel integration’. (Beck and Rygl, 2015, p.175). Cross-channel retailing is different; this is where the consumer experience is not integrated across different retailing platforms and either involves partial integration or partial interaction (Beck and Rygl, 2015). Despite this distinction, there are inconsistencies in literature. Terminology including multichannel retailing, bricks-and-clicks, clicks-and-mortar, cross-channel retailing, cross-shopping and omni-channel retailing (Pantano and Viassone, 2015; Zhang et al., 2010; Luceri and Latusi, 2016; Bhatnagar and Syam, 2014; Cao and Li, 2015; Pauwels and Neslin, 2015) appear to lack distinction. It is important retailers use all type of retailing formats with a clear and consistent proposition whereby consumers can shop and interact across all channels seamlessly and simultaneously (Verhoef et al., 2015).

A negative aspect of these retailing strategies is that it is easy for consumers to switch from one channel to another, which can lead to “showrooming” and “webrooming” behaviour (Rapp et al., 2015; Verhoef et al., 2015). Evidence reveals effects of showrooming include negative salesperson self-efficacy as well as negative staff performance (Rapp et al., 2015). Pauwels and Neslin (2015) observe that while a clicks-and-mortar approach may not necessarily cannibalise in-store sales, it may lead to more returns and exchanges. Though channel integration can help to increase sales growth, this may not be the case if there is strong emphasis on a particular channel (Cao and Li, 2015).

By comparing touchpoints, Pauwels and Neslin (2015) liken the adoption of the online channel for utilitarian purposes, while the store is used more for hedonic experiences. This is also dependent on individual factors, such as consumers’ shopping experience (Herhausen et al. (2015) as well as personality traits, impulsiveness and NFT, which can influence usage of omnichannel behaviour towards fashion clothing consumption (Rodriguez-Torrico et al., 2017). Current fashion retail examples of multichannel and
omnichannel retailing include click and collect, QR technology where shoppers can scan a code or barcode using their apps, such as the Zara app and shopping on a mobile device using the free Wi-Fi while in-store (Rodríguez-Torrico et al., 2017; Pantano and Priporas, 2016; Brynjolfsson et al., 2013).

Predictions that the online channel will take over the offline channel for brick-and-mortar retailers echoed by Verhoef et al. (2007) were unsupported by literature (Herhausen et al., 2015). According to Baxendale et al. (2015), brick-and-mortar communication is the most influential touchpoint. Conversely, newer findings emphasise the importance of m-commerce for future retailing, which includes fashion retail. For example, Rodríguez-Torrico et al. (2017) reveal the mobile channel is more likely to be used to fulfil impulse needs when shopping for fashion apparel.

Research suggests mobile retailing plays an indispensable role, with future growth contingent on this medium. Consumers feel their mobile devices provide great value for shopping (Faulds et al., 2018; Pantano and Priporas, 2016). For consumers, this means more consumer choice, i.e. more access to products, with greater product information (Zhang et al., 2017; Cao and Li, 2015). Omnichannel retailing can, therefore, elevate trust, satisfaction and result in higher purchase decisions with consumer empowerment mediating these relationships (Zhang et al., 2017). M-commerce plays a key role in enabling retailers to ‘interconnect, empower, and engage mobile consumers’ that can facilitate consumers’ decision making and behaviour (Faulds et al., 2018, p.325).
2.6 Chapter Summary

Online shopping for fashion has evolved since the emergence of e-commerce. The impact of online shopping drivers, barriers and shopping motivations is well documented in literature, and there is now greater focus on understanding these aspects from a mobile context. As a result of technological advancements and changes in consumer behaviour, mobile retailing appears to be triggering a paradigm shift. Instead of being a complementary option, m-commerce is seen as an important channel in facilitating consumer interaction and engagement.

Whilst e-commerce literature has explored the influence of visual and textual design elements for online fashion, there is a lack of literature from a m-commerce perspective. Unlike other product categories, there is greater product performance risk when shopping for fashion online as consumers are physically unable to touch and try on apparel. This concern may be amplified when shopping for fashion on a mobile device given the screen size constraints in addition to mobile browsing and purchasing being largely attributed to utilitarian motivations. Since consumers increasingly use their mobile device throughout their decision-making process this emphasises the importance of these devices for retailers, marketers and consumers. In order to understand the influence of verbal and visual product information for fashion apparel on mobile devices, it is helpful to review literature on online atmospherics and product presentation.
Chapter Three: Online Atmospherics and Product Presentation

3.1 Introduction

E-tailers use a number of design elements to display merchandise online. This includes verbal and visual product presentation, which are considered important online atmospheric cues. Displaying fashion products visually requires the use of product presentation. To demonstrate the importance of this atmospheric cue for m-commerce, this chapter is structured as the following. Firstly, atmospheric cues in traditional retailing as well as online retailing are reviewed. Secondly, product presentation that also includes image interactivity is defined and analysed. Thirdly, tactile cues and the role of gestural interactivity are also discussed to explore the potential of these tools for fashion apparel retail from a mobile perspective.

3.2 Traditional Retail Atmospherics

The field of retail atmospherics is widely studied in marketing literature (Lund, 2015; Parsons, 2011; Dennis et al., 2009). Retail atmospherics are defined as ‘any component in a retail environment, consciously designed and external to an individual, which enters within that individual’s perceptual field and stimulates his visual and non-visual senses such as acoustic and olfactory senses’ (Koo and Ju, 2010, p.378). In other words, it is the surrounding atmosphere that is perceived through the senses i.e. stimulation through the five senses that can result in cognitive, emotional effects and social effects. Hence, these components are also referred to as sensory qualities that are comprised of visual, aural, olfactory and tactile dimensions (Soars, 2009; Kotler, 1973).

Originally, atmospherics were divided into three groups: ambient, design and social factors (Baker, 1986; Baker et al., 2002). Turley and Milliman (2000, p.194) extend research by Berman and Evans (1995) i.e. atmospheric stimuli categories, which are based on the five senses. However, of the five senses manipulated in the store environment, taste is often excluded. For fashion apparel stores, Parsons (2011, p.430) states ‘there is no expectation of taste – either functional or non-utilitarian – being present’. Due to parsimony
associated with ambient, design and social factors (Fiore and Kim, 2007), an overview of physical store atmospheric stimuli is provided in Table 3.1.

### Table 3.1 Categories Within Physical Store Atmospheric Stimuli

<table>
<thead>
<tr>
<th>Category</th>
<th>Type of Cue</th>
<th>Examples</th>
<th>Responses Studied</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ambient</td>
<td>Internal</td>
<td>Lighting, scent, music, aroma (smell), colour</td>
<td>Premium product shopping patterns, arousal, satisfaction, store intimacy, approach intentions</td>
<td>Madzharov et al. (2015); Biswas et al. (2017); Roschk et al. (2017); Herrman et al. (2013)</td>
</tr>
<tr>
<td></td>
<td>General</td>
<td>Storefront entrance, window display, window signs</td>
<td>Attitude, product beliefs, retailer effort perceptions, store visits, store entry, product purchase</td>
<td>Velasco Vizcaíno (2018); Lange et al. (2016); Mower et al. (2012)</td>
</tr>
<tr>
<td>Design</td>
<td>Layout/design variables</td>
<td>Fixtures, traffic flow, space allocation, digital signage</td>
<td>Store image, service quality, merchandise quality, brand loyalty, approach behaviour</td>
<td>Baker et al. (1994); Verbeke et al. (1998); Dennis et al. (2010)</td>
</tr>
<tr>
<td></td>
<td>Point of purchase/decoration</td>
<td>Product displays, display signage, shelf facings, mannequins</td>
<td>Price, attitude, willingness to purchase, product choice, store liking, patronage intentions</td>
<td>Chandon et al. (2009); Clement et al. (2015); Mower et al. (2012)</td>
</tr>
<tr>
<td>Social</td>
<td>Human variables</td>
<td>Employees, uniforms, store density, queues</td>
<td>Consumer spending, store atmosphere evaluation, arousal, store patronage intentions</td>
<td>Knoerferle et al. (2017); Grewal et al. (2003); Baker et al. (1992)</td>
</tr>
</tbody>
</table>

Adapted from Baker et al. (1994)

Table 3.1 provides a snapshot of atmospheric stimuli empirically examined in literature, but it is clear literature uses both objective (e.g. consumer spending) and subjective measures (e.g. willingness to purchase, patronage intentions) to understand the effects on various consumer responses.

The relationship between store atmospherics and consumer attitudes and patronage behaviour is well established in consumer research with various stimuli influencing consumers’ cognitive and affective responses as well as approach and avoidance behaviour (Donovan and Rossiter, 1982; Turley and Milliman, 2000; Fiore and Kim, 2007; Francioni et al., 2018). By using particular stimuli, such as information and graphic design, retailers are more likely to facilitate positive emotions and approach behaviour (Loureiro and Roschk, 2014). The SOR framework has featured prominently in retail atmospherics research to assess various cues on these responses (Donovan et al., 1994; Kaltcheva and Weitz, 2006; Baker et al., 1992; Fiore and Kim, 2007). More detail regarding this framework is provided in section 4.2. Using atmospheric cues, physical store environments...
can satisfy both shopping orientations and provide both utilitarian and hedonic value. This can positively influence outcomes, such as satisfaction and loyalty (Hirschman and Holbrook, 1982; Babin et al., 1994; Fiore and Kim, 2007; Scarpi, 2006; Bradley and LaFleur, 2016).

Due to the multi-dimensional nature of the store environment, studies have critiqued previous research based on a singular sensory stimulus (Bäckström and Johansson, 2006; Parsons, 2011; Fiore and Kim, 2007). Though testing one stimulus may yield a result, there are other influences to consider (Biswas et al., 2017). Hence, many papers argue the importance of examining in-store cues holistically (Poncin and Mimoun, 2014; Parsons, 2011; Ballantine et al., 2015) with research based on multi-sensory interactions (Grewal et al., 2003; Madzharov et al., 2015; Balaji et al., 2011; Helmefalk and Hultén, 2017). Although difficult to test, Jang et al. (2018) show it is possible to effectively control atmospheric stimuli by using a virtual store.

Atmospheric cues can help fashion apparel retailers to establish their brand personality and brand positioning (Brengman and Willems, 2009). Such visual merchandising includes the use of mannequins, apparel construction, product allocation and arrangement (Lund, 2015; Lindström et al., 2016) as well as general merchandising such as ‘lighting sources, level, colours, and fixtures/fitting’ (Parsons, 2011, p.430). How visual merchandising is presented can result in different store perceptions. For example, the use of colour can create an impression of warmth (Baek et al., 2018) or intimacy (Roschk et al. (2017) in a fashion retail store. Depending on the size of merchandise assortment, Jang et al. (2018) reveal the level of fashion product ordering can influence visual complexity. The general exterior is also important (Lange et al., 2016) and is advantageous in communicating branding as well as retail-related information (Velasco Vizcaíno, 2018). Fashion retailers such as Zara and Abercrombie & Fitch utilise store-as-a-brand strategy (Kumar and Kim, 2014).

As well as visual stimuli, growing literature posits other non-visual atmospheric cues, i.e. auditory, tactile or olfactory cues should also be manipulated (Spence et al., 2014). Research indicates retailers should offer multi-sensory experiences rather than focussing on the visual aspects of the store environment (Helmefalk and Hultén, 2017; Grewal et al., 2003). For example, fashion retailers Abercrombie and Fitch and Hollister used smell in
their store as part of a branding strategy and authenticity (Lund, 2015). For fashion retail, the tactile cue is an important atmospheric tool. Merchandising strategies such as folded garments on a table help to elicit tactile interactions. This assists customers with their decision-making process (Parsons, 2011; Jansson-Boyd, 2011; Grohmann et al., 2007). In studying the influence of both visual and tactile cues, findings by Balaji et al. (2011) show tactile information to be more important than visual information for haptic goods.

Currently, market reports and literature demonstrate retailers are re-evaluating the role of the physical store to accommodate the shift towards omni-channel retailing and are embracing digital innovation to deliver experiential value to consumers (The Business of Fashion and McKinsey & Company, 2017; Roy et al., 2017) as consumers search for in-store experiences that are immersive, holistic and sensorial (Foster and McLelland, 2015; Sands et al., 2015; Sachdeva and Goel, 2015). Despite the emphasis on digital innovation, traditional store aspects, such as store personnel and store layout, remain important to consumers (Johansson and Bäckström, 2017; Bäckström and Johansson, 2006). This is consistent with recent literature (Esmark et al., 2017; Knoeferle et al., 2017; Badrinarayanan and Becerra, 2018). Overall, this section demonstrates the significance in effectively manipulating and implementing retail atmospherics. Since the physical channel is often a part of a multi-channel or omni-channel strategy, there is also a need to consider atmospherics on the online channel (Poncin and Mimoun, 2014).

### 3.3 Online Atmospherics

An important distinction to note is that unlike physical retailing, online retailing is limited to a PC or a mobile screen. Of the five senses, applicability of tactile cues and olfactory cues is restricted meaning atmospheric cues such as scent, temperature and tactile evaluation cannot be experienced online. As a result of these restrictions, the web interface design is an important consideration to online retailers (Eroglu et al., 2001; Koo and Ju, 2010). With the growth of computer-mediated shopping, understanding the influence of online retail atmospherics has also become a burgeoning area of interest with research focussed on usability to enhance consumers’ web experience (Díaz et al., 2017; Hasan, 2016; Hausman and Siekpe, 2009).
Online atmospherics are based on elements in the virtual environment, which are considered equivalent to elements in the traditional store environment (Childers et al., 2001; Breugelmans and Campo, 2011). Such atmospherics should provide both functional and experiential value. Like the physical store, not only should online atmospherics aid consumers ‘to facilitate the accomplishment of the shopping tasks’, but they should also be designed to be immersive and stimulating (Ettis, 2017, p.51). Manganari et al. (2009) state that although methodologies vary among empirical research on online shopping between 1999 and 2008, most of the findings confirm a significant relationship between online atmospheric cues and consumer shopping outcomes.

Studies have also highlighted the significance of verbal and visual product information (Hong et al., 2004; Kim and Lennon, 2008) as well as visual design (Deng and Poole, 2010) for online retailing. Recently, there has been a greater emphasis on 3D simulated environments in e-commerce literature (Papagiannidis et al., 2017; Krasonikolakis et al., 2018; Visinescu et al., 2015), as well as dynamic online cues (Roggeveen et al., 2015).

### 3.3.1 Online Store Design and Layout

Like the physical store environment, attributes of website design as well as consumers’ online experiences are often evaluated. For example, online atmospherics have been studied to understand its influence on arousal and pleasure (Menon and Kahn, 2002; Koo and Ju, 2010), as well as behavioural outcomes such as the decision-making process (Senecal et al., 2005). However, not all cues are considered equal. Thus, Eroglu et al. (2001) characterise online atmospherics into two categories: a high task-relevant environment and low task-relevant environment (Figure 3.1). The former includes relevant shopping cues such as the product picture, product information and delivery information, which are useful for goal-directed behaviour. The latter includes information, such as the colour and fonts, which are considered less relevant in completing a shopping task online. Eroglu et al. (2001) argue low task-relevant cues do have an important role in influencing how easy the website is to use, consumers’ mood as well as perceptions towards the website. This is supported with findings from Hsieh et al. (2014).
Figure 3.1 SOR Framework Adapted to Study Online Atmospherics

However, evidence reveals by inducing arousal and pleasure even with low-task cues can still facilitate decision-making and purchase intentions (Davis et al., 2008), which is consistent with other literature. By manipulating colours (i.e. yellow versus blue), results from Ettis (2017) reveal the use of colour can affect enjoyment, flow and approach behaviour. Through direct and indirect effects, findings from Kim et al. (2015) demonstrate the importance of both low and high-task cues in facilitating re-visit intentions on luxury fashion websites. Recently, research has also focussed on online product reviews as a high task cue, which has both positive and negative effects on consumer behaviour (Lee and Shin, 2014; Moore, 2015; Antico and Coussement, 2017).

Based on the SOR framework, the model displayed in Figure 3.1 is often adapted in e-commerce literature (Loureiro and Roschk, 2014; Koo and Ju, 2010). By using different atmospheric stimuli, findings confirm it is possible to create a more enjoyable shopping experience, which may have greater enjoyment for some consumers (Menon and Kahn, 2002) as well as satisfying utilitarian needs (Roggeveen et al., 2015).

Essentially, well-designed websites positively influence satisfaction (Luo et al., 2012). According to Manganari et al. (2009), designing an effective webpage through the use of layout, atmospherics as well as theatrics is highly important, and so retailers should recognise it as a marketing strategy. The use of online atmospheric cues can result in greater customer loyalty towards physical stores (Savelli et al., 2017). Like the physical environment, the use of online atmospherics should be carefully applied; it ‘should not be coincidental, but the result of systematic and conscious design of online stores’ (Manganari et al., 2009, p.1144). Due to differences in results, Loureiro and Roschk

Source: Eroglu et al. (2001, p.179)
(2014) caution against applying the same type of atmospherics from the physical store of
the online store and generalising findings. Results also show a significant effect for
information design, so much so the authors recommend studying this atmospheric cue over
graphic design (Loureiro and Roschk, 2014).

3.3.2 Visual and Verbal Product Information

As there are different formats in presenting product information online, it is essential to
acknowledge how product information, which is considered a high-task relevant cue
(Eroglu et al., 2001), can affect consumers’ attitudes, namely cognitive and affective
attitudes. Product information is comprised of two elements, i.e. visual (product picture)
and verbal cues (textual product information). Various papers have compared the influence
of visual and textual information presented on e-commerce user interaction (Kim and
Lennon, 2008; Hong et al., 2004; van Rompay et al., 2010; Eroglu et al., 2001). Devised
by Paivio (1971, 1990), the dual coding theory is often used as a measure to analyse the
effects of verbal and pictorial information (Kim, 2018, Yoo and Kim, 2014; Jiang and
Benbasat, 2007; Hong et al., 2004). Section 4.4 provides further detail on dual coding
theory.

However, research tends to pay greater attention on pictorial information and how this
influences consumer behaviour rather than the influence of verbal information (Blanco et
al., 2010; Kim and Lennon, 2008). For fashion websites, product information has greater
relevance given the lack of tactile capabilities online (de Klerk et al., 2015; Ballantine,
2005). Such information includes ‘style descriptions, fibre content, construction details,
fabric construction, care instructions, colour, country of origin, price, and sizing
information’ (Kim et al., 2009b, p.10). Retailers may also provide addition information,
such as sales and stock information, which is shown to help determine perceptions of
product quality (He and Oppewal, 2018).

With varying levels of vividness, different types of visual product presentation can help the
consumer to imagine the product when shopping online (Flavián et al., 2017). However,
the effective use of imagery and text is a well debated subject in advertising and e-
commerce research. Some argue pictorial elements are more important (Li et al., 2016b),
while others emphasise the importance of textual elements (Pieters and Wedel, 2004; Hong et al., 2004). Blanco et al. (2010) argue this is dependent on how online product textual information is presented; a schematic presentation can ease processing and decision making while a block paragraph of text can make it difficult to recall product information.

Kim and Lennon (2008) evaluate both cues in an online fashion context and found verbal information to have a stronger influence on purchase intentions than visual information. The authors stipulate online shoppers may be able to gather more product information from product descriptions, such as fabric construction, than with large images or zoom function. However, this effect was significant ‘only when small pictures were used, and it was a small effect’ (Kim and Lennon, 2008, p.166). By drawing comparisons of high vs low information loads, results by Li et al. (2016b) also support this; textual information is considered influential in driving decision making in low information condition. Nevertheless, Hong et al. (2004) posit pictures are more likely to be remembered than text or words. Using eye tracking, Pieters and Wedel (2004) also confirm greater attention is given to the visual cue than textual or branding cues.

Interestingly, results by Blanco et al. (2010) show no difference on perceived quality, product information recall or perceived information of product recall when comparing the influence of the product image versus without. However, this research was conducted using websites selling electronic goods, which does not correlate with extant literature that asserts the positive influence of both online cues on consumer behaviour irrespective of product category. Despite contrasting findings, many papers agree both visual and verbal product information should be used in conjunction (Kahn, 2017; Kim, 2018; Wedel and Pieters, 2004). Kim and Lennon (2008, p.166) warn against using either form of presentation format without the other and that an ‘optimal combination of visual and verbal information’ is helpful for consumers in facilitating positive attitudes and behavioural intentions. Similarly, Hong et al. (2004) also confirm users’ responses were more favourable when using both text and images modes. Kim and Lennon (2008) extend this and posit the use of a zooming function may be more useful than just using large images in increasing purchase decisions as consumers can acquire more product details.

The amount of information provided is also an important consideration. Ballantine (2005) states fashion websites should list as many product attributes that are necessary in
providing product information to increase consumer satisfaction. However, this may also have a negative effect. As well as providing benefits, information available online may have a detrimental effect on the individual. Sicilia and Ruiz (2010, p.33) argue this is dependent on consumers’ information processing ability as individuals exhibit differing levels of need for cognition, which can influence a ‘person's motivation to process persuasive communication’. Results show increasing product information does not necessarily lead to an increase in information processing but leads to a U-shaped effect for individuals with low levels of need for cognition (Sicilia and Ruiz, 2010). This is consistent with recent papers who emphasise the importance of understanding the underlying mechanism of how consumers process product information online. Variables such as information load, need for cognition and processing motivation are considered moderating variables (Li et al., 2016b; Kim, 2018; Orús et al., 2017). Overall, there are calls to provide good quality product information that is well presented to facilitate information processing.

### 3.4 Online Interactivity

Websites are a multimedia form of marketing, of which interactivity is considered an important aspect. Examples include ‘audio, video, graphics or text’ (Wu, 1999, p.255). There have been many scholarly definitions of interactivity (Liu and Shrum, 2002). Wu (1999) states previous definitions of interactivity did not articulate a strong distinction between interactivity on the web and the other types of interactivity, such as engaging with a magazine. By capturing different types of interactivity, Liu and Shrum (2002, p.54) define interactivity as ‘the degree to which two or more communication parties can act on each other, on the communication medium, and on the messages and the degree to which the such influences are synchronised’. Communication appears to be a key term in interactivity in which the process is described as a two-way mechanism with consumers having a level of active control (Mollen and Wilson, 2010). Hence, interactivity is described as a multidimensional construct that is comprised of three underlying dimensions (Steuer, 1992; Liu and Shrum, 2002, Shih and Huang, 2014) (Table 3.2).
Table 3.2 Dimensions of Interactivity in Online Shopping Websites

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Importance</th>
<th>Example(s)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Active control</td>
<td>Users can shop and control their voluntary navigation on a shopping website; it is up to the user to operate the features.</td>
<td>Banner advertising, language choice, downloads, store locator, menu, product presentation, i.e. visual and virtual control</td>
<td>Liu and Shrum (2002); van Noort et al. (2012); Algharabat et al. (2017)</td>
</tr>
<tr>
<td>Two-way communication</td>
<td>Consumers and retailers can interact with each other using a feedback process. This can lead to higher engagement.</td>
<td>Emails between consumer and retailer, discussion forums, contact (i.e. email address hyperlink), product recommendations agents</td>
<td>Liu and Shrum (2002); van Noort et al. (2012); Flanagin et al. (2014); Wang and Benbasat (2016)</td>
</tr>
<tr>
<td>Synchronicity</td>
<td>Interaction with a website occurs in real-time as there is no delay in the input and communication received.</td>
<td>Purchasing a product online i.e. transaction process, sales and stock level information</td>
<td>Liu and Shrum (2002); Yoon et al. (2008); He and Oppewal (2018)</td>
</tr>
</tbody>
</table>

Literature also differentiates between low and high interactivity concerning various website features. It is important to note verbal and visual cues can also differ in interactivity as illustrated in Table 3.3.

Table 3.3 Comparison of Low and High Online Interactive Conditions

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Website feature</th>
<th>High</th>
<th>Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two-way communication</td>
<td>Contact details</td>
<td>Online form to complete</td>
<td>Verbal description of address, email and telephone details</td>
</tr>
<tr>
<td></td>
<td>Email registration</td>
<td>Email newsletter sign-up</td>
<td>No option provided</td>
</tr>
<tr>
<td></td>
<td>Personalisation</td>
<td>User’s name, use of language such as “hello”</td>
<td>Non personalised webpage</td>
</tr>
<tr>
<td></td>
<td>Order status</td>
<td>Tracking number</td>
<td>No option provided</td>
</tr>
<tr>
<td>Control</td>
<td>Store locator</td>
<td>Interactive store locator map</td>
<td>List of stores verbally listed</td>
</tr>
<tr>
<td></td>
<td>Product review</td>
<td>Option to write a review</td>
<td>No option provided</td>
</tr>
<tr>
<td></td>
<td>Language</td>
<td>Selection of different languages</td>
<td>No option provided</td>
</tr>
<tr>
<td></td>
<td>Product presentation</td>
<td>3D product display</td>
<td>Static image</td>
</tr>
</tbody>
</table>

Adapted from: van Noort et al. (2012) and Dholakia and Zhao (2009)

When there is high interactivity, greater cognitive involvement is required. In other words, using an interactive website demands a higher level of attention and cognition (Liu and Shrum, 2002). In comparison to other types of online multimedia, online shopping requires high levels of all three interactivity dimensions. Currently, this has greater relevance due to the variety of online interactive tools as well as shopping environments that offer greater
personalisation and customisation (Pappas et al., 2016). In trying to improve interactivity, it is simply not just adding more interactive elements, it also depends on how interactive the features are, and its overall influence on consumers behaviour (Liu and Shrum 2002).

### 3.4.1 Effects of Online Interactivity

Often in e-commerce research, the level of interactivity is manipulated and tested with a low interactive condition versus a high interactive condition (Beuckels and Hudders, 2016; van Noort et al., 2012, Dholakia and Zhao, 2009). Literature outlines the positive effects of an interactive shopping environment. For example, a high level of perceived interactivity is shown to elicit high levels of online flow (van Noort et al., 2012; Sicilia et al., 2005) and user satisfaction (Yoo et al., 2010; Teo et al., 2003; Ballantine, 2005). Results show these factors mediate the relationship between interactivity and affective, cognitive and behavioural responses for product-related thoughts (van Noort et al., 2012).

Findings also reveal an interactive shopping website can fulfil both hedonic and utilitarian shopping styles (Childers et al., 2001; Yoo et al., 2010; Hoffman and Novak, 1996). However, Fortin and Dholakia (2005) argue increasing interactive elements may not produce positive emotional and behavioural effects and suggest there needs to be an equal measure of interactive elements with design elements online. While manipulating elements such as images, colours and videos can produce higher levels of vividness, manipulating these elements may generate a stronger effect on vividness than increasing interactivity (Fortin and Dholakia, 2005). Between interactivity and providing verbal product attributes for fashion products online, Ballantine (2005) argues there should be greater emphasis on interactivity in providing a satisfying shopping experience. Interactivity also plays a significant role in enhancing product visualisation (Kim, 2018; Orús et al., 2017; Fiore et al., 2005b). As such, these interactive elements are often described as rich multimedia comprised of sensorial and immersive qualities that offer a closer and more realistic experience that is reflective of the physical store environment (Flavián et al., 2017). Categorised as a type of user control interactive condition, the use of product presentation and image interactivity for fashion products is of particular importance.
3.5 Product Presentation and Image Interactivity Technology (IIT)

Although shopping online is no longer a new phenomenon, perceived product risk continues to be a concern today. Unlike physical shopping, there is greater difficulty in accessing relevant product information, such as quality, that is required to aid consumers with their decision-making process (Verhagen et al., 2014; Peck and Childers, 2003b). To offset these issues, online retailers currently employ a variety of multimedia technology to help recreate or mimic offline interaction, which is often referred to as product presentation or IIT. Product presentation is generally regarded as product information that encapsulates both textual and visual elements (Li et al., 2016b; Kim and Lennon, 2008), while IIT is defined as a visual website function that is able to ‘enable creation and manipulation of product or environment images to simulate (or surpass) actual experience with the product or environment’ (Fiore et al., 2005b, p.39). There has been growing academic research in this area with many evaluating the influence of these tools on approach-avoidance behaviour (Table 3.6). Recent studies have focussed on how these visual stimuli affect information processing (Kim, 2018; Flavián et al., 2017; Orús et al., 2017; Li et al., 2016b). According to Kahn (2017), processing visual stimuli occurs very quickly that results in automatic perceptions towards a website. Analysing the influence of these visual imagery tools on information processing can therefore provide greater insight on consumers’ decision making when shopping online.

To date, literature has not distinguished between product presentation and IIT. This is important to emphasise because despite the difference, i.e. inclusion and exclusion of verbal product information, usage of these terms overlap. In other words, they are often applied to the same visualisation tools. This inconsistency in taxonomy is highlighted in Table 3.4. Confusingly, other papers also refer to different but related terminology.
### Table 3.4 Taxonomy of Online Product Visualisation

<table>
<thead>
<tr>
<th>Terminology</th>
<th>Visualisation Tools</th>
<th>Example of Reference(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product presentation</td>
<td>Product views (static images), alternative views, model view, zoom function, videos, extrinsic and intrinsic verbal stimuli</td>
<td>Algharabat <em>et al.</em> (2017); Jiang and Benbasat (2007); Orús <em>et al.</em> (2017); Kim and Lennon (2008); Jeong <em>et al.</em> (2009); Yoo and Kim (2014)</td>
</tr>
<tr>
<td>IIT</td>
<td>Zoom, product rotation, virtual modelling technology, fabric scrunch, mix and match</td>
<td>Cano <em>et al.</em> (2017); Beuckels and Hudders (2016); Lee <em>et al.</em> (2010); Yang and Wu (2009); Lee <em>et al.</em> (2006); Fiore <em>et al.</em> (2005b)</td>
</tr>
<tr>
<td>Product virtualisation technology</td>
<td>3D rotation views, Virtual Try-on</td>
<td>Kim and Forsythe (2007)</td>
</tr>
<tr>
<td>Sensory-enabling presentation</td>
<td>Zoom, rotation video</td>
<td>Jai <em>et al.</em> (2014)</td>
</tr>
<tr>
<td>Sensory-enabling technologies</td>
<td>2D views, alternative views, 3D rotation view, Virtual Try-on</td>
<td>Kim and Forsythe (2009)</td>
</tr>
<tr>
<td>Product-oriented web technologies</td>
<td>Zoom, alternative photos, colour swatch</td>
<td>De <em>et al.</em> (2013)</td>
</tr>
<tr>
<td>Communication medium</td>
<td>Static images, moving images, images with both static and moving elements</td>
<td>Ashman and Vazquez (2012)</td>
</tr>
<tr>
<td>Functional product viewing</td>
<td>Product photos, graphics, IIT including catwalk videos</td>
<td>McCormick and Livett (2012)</td>
</tr>
</tbody>
</table>

Despite these differences in terminology within e-commerce literature, there is overall agreement of the capabilities surrounding these visualisation tools. Though visual information with the use of images greatly assists consumers in obtaining accurate product evaluations (Balaji *et al.*, 2011), the use of these tools can enhance this effect. By simulating a product online, retailers allow consumers to actively engage with the product image. The use of large product images, alternative product views in addition to interactive elements, such as videos and zoom function, enables the consumer to visualise the product from different angles and distances to obtain a greater sense of product features and attributes (Fiore and Jin, 2003; Park *et al.*, 2008; Beuckels and Hudders, 2016; Jeong *et al.*, 2009; De *et al.*, 2013). Consumers can also learn more about product qualities including product performance that is otherwise difficult to determine just by looking at a static image (Algharabat *et al.*, 2017). As outlined in Chapter 2, this issue is a particular problem that can create high levels of perceived product risk when shopping for fashion apparel products online as consumers are unable to touch and try on products (de Klerk *et al.*, 2015).

As there are different types of visualisation techniques, there are also varying levels of interactivity or vividness (Flavián *et al.*, 2017; Roggeveen *et al.*, 2015; Yang and Wu, 2009). For example, static and two-dimensional fashion images that can be manipulated from a front view to a back view is considered to have lower interactivity than dynamic...
media that offers greater manipulation or 3D viewing (Beuckels and Hudders, 2017). There are also discrepancies in usage of visual formats among online retailers. According to Roggeveen et al. (2015) utilisation of these tools among top online retailers is high while it is lower among online retailers who perform less well. Hence, it is not surprising that adoption of these tools is increasingly commonplace and are routinely utilised across a broad spectrum of fashion websites that range from fast fashion to high-end luxury fashion (Beuckels and Hudders, 2016). For fashion pure-plays, this is the only experience and communication medium consumers have with the fashion products prior to purchase (Ashman and Vazquez, 2012), which demonstrates the significance of these tools on fashion consumers’ purchasing behaviour. However, not all fashion products are displayed uniformly. This is demonstrated in Table 3.5 that summarises current usage of visual product formats by online fast fashion retailers. Items sold on luxury fashion pure-play retailers, whereby examples include Net-a-Porter and Matches Fashion, often include various brands that can also be experienced in a physical environment, such as the brand’s physical stores or in department stores. With the exception of ASOS, which feature a few brands that sell offline too, this is usually not the case for fast fashion pure-plays. For this reason, only fast fashion retailers were considered.
Table 3.5 Snapshot of Online Fashion Product Presentation (July 2018)

<table>
<thead>
<tr>
<th>Product Presentation</th>
<th>Observations</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Product image (static)</strong></td>
<td>Availability</td>
<td>It is rare to come across fashion e-commerce sites of available products without at least one static image.</td>
</tr>
<tr>
<td></td>
<td>Operation</td>
<td>Additional product views often presented as a thumbnail or indicated with the use of arrows besides main image. On mobile devices, it is usually possible to change the image by swiping.</td>
</tr>
<tr>
<td></td>
<td>Variation</td>
<td><strong>Number of product images:</strong> Variations in the number of product images, image size, image quality and stylistics. ASOS use 4 product images. In some cases, H&amp;M only use 1 image, which was without the model. Topshop uses 6 while Zalando uses 7 product images.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Image size:</strong> Fashion images on Topshop and Zara are comparatively larger than images on H&amp;M website.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Image quality:</strong> Some fashion retailers offer better quality product images that are clear and sharp.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Stylistics:</strong> The way the images are captured and presented can vary from looking like magazine content including the way the model is posing to standard model posing in a straightforward manner.</td>
</tr>
<tr>
<td><strong>Image enlargement (zoom)</strong></td>
<td>Availability</td>
<td>Zoom is the most common tool used by different types of fashion retailers online and on mobile.</td>
</tr>
<tr>
<td></td>
<td>Operation</td>
<td>There is normally indicated with the use of hand cursor or magnifying glass cursor (+) when hovering over the image. For m-commerce, there may not be an obvious zoom function available. However, consumers may be able to pinch and zoom further into product images using their fingers. Fashion example: Zara</td>
</tr>
<tr>
<td></td>
<td>Variation</td>
<td>Product images on fashion websites and apps, such as Zara, expand into a full screen size photo. For other retailers the zoom may not be as large, but consumers may have more control with incremental changes in zooming in and out.</td>
</tr>
<tr>
<td><strong>360° product rotation</strong></td>
<td>Availability</td>
<td>Current usage of this tool appears to be limited for fashion apparel. However, it is employed by fashion retailers such as ASOS, Schuh and Ray-Ban for other product categories, such as shoes and accessories.</td>
</tr>
<tr>
<td></td>
<td>Operation</td>
<td>Once loaded to 100%, the use of a hand icon signifies a grab like motion to rotate the product. Consumers can rotate products 360°.</td>
</tr>
<tr>
<td></td>
<td>Variation</td>
<td>This tool works similarly across websites and apps.</td>
</tr>
<tr>
<td><strong>Catwalk video</strong></td>
<td>Availability</td>
<td>This tool is more commonplace among pure-play retailers (example: ASOS, Pretty Little Thing, Boohoo).</td>
</tr>
<tr>
<td></td>
<td>Operation</td>
<td>There is usually indicated by a play button link. Fashion retailers such as ASOS and Missguided also use text (such as VIDEO or play video) besides the play button. It is possible to pause, replay or click on any segment of the video.</td>
</tr>
<tr>
<td></td>
<td>Variation</td>
<td><strong>Length of videos:</strong> Videos on ASOS are typically longer in length than videos on Missguided or Pretty Little Thing and show more detail. <strong>Other types of videos:</strong> Although not product videos, there is greater usage of promotional videos on the homepage and assortment page. This is observed with Zara, Ted Baker and Mango.</td>
</tr>
</tbody>
</table>

Although nearly all fashion retailers utilise a front and back image of the product online, not all fashion retailers invest in more than one type of product presentation in addition to static product images. For example, fast fashion retailers Zara, H&M and Topshop only use image enlargement for dynamic product viewing. Observations outlined above reveal established fashion pure-play retailers implement a variety of product presentation tools in comparison to traditional fashion retailers who also operate online. Retailers such as
Missguided use image enlargement, catwalk video as well as multiple product views and colour manipulation (Figure 3.2).

**Figure 3.2** Product Visualisation on the Missguided Website (July 2018)

Department store e-tailers or multi-brand e-tailers may apply particular visual formats to a specific product category. For example, Amazon use promotional and demonstration videos for products such as electronics and travel pillows, but catwalk videos for fashion products are currently unavailable. Thus, there are differences and inconsistencies in the product format across online fashion retailers.

For branded merchandise, such as cameras and coffee makers, that are typically sold on various online websites, such as monobrand sites, marketplaces and multi-brand e-tailers, this may result in preference of one website over another depending on the product format (Roggeveen et al., 2015). Thus, these tools and the type of product format selected can be hugely influential in driving online sales. As experience (i.e. hedonic) products, literature corroborates there is huge potential for online retailers in displaying fashion apparel products using a dynamic visual format (Roggeveen et al., 2015; Beuckels and Hudders, 2016; Cano et al., 2017). Existing literature on fashion apparel has studied certain functions of product visualisation and its effect on approach responses. An overview of each type is provided in the following sub-sections.
3.5.1 Static Images

Static product images are often manipulated in studies as a baseline or as a control condition (Orús et al., 2017; Wang et al., 2016; Roggeveen et al., 2015; Choi and Taylor, 2014; Jiang and Benbasat, 2007). However, this online atmospheric cue plays an essential role in depicting product information and was the first type of visual product format employed by retailers online (Verhagen et al., 2014). The effects of static product images have thus been explored from a variety of perspectives including image size, image quality, number of images in addition to the presence of a model. As well as the front product view, online retailers may offer alternative product views including a back view, an enlarged product view as well as the apparel item from different angles (Figure 3.3). Fashion apparel may be featured alone or on a model (Jeong et al., 2009; De et al., 2013).

**Figure 3.3 Various Product Views on ASOS**

In an online fashion context, literature shows dichotomous results. For example, the use of a model’s face on the product page can hinder the perceived amount of information, and therefore may be distracting when shopping for fashion online (Yoo and Kim, 2012). Results by Park et al. (2005) show image size manipulation did not yield any significant effects on constructs mood, perceived risk, or purchase intention (Park et al., 2005). Although larger images provide greater product information, the authors argue that this effect should have also influenced perceived risk. Alternative product views can also lead to higher product returns and lower overall net sales. Specifically, usage of one-time
observation of alternative product views increased returns by 5% (De et al., 2013). This finding is explained by how consumers perceive information. Consumers who view alternative product views and make a purchase online do so due to impression-based information of how they may look rather than assessing factual information, and that impression-based information is more salient than the factual information observed (De et al., 2013).

Conversely, Song and Kim (2012) state displaying larger image sizes and a number of product views of handbags online increases the amount of product information and decreases mental intangibility. According to Song and Kim (2012), this is important as results demonstrate this lowers perceived risk, which is considered an important driver of online purchase intentions. This is also supported by Kim (2018); larger images of fashion apparel can facilitate higher imagery processing as well as discursive processing, which can help consumers to imagine product interactions. Using SOR, findings confirm these types of cognitive responses are directly related to behavioural intent (Kim, 2018).

Static product images have also been compared to more dynamic multimedia, such as catwalk videos (Ashman and Vazquez, 2012). Findings reveal only static images of fashion apparel were positively associated with purchase intentions, which suggests consumers perceive this type of presentation to be more important than dynamic viewing during their decision making. In comparing static images of sunglasses to product rotation and virtual mirror, results by Verhagen et al. (2014) indicate static images still influences local presence, product intangibility and product likability, thereby facilitating purchase intentions. While static images are considered a basic visual format, these findings reveal fashion retailers should be careful in their visual merchandising efforts. For example, findings by Song and Kim (2012) also reveal there is greater product information with one large image of a fashion apparel product than there is with four small images. Based on this finding, dynamic and interactive tools may not be a huge necessity if static product images are considered large, clear, accurate and well presented.
3.5.2 Image Enlargement

This is otherwise known as a zoom function and permits the user to zoom into the image in order to visualise product information in greater detail (Kim and Lennon, 2010; Kim et al., 2007). Images with products enlarged are regarded as factual information (De et al., 2013). Typical zoom-ins may focus on the product attributes such as the material, fabric, quality, texture, print, stitching details, the overall fit assessment, which may include how the product fits on the model, as well as specific ornamental features such as zips, buttons and embellishments (De et al., 2013). This type of image interactivity is commonly adopted by online fashion retailers (Kim, 2018; Beuckels and Hudders, 2016; Jai et al., 2014; Choi and Taylor, 2014; Kim and Lennon, 2010; Jeong et al., 2009; Kim et al., 2007).

Usage of this interactive tool has shown to facilitate fewer product returns. De et al. (2013) stipulate one-time usage of image enlargement can decrease product returns by 7%. In comparison to product rotation and virtual model technology, this function is regarded as less interactive (Choi and Taylor, 2014; Lee et al., 2010). Using fMRI, findings by Jai et al. (2014, p.347) suggest image enlargement is more effective than static images in displaying detailed product information. However, this function ‘did not stimulate a larger sense of “touching” the garment than the static pictures’. Findings also reveal there was no stimulation difference between this tool and static product images in affecting participants’ emotions and attitude towards the product image. As noted in Table 3.5 fashion retailers often provide enlarged static images. Coupled with the findings by Jai et al. (2014), this indicates the use of zooming technology may not be perceived as a hugely different tool on fashion consumers’ behaviour.

3.5.3 360° Product Rotation

Based on a Mintel report (2014), 3D products with a spin facility would encourage more than a quarter of consumers to switch to an alternative website. Unlike other types of IIT, product rotation facility has higher levels of active control. Here, an individual can control the extent, i.e. the speed and angle, of the 360° rotation and view the product from any angle that provides a 3D representation of the product (Park et al., 2005) and greater sensory information (Choi and Taylor, 2014). Currently, this type of image interactivity is
popular for accessories and shoes. For example, ASOS utilise product rotation for handbags (Figure 3.4) while shoe retailer Schuh have implemented product rotation for footwear.

**Figure 3.4 Product Rotation on ASOS**

Source: ASOS (2018)

Empirical research confirms this visual format for fashion apparel can increase mental imagery (Choi and Taylor, 2014) telepresence (Beuckels and Hudders, 2016) and perceived information quality (Park et al., 2008), all of which contribute towards helping the user with product visualisation. This is coherent with results from Jai et al. (2014) who find product rotation elicits greater visual imagery in the brain. As well as functional aspects, these tools can also drive emotional responses, such as enjoyment (Kim and Forsythe, 2009), mood (Park et al., 2008) as well as arousal and pleasure (Jai et al., 2014). Outcomes are positive; implementation of product rotation can enhance user engagement (Cano et al., 2017) and lower perceived risk, which positively influences purchase intentions (Park et al., 2008; Park et al., 2005).

Overall, this type of visual format can influence different types of responses including affective, cognitive and conative that can drive decision-making when shopping for fashion apparel online. Findings reveal an authentic representation is the most influential aspect of 3D quality (Algharabat et al., 2017). Thus, it is important for fashion retailers to maintain a realistic and accurate product rotation tool. For luxury fashion retailers, this
type of IIT can offer a point of differentiation by increasing levels of telepresence and may help to compensate lack of tactility that is regarded as a reason why consumers don’t purchase luxury fashion online (Beuckels and Hudders, 2016).

### 3.5.4 Catwalk Video

Catwalk video usage has become widespread across UK fashion retailers among pure-play retailers as well as traditional retailers (Figure 3.5). This tool enables consumers to see how apparel moves with the model i.e. provides detail on the material and its drape-ability properties.

**Figure 3.5 Catwalk Video on ASOS**

![Catwalk Video on ASOS](image)

Source: ASOS (2018)

Interestingly, although this type of visualisation tool positively influences trust and loyalty, catwalk video was found to be less influential than static images in driving purchase intentions (Ashman and Vazquez, 2012). This could be explained by findings by McCormick and Livett (2012); consumers perceive this tool as an extension to other fashion product presentation tools in providing utilitarian value. However, both studies claim this visualisation tool can also satisfy hedonic shopping motivations. This is consistent with findings from Flavián et al. (2017) who assessed videos for smartphone purchase online. Results show participants experienced arousal when watching videos, but
that it also helped them to obtain accurate and realistic sense of product attributes that positively influenced attitudes and purchase intentions.

Other than catwalk video, retailers also use promotional and demonstrational videos. For example, retailers selling electronics online also use audiovisual videos to explain more details about the product and may embed their own video platform into the website or embed a YouTube video (Jiang and Benbasat, 2007; Orús et al., 2017; Flavián et al., 2017). Watching these videos can increase the ease of imagining the product. However, the way this information is used by individuals can vary depending on their motivation for processing, which can impact their subjective experience, such as attitude towards the product (Orús et al., 2017).

Exposure to videos that correlate to shopping are increasingly prevalent with a greater number of individuals choosing to watch product review videos, such as clothing hauls, on YouTube (Xu et al., 2015). Such videos posted by YouTube bloggers appear popular with younger consumers (Treadgold and Reynolds, 2016). This demonstrates the popularity of viewing fashion apparel being worn on an individual who models the clothing three-dimensionally, i.e. walks around to display clothing from different angles. In comparison to text-based and image-based presentations for product reviews, this type of presentation format is the most influential on consumer perceptions and purchase intentions according to Xu et al. (2015).

However, these influences can vary according to the product type, if they are an experience good or search good. Experience goods, such as backpacks, were found to be more influential than cameras, since it is difficult to get a sense of product attributes for experience products, such as material and quality, from the text and pictures alone, and therefore may require greater vivid information (Xu et al., 2015). This was less of an issue for search goods, which implies fashion products viewed by video are more influential than static product presentation as well as videos used for search goods. Fashion retailers are increasingly using this type of multimedia across their website. In addition to using videos for product viewing on the product page, fashion retailers such as Zara, Mango and Ted Baker feature promotional videos on their home page and product assortment page. Such videos are more akin to TV advertising. In comparison to other types of visual formats, understanding the influence of catwalk video as a product presentation tool in
literature is less well understood. Currently, usage of this tool is popular among pureplay fashion retailers. In addition to inconsistencies in literature, there is a gap in understanding up to date influence of catwalk videos on fashion consumer behaviour.

3.5.5 Colour Manipulation

Colour manipulation permits consumers to view a product in a variety of colours using a larger frame. The colour change function is one of the most common interactive tools on fashion websites (Beuckels and Hudders, 2016; Kim and Lennon, 2010). This type of product manipulation was found to have an inconsequential effect of product returns; this did not increase or decrease product returns (De et al., 2013). Although this particular tool is also considered to encompass both factual information and impression-based information, De et al. (2013) assert neither aspect is considered significant as the consumer can see the different colours the product is available in before clicking on individual colours.

3.5.6 Fabric Scrunch

Originally developed by Shoogleit technology, this online tool enables the user to actively control and manipulate the fabric on a touchscreen device (Perry et al., 2013). Thus, this type of image interactivity is used to simulate a tactile or a physical touch gesture. To determine the influence of this IIT, studies have compared fabric scrunch to a static product images of a fashion apparel item (Overmars and Poels, 2015b; Cano et al., 2017). Since the user has a higher level of active control when manipulating the image, this can result in enhanced tactile sensations, which assists users in acquiring product attributes (Overmars and Poels, 2015b). However, findings also reveal these relationships were only supported for experience products, such as fashion apparel.

Studies have also shown influences of fabric scrunch on consumer behaviour. For example, findings demonstrate usage of this tool enhances user engagement on a touchscreen interface. Manipulating fashion apparel in this way can provide experiential value as well as greater sensorial information when shopping from a mobile device (Cano et al., 2017). In a separate study, Overmars and Poels (2015a) demonstrate such an
interaction can facilitate affective responses and that variables such as consumers’ motivations and need for touch moderate this influence. For consumers shopping online, employing a tool which requires gestural input can increase real life simulation of scrunching the fabric that consumers would otherwise experience when handling fabrics and clothing in store.

### 3.5.7 Virtual Model Technology (VMT)

This type of product presentation is also referred to as a virtual mirror and virtual try-on. Essentially, VMT was designed ‘to create the illusion of the product being present in the consumer’s physical environment’ (Verhagen et al., 2014, p.271). In comparison other types of product presentation, VMT is considered to have higher levels of interactivity and vividness, which results in higher levels of telepresence (Yang and Wu, 2009). Interaction with VMT can increase consumer enjoyment, but it also has a negative effect on perceived risk that can foster positive attitudes towards the website (Lee et al., 2010).

Such technology is considered to facilitate higher levels of local presence (Verhagen et al., 2014). An example can be found on the Specsavers Opticians website. Using the try-on feature alongside frame recommendation technology, users can upload their facial data to see how the glasses would look on themselves in a virtual context. Vyking, a technology start-up company, demonstrates it is possible to use a smartphone to virtually try on trainers in real time allowing the user to move their feet in relation to the virtual trainer (Gershgorn, 2018). Overall, literature confirms this technology is comprised of both hedonic and utilitarian value in providing richer product information as to what the apparel will look like on the body, but it also creates a sensorial experience that can attract consumers who are seeking adventure (Fiore et al., 2005a, Yang and Wu, 2009; Lee et al., 2010).

However, empirical findings relating to VMT may not be applicable to online fashion retail today as studies were originally conducted under lab experimental conditions involving a mock website such as ImaginariX.com (Fiore et al., 2005b; Lee et al., 2006; Kim et al., 2007; Kim and Forsythe, 2007; Yang and Wu, 2009; Lee et al., 2010). Despite
the fact that it was classified as an emerging format (Verhagen et al., 2014), it is currently not widely adopted by fashion retailers. This may be because creating this software is a timely and costly measure (Fiore et al., 2005b). Nevertheless, adoption of this technology for innovative fashion companies would create a point of differentiation and help garner consumer loyalty (Fiore et al., 2005b). Although retailers have yet to implement the technology to map fashion apparel on a realistic full human body, evidence and market research data suggests virtual fitting rooms are in the pipeline and may soon be unveiled on online fashion websites (Mintel, 2017).

### 3.5.8 Mix and Match

This type of IIT enables the consumer to visualise and interact with outfit combinations by manipulating the top and the bottom i.e. skirt or jeans for example. Currently, this tool does not appear to be employed by online fashion retailers and no longer exists on fashion websites, such as Guess.com that was originally studied by Fiore and Jin (2003) and Fiore et al. (2005a) to determine the influence of the mix and match function. However, evidence suggests that this type of tool could be implemented as part of virtual fashion stores using 3D technology (Wu et al., 2013). The mix and match function is also similar to product coordination where fashion retailers emphasise fashion apparel by coordinating the whole look as an outfit on the model. While this approach uses static product images and therefore may be limited in interactivity, it can still generate favourable responses towards the product and website (Yoo and Kim, 2012).

### 3.5.9 Influence of Visual Product Presentation on Consumer Behaviour

Since the early 2000s, research on product visualisation tools continues to be studied (Kim, 2018; Orús et al., 2017, Fiore and Jin, 2003). While online retailing has evolved with the use of more advanced technology, literature overwhelmingly confirms the impact of IIT and product presentation is positively associated with consumer behaviour outcomes. These tools are considered to play a vital role in online retailing that can help consumers overcome barriers and perceived risk when shopping online, particularly for items that are perceived more riskier to purchase online such as luxury fashion apparel (Beuckels and Hudders, 2016).
Since the earlier papers on IIT and product presentation, there has been greater advances towards the studying the influence of a 3D online shopping environment (Orús et al., 2017; Flavián et al., 2017; Wu et al., 2013; Algharabat et al., 2015; Cano et al., 2017; Beuckels and Hudders, 2016; Choi and Taylor, 2014).

The importance of these tools is well established; different levels of product presentation positively influence all three types of consumer responses, i.e. cognitive, affective and conative, which can shape behavioural outcomes such as attitude and purchase decisions (Lee et al., 2010; Verhagen et al., 2014). An example of a cognitive process is perceived risk, which has instrumental value (Yang and Wu, 2009). Positive attitudes towards the shopping website and product presentation can drive consumer satisfaction, of which attitude towards product presentation has a stronger effect (Algharabat et al., 2017). A total of 31 papers that have manipulated and examined visual product presentation were found (Table 3.6).
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</table>

Product presentation tools have been tested by manipulation or by comparing different types of product presentation according to levels of interactivity and vividness. However, this is not the case for all product presentation studies. Table 3.6 shows a number of different combinations of visual product formats have been evaluated along with various consumer outcomes. Findings by De et al. (2013) confirm different types of product presentation can result in different impacts on product returns. Literature also favours testing low versus higher interactive formats against a particular framework (Fiore and Jin,
2003; Fiore et al., 2005b; Park et al., 2005; Lee et al., 2006; Park et al., 2008; Song and Kim, 2012).

While most papers evaluate product presentation from a fashion apparel context, which is an experience good (Kim, 2018), others such as Algharabat et al. (2017) explore product presentation for search goods, which are associated with utilitarian attributes. Scholars acknowledge results may vary according to product type (Algharabat et al., 2017). Although dynamic presentation of experience and search goods positively influence choice behaviour, willingness to pay for products with hedonic attributes was found to be much higher when the product is presented in dynamic condition that compared to a static condition (Roggeveen et al., 2015). Thus, papers suggest exercising caution when generalising results to other types of product categories online (Li et al., 2016b; Kim, 2018; Verhagen, 2014). Beuckels and Hudders (2016) emphasise the importance of these tools for luxury fashion; due to high price points and social perceptions, the lack of tactile accessibility is considered a greater barrier.

A wide variety of underlying mechanisms and frameworks have been adopted to examine the influence of this type of online visual cue. Common frameworks include the SOR model (Jeong et al., 2009; Jai et al., 2014), dual coding theory (Kim, 2018) and more recently imagery fluency (Flavián et al., 2017; Orús et al., 2017). Many studies also look at the influence of functional and experiential influences. While studies have mostly used distinct hedonic and utilitarian constructs to study the influence of IIT, others such as Algharabat et al. (2017, p.203) conceptualise and incorporate various 3D product quality measures, which includes ‘information quality, system quality, authenticity and enjoyment’ into one multi-dimensional construct.

From Table 3.6, it is clear that literature has greater preference for quantitative data collection. Majority of research has been undertaken using surveys to understand consumer responses towards product presentation. Two studies use a mixed method approach via focus groups and a survey to corroborate findings (Kim and Forsythe, 2007; Kim and Forsythe, 2009). Only one study used qualitative data collection, i.e. in-depth interviews, alongside other qualitative measures to explore consumers’ interaction with fashion apparel online (McCormick and Livett, 2012). Using fMRI, Jai et al. (2014) reveal
different product presentation produce different effects on the brain and vary according to the encoding and decision-making process when apparel shopping.

By evaluating actual purchasing information, De et al. (2013) asserts most studies rely on self-reported measures, i.e. surveys, which are subjective in nature, and therefore may be limiting. Although it may give an indication on how consumers feel, it may not be a reliable indicator of actual purchasing behaviour and whether these technologies are considered useful enough in lowering product returns. De et al. (2013) consider collecting data on purchasing as an objective measure. However, they also acknowledge this approach does not account for the influence of IIT for shopping when no purchase is involved.

Product presentation literature also illustrate varying direct and indirect influences of these visual cues on approach responses. Algharabat et al. (2017) state 3D product quality directly influences attitudes towards the website as well as attitudes towards the product presentation. Consistent with marketing literature that evaluates the influence of store atmospherics and other online atmospheric cues, effects of product presentation are determined by a variety of intervening variables, including mediators and moderators. Important mediators can include affective and cognitive responses, such as mood and perceived risk (Park et al., 2005). In the study by Lee et al. (2006, p.636), the relationship is facilitated by TAM mediators ‘perceived usefulness, perceived ease of use, and perceived enjoyment’. Yang and Wu (2009) argue the importance of satisfaction as a mediator on behavioural intention, facilitated by hedonic and utilitarian value.

Depending on the levels of vividness and interactivity, product presentation can generate high levels of imagery that can help consumers with their decision-making (Park et al., 2005). Vividness and interactivity are considered to be antecedents of telepresence in helping to create a virtual reality when shopping for fashion, which is also noted as an important driver of both shopping motivations (Yang and Wu, 2009; Fiore et al., 2005b). Telepresence is described as the ‘the experience of presence in an environment by means of a communication medium’ (Steuer, 1992, p.76). The positive and significant influence of telepresence confirms these tools simulate a lifelike interaction, i.e. there is higher realism, which can offset perceived risk (Yang and Wu, 2009; Park et al., 2005). Authenticity is an important aspect. Thus, Algharabat et al. (2017) assert the need to
understand telepresence of 3D product presentation, which was not assessed by Jiang and Benbasat (2007).

In fashion retailing, it is apparent that experience with IIT is stimulating creating heightened emotional arousal and pleasure, which does lend towards approach responses (Fiore et al., 2005a; Fiore and Jin, 2003). Using these tools can facilitate an enjoyable shopping experience (Algharabat et al., 2017; Beuckels and Hudders, 2016; Yoo and Kim, 2014). Similarly, Jeong et al. (2009) demonstrate three of four experience dimensions, i.e. entertainment, escapist, and esthetic experience, from Pine and Gilmore (1998) are enhanced when there is a higher level of product presentation. These dimensions play a mediating role in increasing arousal and pleasure when shopping online. Others such as Kim et al. (2007) posit high levels of interactivity increase overall store perception due to enjoyment and involvement. This is because consumers engage more with the shopping experience if they are presented with highly interactive channels (Kim et al., 2007). Evidence also demonstrates product visualisation technologies also sway shopping behaviours towards impulse purchases (Park et al., 2012).

Although the SOR framework was adopted by Jeong et al. (2009) in testing the influence of advanced product presentation on arousal and pleasure via experience dimensions, findings reveal an entertaining and aesthetically pleasing experience with these tools can directly influence patronage intentions. Using previous findings (Mathwick et al., 2001), Jeong et al. (2009) stipulate such hedonic experiences can directly facilitate utilitarian value. This is confirmed by product presentation literature. While the effects were not as significant on behavioural responses, perceived enjoyment was found to have a significant effect on attitude towards the online retailer in the study by Lee et al. (2006).

Of the two shopping motivational values, papers agree product presentation has greater utilitarian value, which is positively associated with positive behavioural intentions, such as purchase intentions and choice behaviour (Kim, 2018; Roggeveen et al., 2015; Lee et al., 2006; Ashman and Vazquez, 2012; McCormick and Livett, 2012; Fiore et al., 2005b; Park et al., 2005; Lee et al., 2006; Park et al., 2008; Lee et al., 2010). The most important aspect of these tools that is that they provide detailed product information and convenience that can help consumers to accurately assess the product and what it will look like when physically interacting with it as well as when it is worn on the body. The way product
images are displayed via aesthetics is also an important consideration in facilitating hedonic and utilitarian value (Jeong et al., 2009).

Crucially, it is important to note not all consumers will be affected to the same extent. This depends on the individual and the level of active control the consumer displays (Richard et al., 2010; Liu and Shrum, 2002). Consumers may also process visual imagery differently or may have different processing motivations (Kim, 2018; Orús et al., 2017). Some consumers are intrinsically motivated, which is shown to mediate the relationship between IIT and willingness to patronise the online store (Yang and Wu, 2009; Fiore et al., 2005b). Whether consumers are shopping with low or high involvement can also have a difference (Li et al., 2016b). Wang et al. (2016) imply product presentation itself may not yield positive product evaluations if consumers display low involvement. This is confirmed by Roggeveen et al., (2015); dynamic product presentation is more impactful on consumers higher levels of involvement.

3.6 Tactile Cues

In addition to visual input, consumers require a tactile input to generate positive affective assessments (Grohmann et al., 2007). Although research demonstrates the importance of these cues in increasing consumer confidence, positive evaluations, decision-making process and product ownership (Peck and Childers, 2003b; Grohmann et al., 2007; Jin, 2011; Vieira, 2012; Liu et al., 2017), conflicting research finds tactile cues do not influence consumers’ perceptions (Marlow and Jansson-Boyd, 2011) or purchase intentions (McCabe and Nowlis, 2003). Liu et al. (2017) argue this may be due to the level of mental representation required; whether individuals require concrete or abstract product information. Peck et al. (2013) liken product touch to imagining touching a product with the use of mental imagery, whereby consumers also gain a sense of ownership and physical control. These findings are also consistent with Brasel and Gips (2014); who also confirm a link between consumer touch and psychological ownership.

The lack of tangibility reduces acquisition of haptic information (Peck and Childers, 2003b) and is therefore a limitation of online shopping which can obstruct consumers’
from making purchase decisions (Citrin et al., 2003; Peck and Childers, 2003b; McCabe and Nowlis, 2003). Unlike physical stores, online shoppers are unable to “try before you buy” before selecting their items, and so direct haptic feedback is only experienced when the parcel arrives (Magnarelli, 2018). Online retailers are attempting to bridge this haptic gap with various strategies. For example, beauty retailers offer free samples. Online fashion retailers have implemented try on and pay later schemes, such as Klarna with ASOS and Amazon Wardrobe, to minimise the touch barrier and associated perceived risk (Magnarelli, 2018; Joseph, 2017). As a strategic decision to compensate intangibility, González-Benito et al. (2015) highlight the need for strong branding online.

For online fashion apparel, visual cues such as written and visual descriptions are also useful aids in delivering enhanced haptic information (Rodrigues et al., 2017). Such information available online can vary depending on the material properties that involve ‘texture, hardness, temperature, and weight’ (Peck and Childers, 2003b, p.35). Hence, there is emphasis on investing in haptic marketing to provide a multisensory interaction in a physical or online retail setting (Vieira, 2012).

3.6.1 Consumers’ Need For Touch (NFT)

In order to measure differences among consumers, Peck and Childers (2003a, p.430) generated a NFT scale ‘designed to measure individual differences in preference for haptic (touch) information’. NFT has become a well-established construct within physical and online shopping literature with application in areas such as branding (González-Benito et al., 2015), virtual technology (Kim and Forsythe, 2008) and mobile shopping (Cano et al., 2017). Peck and Childers (2003a, p.431) conceptualise NFT further by differentiating between instrumental and autotelic NFT. Since there are different consumer motivations, the NFT also differs with the former related to goal-directed touch and the latter related to hedonic motives with ‘touch as an end in and of itself’. By comparing fashion consumer groups and gender, Workman (2010) confirmed a difference in their NFT as proposed in Figure 3.6; male consumers and fashion followers are more likely to have lower NFT that is instrumental, and utilitarian is nature. While female consumers and fashion change agents touch based on autotelic reasons, they also exhibit instrumental NFT too.
Despite multimedia graphics that currently exist in place, consumers are unable to access a complete multisensory input online (Citrin et al., 2003). According to Peck and Childers (2003b), this effect is more likely to have an effect for consumers with a higher NFT leading to consumer frustration as these consumers have a greater predilection in physically touching a product, which cannot be directly experienced when shopping online. Findings demonstrate the NFT varies according to the product and individual (Peck and Childers, 2003b; González-Benito et al., 2015). This is consistent with other literature. Compared to men, women have a higher NFT (Citrin et al., 2003) and are more likely to rely on both types of NFT when shopping (Workman, 2010). According to Cho and Workman (2011), fashion consumers with high NFT are more likely to shop in physical stores. Recent findings indicate online fashion consumers with high NFT prefer to shop on desktops than mobile devices (Rodrigues et al., 2017).

Similarly, Liu et al. (2017) state individuals that require concrete information are more likely to shop in physical stores to make purchase decisions. Results confirms increased perceived ownership and decreased perceived risk moderate this effect. In a digital age where consumers are shopping on different channels at different stages of the decision-making process, this indicates consumers’ NFT in a physical setting is an advantage for multi and omni-channel retailers. Hence, for pure-play retailers, there is greater significance to provide a multisensory experience online that permits consumers to acquire tactile information using haptic technology (Citrin et al., 2003; Grohmann et al., 2007).
3.6.2 Gestural Interactivity

Heikkinen et al. (2009, p.288) define gesture as a ‘movement in three-dimensional space, stroking on a touch-sensitive surface or by means of other input methods such as squeezing’. More specifically, gestural interactivity is associated with virtual environments whereby a gesture-based haptic input occurs on a touchscreen interface (LaViola, 2013; Heikkinen et al., 2009). Unlike static imagery, manipulating dynamic imagery via gestural interactivity during online shopping can provide a richer experience online. These sensations were much higher for the interactive interface that required simulated stroking gestures. By using product presentation tools such as fabric scrunch, it is possible to simulate the touch modality in providing greater product information when actual touch is not possible (Cano et al., 2017; Overmars and Poels, 2015b).

Given the individual control of the shopping experience that can help fulfil hedonic and utilitarian requirements, gestural interactivity via simulated stroking gestures compensate for tactile input that is regarded to not be fully comprehensive online (Overmars and Poels, 2015b). As well as some laptops, mobile devices mostly rely on direct touch. Thus, research highlights the capacity of touchscreen interfaces to provide greater gestural interactivity. Research confirms interaction with online products in this manner results in higher psychological ownership where consumers are able to imagine physically owning a product (Brasel and Gips, 2014). By comparing direct and indirect interfaces, de Vries et al. (2018) extend this research to evaluate the influence of static and dynamic imagery of food products on psychological ownership and higher product evaluations. In contrast to Brasel and Gips (2014), results did not show a difference in the interface and latter behavioural outcomes. However, de Vries et al. (2018) acknowledge the level of image interactivity did have an influence. Unlike food, greater touch is required for fashion products, which suggests manipulation of fashion IIT via gestural interactivity may yield greater effects.
3.6.3 Product Presentation on Mobile Devices

Despite the vast amount of research on physical store and online store atmospherics, there is a huge gap in understanding the influence of mobile atmospherics (Lee and Kim, 2018). Hence, product presentation literature that largely refer to e-commerce via a PC or a desktop device may vary when applied to m-commerce. As outlined in Chapter 2, there is greater reliance and usage of smartphone and tablet devices throughout consumers’ decision-making. Factors of m-commerce such as perceived control and usability are important variables in allowing consumers to access information with ease and minimal fuss (Lee et al., 2015). However, these are also important aspects of product presentation and IIT, which warrants greater research of product visualisation on these devices. Although Lee and Kim (2018) explore hedonic shopping orientations towards mobile atmospherics, product presentation is usually associated with utilitarian value (Kim, 2018).

Kahn (2017) and Sohn (2017b) emphasise the importance of studying visual design on a mobile interface. On a smaller screen, processing verbal and visual information requires greater processing, which signifies the relevance of effective product presentation in reducing cognitive processing. For fashion retailers that have a large assortment of products, Kahn (2017) recommends manipulating both cues that can result in lower processing complexity. Therefore, understanding the influence of different levels of product presentation on a mobile interface will provide greater clarity on the impact of m-commerce product presentation on consumer’s behaviour and how these tools can be effectively managed by online fashion retailers. If mobile devices are being used as alternative to online shopping on a PC or laptop, interaction with product presentation should be equal or greater in terms of its performance when shopping on the m-commerce channel.
3.7 Chapter Summary

As an online atmospheric cue, the use of visual product presentation including IIT plays a vital role in depicting product attributes. Literature demonstrates the importance of these tools that offer fashion consumers both utilitarian and hedonic value. Although not all product visualisation tools are equal in their effect on consumer behaviour, findings overall depict positive relationships between these tools and cognitive, affective and behavioural responses that may occur in a direct or indirect fashion. Recently, there has also been a greater focus on understanding how these tools affect cognitive processing. Using advanced product presentation enhances imagery processing that is required to visualise the product in more detail (Kim, 2018).

Given the challenges of processing information on a smaller screen, this implies the use of these tools are even more important on a mobile device. Thus, greater research is required to understand the influence of these tools from a mobile perspective. The above literature also suggests the way consumers shop for fashion products on a touchscreen interface via gestural interactivity may offer further advantages for fashion retailers to exploit haptic capabilities in order to provide greater product information. To address these research gaps, hypotheses were outlined in the next chapter based on an appropriate theoretical framework.
Chapter Four: Theoretical Framework Development

4.1 Introduction

In order to effectively understand the influence of visual product presentation on consumers’ behaviour for multi-modal devices, an appropriate measure is required to assess and test underlying theoretical assumptions. This underpins the need to develop a theoretical framework, which provides a useful guide in assembling and testing theory. This requires careful consideration as theory governs all aspects of the research process including the implications of the results and analysis (Herek, 2010). Therefore, the following frameworks were selected on the basis of relevance relating to key research areas of this study, such as the physical and online store environment, which validates the application of these theories to this study. Based on the theoretical framework, research hypotheses, propositions and research measures are introduced in the following sections.

4.2 Stimulus-Organism-Response (SOR) Framework

Stemming from environmental psychology, the Stimulus-Organism-Response (SOR) model was developed by Mehrabian and Russell (1974). This paradigm is used a basis to explain a state of feeling (Donovan et al. 1994), whereby the stimulus (S) relates to an aspect of the environment, organism (O) refers to emotional states an individual exhibits that mediate an individual’s approach or avoidance behaviour (R) (Figure 4.1). According to Havlena and Holbrook (1986), data collection was deemed easier with the SOR framework and was found to be preferable to previous emotion measures. Many papers studying the retail environment refer to the S-O-R paradigm in which external stimuli influence consumers’ internal states in generating different types of responses (Donovan and Rossiter, 1982; Machleit and Eroglu, 2000; Mazaheri et al., 2012; Dennis et al., 2009; Hsieh et al., 2014; Brunner-Sperdin, 2014).
According to the S-O-R model there are three basic emotional dimensions; Pleasure, Arousal and Dominance (PAD) (Figure 4.2). Mehrabian and Russell (1974) state these three dimensions are necessary to sufficiently convey any emotional state, and whilst these dimensions can occur simultaneously, they are also independent from one another. Pleasure is likened to feelings of joy and happiness. Arousal refers to the degree a consumer feels excited or stimulated and dominance is associated with the level of control a consumer feels as a result of a particular situation (Figure 4.2).

It is also important to note each dimension is associated with a type of response. Pleasure and arousal states are related to affective responses whilst dominance is associated with cognitive responses (Mehrabian and Russell 1974). Interestingly, Bakker et al. (2014) argue arousal is likened to a mental activity, which usually denotes a cognitive association. In this regard, arousal could be considered a cognitive state as the store environment also has a significant effect on consumers’ mental states.
Whilst some academics pay attention to dominance (Hsieh et al., 2014), others question the role of this dimension in relation to cognition and affect as Donovan and Rossiter (1982) found this dimension to be less important in relation to the approach-avoidance measures being examined in their exploratory study (Bakker et al., 2014). Subsequently, dominance has been disregarded in some studies with attention centred on pleasure and arousal (Kaltcheva and Weitz, 2006; Vieira and Torres, 2014; Koo and Ju, 2010; Menon and Kahn, 2002; Jeong et al., 2009), as they also demonstrate the most variance (Russell and Pratt 1980). However, dominance could be particularly relevant in cases where a consumer’s control over their retail environment could become a problem. Crowding is given as an example (Machleit and Eroglu, 2000).

As well as conveying emotional and cognitive responses, the use of these dimensions is often incorporated in studying the impact of environment stimuli on behavioural responses. A response may be classified as an approach or avoidance behaviour (Mehrabian and Russell, 1974). A criticism of this model is that it can be difficult to differentiate constructs that belong in a specific grouping, i.e. whether it belongs in the stimulus, organism or response realm (Jacoby, 2002). Nevertheless, empirical evidence corroborates a connection between environmental stimuli and emotional responses that lead to positive approach responses, such as willingness to return to store (Donovon and Rossiter, 1982), behavioural intentions (Koo and Ju, 2010) and purchase intentions (Mazaheri et al., 2012) as well as online impulse buying behaviour (Chan et al., 2017).

The importance of studying emotional responses lies in the fact that emotions have an effect on consumer decision-making and that the shopping environment has a mediating role in influencing this relationship (Sherman et al., 1997). The PAD paradigm also provides a basis for other emotional responses, and so it is applicable to feelings that may reflect an assortment of the three dimensions (Mehrabian and Russell, 1974).

The SOR framework is also applied in product presentation literature (Table 4.1). Incorporation of various constructs as well as different types of product presentation stimuli demonstrates the versatility of this framework for this study. Some studies have focussed on specific product presentation attributes (Yoo and Kim, 2012), while others have done so holistically (Jeong et al., 2009). Evaluation of cognitive states in addition to emotional organism states indicates the importance of understanding how product
presentation affects cognitive processing. While some variables are referred to as a response, others refer to the same type of variable as an organism state. For example, the use of attitude as an organism state by Jai et al. (2014) is also referred to as an outcome in other product presentation literature (Choi and Taylor, 2014; Orús et al., 2017; Lee et al., 2010).

Table 4.1 Review of SOR in Product Presentation Literature

<table>
<thead>
<tr>
<th>Reference</th>
<th>Stimulus</th>
<th>Organism</th>
<th>Response</th>
<th>Intervening variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kim (2018)</td>
<td>Image size, verbal information (abstract vs concrete)</td>
<td>Imagery processing; discursive processing</td>
<td>Behavioural intent</td>
<td>Need for cognition</td>
</tr>
<tr>
<td>Jai et al. (2014)</td>
<td>Picture, zoom, rotation</td>
<td>Visual perception, mental imagery, emotion, positive attitude</td>
<td>Evaluation difficulty</td>
<td>N/A</td>
</tr>
<tr>
<td>Yoo and Kim (2012)</td>
<td>Product coordination; model’s face</td>
<td>pleasure arousal, perceived amount of information</td>
<td>Purchase intention</td>
<td>N/A</td>
</tr>
<tr>
<td>Song and Kim (2012)</td>
<td>Image size, number of product views</td>
<td>Mental intangibility, perceived info, perceived risk</td>
<td>Patronage intent</td>
<td>N/A</td>
</tr>
<tr>
<td>Jeong et al. (2009)</td>
<td>Product presentation features</td>
<td>Pleasure, arousal</td>
<td>Website patronage intention</td>
<td>Experience realms: entertainment, educational, escapist, aesthetic</td>
</tr>
</tbody>
</table>

Table 4.1 reflects usage of SOR framework in different ways. Despite the need for some modifications for this research, the effectiveness of this particular framework is evident in the number of journal papers that utilise this paradigm.
4.3 Technology Acceptance Model (TAM)

Developed as a measurement scale to study attitudes and acceptance of computers in the workplace, the TAM framework originally asserted an individual’s intention to use technology is based on two beliefs: *perceived usefulness and perceived ease of use* (Davis, 1989). Further empirical research confirmed the suitability of an additional belief, i.e. *perceived enjoyment* (Davis et al., 1992). The modified TAM framework hypothesises all three antecedents to positively influence attitude, which in turn facilitates usage intentions. This paradigm is relevant as not only is it applied to several fashion m-commerce papers (Chi, 2018; Kim et al., 2009; Ko et al., 2009), it has also been used to study the influence of product presentation (Kim and Forsythe, 2007; Lee et al., 2006; Kim and Forsythe, 2009) (Figure 4.3).

**Figure 4.3 Original TAM Framework Tested in Literature**

![Original TAM Framework Tested in Literature](source: Adapted from Davis (1989))

Although current adoption of this framework for e-commerce research is not as high as it was between the years 2000-2010, newer literature indicates the usefulness of this model in understanding consumers’ attitudes and behaviour in less established in e-commerce markets (Kurnia et al., 2015; Faqih, 2016). TAM is frequently adopted in other technology-related contexts, such as E-learning (Abdullah and Ward, 2016) and smart watches (Kim and Shin, 2015).

Perceived usefulness is considered to be the most influential in driving positive behavioural intentions towards technology adoption (Davis, 1989) including online and mobile shopping acceptance. Literature indicates this construct appears to have the most
predictive power and the most variance (Chi, 2018; Sohn, 2017a, Legris et al., 2003; Gefen et al., 2003; Ha and Stoel, 2009; Childers et al., 2001). Some papers use the original TAM model with a focus on perceived usefulness and perceived ease of use, which are considered utilitarian drivers (Chi, 2018; Faqih, 2016; Morgan-Thomas and Veloutsou, 2013; van der Heijden et al., 2003; Gefen et al., 2003; Vijaysarathy, 2004; Legris et al., 2003). Other papers have tested an extended version of TAM (Davis et al., 1992) that includes perceived enjoyment; findings demonstrate empirical support for all three constructs in influencing online shopping (Chiu et al., 2009; Ha and Stoel, 2009; Childers et al., 2001) as well as mobile shopping (Agrebi and Jallais, 2015).

Whilst older fashion m-commerce literature emphasise the importance of providing utilitarian value (Kim et al., 2009a; Ko et al., 2009), this is also consistent with recent findings (Chi, 2018). Nevertheless, e-commerce and m-commerce findings also support the use of perceived enjoyment as an important driver on behavioural outcomes (Ingham et al., 2015; Agrebi and Jallais, 2015, Groß, 2015; Chiu et al., 2009; Childers et al., 2001).

There appear to be several inconsistencies in regard to TAM usage. According to Legris et al. (2003, p.196) ‘there is no clear pattern with respect to the choice of the external variables considered’. Some measure usage intentions (Agrebi and Jallais, 2015; Kim et al., 2009a), while others measure purchase intentions (van der Heijden et al., 2003), repurchase intentions (Chiu et al., 2009), continuance purchase intentions (Gao et al., 2015) or contextual based outcomes, such as m-trust (Li and Yeh, 2010). Attitude is sometimes overlooked in e-commerce and m-commerce literature that employ TAM (Faqih, 2016, Gao et al., 2015; Li and Yeh, 2010). Ingham et al. (2015, p.53) acknowledge the importance of attitude; not only does it act as a mediator, it also ‘captures other very important beliefs (such as enjoyment and perceived risk) in an e-shopping context’.

Often, TAM constructs are often integrated, extended or remodelled with other constructs to boost explanatory power and generate a broader framework for e-commerce research. In some cases, the need to study characteristics of different technology is also required (Ingham et al., 2015; Legris et al., 2003). Thus, the model has also been extended and re-named as TAM2 (Venkatesh and Davis, 2000) and TAM3 (Venkatesh and Bala, 2008, Faqih and Jaradat, 2015). Due to inconsistencies within previous research, Chui et al. (2009) remodelled TAM with trust to assess the influence of these constructs on
repurchase intentions. Some papers also base antecedents on multi-dimensional constructs that are used to evaluate a specific perspective. Examples include online shopping quality (Ha and Stoel, 2009) or online brand experience (Morgan-Thomas and Veloutsou, 2013). Chi (2018) extends TAM to understand the influence of fashion m-commerce intention by incorporating two multi-dimensional constructs (brand equity and website quality) into the model as antecedents.

Product presentation papers employ a general TAM approach (Kim and Forsythe, 2007; Lee et al., 2006; Kim and Forsythe, 2009). Adopting a general approach may be limited in that other antecedents that are considered relevant to the research area may not be investigated (Legris et al., 2003). Although remodelling or extending TAM enables researchers to incorporate different variables and behavioural outcomes as well as particular contextual factors in providing greater scope of understanding online consumer behaviour, Ingham et al. (2015) posit rather than suggesting relationships as based on TAM, researchers should focus on providing clear theoretical support between the TAM beliefs in relation to the research context in question. Nevertheless, this framework continues to be regarded as a parsimonious, well-tested and robust model in explaining factors that affect technology usage and adoption (Marangunić and Granić, 2015; van der Heijden et al., 2003; King and He, 2006).
4.4 Dual Coding Theory (DCT)

Established in cognitive psychology literature, DCT hypothesises there are two separate coding systems in the brain that are required to process verbal and non-verbal information (Paivio, 1990, Paivio, 1971). Respectively, this is referred to as textual and imagery (i.e. visual) information in e-commerce literature (Kim and Lennon, 2008; Kim, 2018). Each sub-system is considered a distinct system as they can be operational without the other. This is also observed in the type of processing; visual stimuli processing is regarded as imagery processing, while verbal information processing is denoted as discursive processing (Paivio, 1971). However, both systems are also interrelated whereby operation of one sub-system can influence the other sub-system (Paivio, 1990). While previous literature researched visual and verbal aspects on processing separately, DCT accounts for both coding systems in conjunction with each other (Paivio and Begg, 1974, Paivio, 1990). The stages of a dual-coding approach are displayed in Figure 4.4.

Figure 4.4 Processing Stages in a Dual Coding Approach

The processing stages in Figure 4.4 demonstrates it is possible to process verbal information that corresponds to the non-verbal system and vice versa. Another important assumption of DCT is that each sub-system is processed differently; verbal coding occurs in a sequential manner while the non-verbal coding occurs in a parallel and instantaneous formation (Paivio, 1990). Findings by Paivio and Begg (1974, p.521) confirmed a dual coding approach as ‘items that are cognitively represented both verbally and as non-verbal images can be searched and compared in either mode’. The use of the use of a dual
processing approach towards visual and verbal stimuli continues to be supported and has been researched under different contexts. DCT is therefore described as a useful theory in understanding the influence of multimedia with application varying from education and learning (Koć-Januchta et al., 2017) to online advertising (Lwin et al., 2010) as well as online shopping sites (Hong et al., 2004) that include product presentation (Kim, 2018; Jiang and Benbasat, 2007; Kim and Lennon, 2008).

Visual stimuli that elicits non-verbal and verbal processing is empirically confirmed to be more influential on processing. Hence, the visual sub-system is deemed superior and is therefore dubbed as the “visual superiority effect” (Paivio, 1971; Childers and Houston, 1984). To confirm this effect for online shopping, Hong et al. (2014) compare image and text condition with a text only condition. Findings support this effect with greater product recall and shorter search times towards the image-text condition. However, Hong et al. (2004) noted DCT may yield dichotomous results as the same results were not found for brand names, which implied individuals’ attention may be diverted away from textual information when an image is present. In terms of fashion apparel product presentation, inconsistent results have been found (Table 4.2). Unlike Hong et al. (2004), Kim and Lennon (2008) found stronger effects for textual information than for visual information on attitudes and purchase intention.

**Table 4.2 DCT Results in Product Presentation Literature**

<table>
<thead>
<tr>
<th>Reference</th>
<th>Condition</th>
<th>Stimuli</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yoo and Kim (2014)</td>
<td>Image (concrete background v solid background) x text</td>
<td>Influence of stimuli dependent on consumers’ style of processing.</td>
</tr>
<tr>
<td></td>
<td>(concrete descriptions vs. no descriptions)</td>
<td>Greater mental imagery for visualisers.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Text stood out if there was a consumption background otherwise there was no effect.</td>
</tr>
<tr>
<td>Kim (2018)</td>
<td>Image (size) x text (concrete vs. abstract)</td>
<td>Using large pictures elicits imagery and discursive processing.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Using verbal information also elicits imagery and discursive processing.</td>
</tr>
</tbody>
</table>

Using fashion apparel websites, Kim and Lennon (2008) indicate verbal information can also facilitate both types of processing, due to concrete verbal stimuli that enables the consumer to visualise the product from the product description online, particularly when
textual construction and style information was provided. Conversely, findings by Kim (2018) demonstrate both types of product presentation stimuli facilitate both types of processing. Relating these findings to the visual superiority effect, Kim and Lennon (2008) posit products images online may not be adequate enough to provide product information, and so there is a greater reliance on detailed product description to compensate for this and do so instead. Kim (2018) also supports the influence of verbal superiority effect.

However, verbal stimuli may not yield the same effects if presented without the visual information (Kim and Lennon, 2008). Yoo and Kim (2014) stipulate the influence of stimuli is dependent on consumers’ style of processing. By dividing participants into low (i.e. verbalisers) and high level of processing (i.e. visualisers), results show there is greater mental imagery experienced towards the fashion product image for visualisers. Thus, for visualisers, product images are more concrete than textual information as they provide greater sensorial information (Yoo and Kim, 2014). Overall, findings indicate the importance of product presentation with both visual and textual presentation modes. Both types of stimuli are considered important in facilitating both types of cognitive processing (i.e. imagery and discursive) (Kim, 2018) confirming stages 2 and 3 that is hypothesised according to DCT.

Often, the use of DCT is often applied with another framework in e-commerce studies. For example, Kim (2018) uses DCT alongside the SOR framework. Similarly, Yoo and Kim combine DCT with emotion literature. For this study, the use of this theory alone may not be sufficient to understand the influence of visual product information on consumer behaviour. It is useful in comparing visual to textual information and evaluating concreteness of both types of information, but if the primary goal is to understand the differences of varying visual product presentation on consumers’ approach behaviour, this may require an additional theory such as SOR, which is illustrated by Kim (2018).

In terms of advertising, similar findings are found in which the influence of visual and verbal information depends on the individual. Findings from Flores et al. (2014) reveal DCT has limitations in that this theory is supported when individuals are highly involved towards visual display ads, but not when there was low involvement. Li et al. (2016b) criticise earlier studies that researched product presentation online for contrasting findings and argue the need to study additional mediating and moderating factors such as
information load to help provide greater clarity. Depending on how stimuli is presented may be simple to process or require complex processing, such as processing towards faces (Paivio and Begg, 1974). Visual fluency is salient in understanding this phenomenon from an online product presentation perspective (Song and Kim, 2012; Kim and Lennon, 2008).

### 4.5 Fluency Theory

A stimulus can have an effect on mental processing, even when the processing occurs unconsciously (Zajonc, 1980). Processing fluency is a relatively new area in explaining the underlying mechanism of visual stimuli. There are two processes: perceptual fluency and conceptual fluency. The former relates to how easy it is to process the physical traits of a stimulus, whilst the latter places emphasis on the ease of establishing the meaning in the mind (Reber et al., 2004a). Unlike conceptual fluency, which is more controlled and cognitive, perceptual fluency is more geared towards automatic processing that is based on initial impact. Reber et al. (2004b, p.47) define perceptual fluency as ‘the subjective experience of ease with which an incoming stimulus is processed’. All perceptual acts result in this experience. For example, aesthetic judgements towards a stimulus occur automatically (Graf and Landwehr, 2015). As such, perceptual fluency is considered to be bottom-up processing (Lee and Labroo, 2006). According to Wu et al. (2016), a low level of fluency is labelled as perceptual, whereas a high level of fluency is conceptual. However, processing fluency is often used to explain commonalities between the two forms of fluency (Reber et al., 2004a), and is also referred to as a dual-process theory (Graf and Landwehr, 2015; Janiszewski and Meyvis, 2001).

Put simply, how a stimulus is presented and processed can affect fluency. This, in turn, however, can have implications on consumer behaviour (Ketron, 2018; Cho and Schwarz, 2010). It is important to distinguish between subjective and objective aspects concerning a stimulus. For example, objective categorisation of fluency includes aspects such as speed and accuracy (Winkielman et al., 2003), while subjective categorisation refers to perceived processing fluency. Perceived perceptual fluency is shown to have an impact on consumers’ feelings and attitudes, which can affect product appraisals as a high processing fluency is related to positive product evaluations and vice versa. An example is shown in Figure 4.5. In effect, increasing perceptual fluency is associated with affective responses.
and is therefore considered to be “hedonically marked” (Winkielman and Cacioppo, 2001; Winkielman et al., 2003; Reber et al., 2004b, Berger and Fitzsimons, 2008; Lee and Labroo, 2004). This also supported by findings evaluating the online shopping environment including cues such as product images (Mosteller et al., 2014, Wu et al., 2016, Sohn, 2017b).

Findings by Wu et al. (2016) verify a correlation between processing fluency and pleasantness towards product images online. If visual product information is perceived to be easy to process, consumers are more likely to exhibit positive feeling towards the image and website. Reber et al. (2004a) state an object that is high in processing fluency with a positive aesthetic experience is not necessarily considered to be beautiful; it is the aesthetic value that is of importance and not beauty. Responses such as attractiveness and aesthetic evaluation are studied since this type of response mediates the impact of perceptually fluent stimuli (Reber et al., 2004a; Im et al., 2010). As well as pleasure, fluency can also result in displeasure. It is possible to have a negative evaluation of an object that is also processed fluently. This is known as “fluent ugliness” due to negative associations attached to the stimulus (Graf and Landwehr, 2015).

**Figure 4.5 Proposed Fluency Model by Visual Quality Manipulation**

![Fluency Model](image)

Source: Im et al. (2010)

Reactions to conceptual fluency are also shown to be affective; as exposure to a target increases familiarity and decreases uncertainty, and therefore liking (Lee and Labroo, 2004). Zajonc (1968, 1980) explains there is a feel-good factor if a stimulus is processed with fluency; as an individual becomes accustomed to the stimuli it is perceived as less harmful. In such a scenario, it is also important to note rather than the product attributes, affective responses are generated due to fluent processing (Berger and Fitzsimons, 2008).
In other words, it is a stimulus-induced affect rather than mood-based affect (Im et al., 2011).

Conversely, if processing stimuli is challenging and considered difficult, this may lead to avoidance behaviour. By varying the font type from an easy read font to a more challenging font type, findings from Song and Schwarz (2008) confirm the former was perceptually more fluent, and so the task was perceived as one that required less time. This illustrates individuals may interpret a stimulus and draw conclusions about the product depending on how they processed the stimuli. Individuals may be less willing or less engaging towards a stimulus that is perceptually difficult as Song and Schwarz (2008, p.287) assert their findings ‘extend the observation that people draw on their metacognitive experiences in making a wide variety of judgements’. Research confirms the effect of moderating variables such as individual differences (MacInnis and Price, 1985; Ferraro et al., 2009), stimuli congruency (van Rompay et al., 2010) and regulatory goal fluency (Lee and Labroo, 2006). It is also important to note fluency may not necessarily lead to liking as this is dependent upon prior attitudes towards the stimuli, due to familiarity or stimuli-related attitudes (Ferrarro et al., 2009).

Whether the fluent processing is expected or not expected can yield different results. Specifically, fluency positively influences judgment if the fluency is unexpected. However, not all direct exposure towards a given stimulus will results in positive judgments as some of it may be indirect, as in “primed”. Berger and Fitzsimons (2008, p.2) explain this is more detail; ‘when people are exposed to an object that is cognitive linked with the target – may be especially likely to produce positive judgments, because people are unlikely to attribute the fluency to exposure to a seemingly irrelevant object’. Hence, memory can play a huge role as certain stimuli can “prime” consumers when these stimuli are observed repeatedly. Previous exposure to the stimuli is known as the mere exposure effect (Zajonc, 1968, 1980), which can help to explain why marketing strategies as well as the retail environment in general have a huge influence. Research empirically confirms exposure to stimulus can affect brand choice (Lee and Labroo, 2004; Garbarino and Edell, 1997). Thus, fluency can occur as a result of new and familiar stimuli (Berger and Fitzsimons, 2008).

While application of fluency theory to marketing and consumer behaviour research is growing, there appears to be a lack of literature in understanding antecedents that have an
effect on processing fluency (Sohn, 2017a; Mosteller et al., 2014). While studies have evaluated the influence of online images, it has done so as an overall holistic impression of the website by studying other variables in addition to the product picture (Sohn, 2017b; Im et al., 2010) or from a different context, such as advertising (Wu et al. 2016) or product size perception (Ketron, 2018).

Additionally, fluent processing has been applied to other areas of marketing research that do not relate to visual stimuli. For example, Hermann et al. (2013) argue previous research did not provide a satisfactory theoretical explanation for the analysis on olfactory cues, and so simple scents versus complex scents were compared in terms of cognitive processing on purchase behaviour. Although originally investigated in psychology literature, the use of fluency has filtered into marketing research including online atmospherics (Table 4.3). To test the effects of fashion apparel websites cues on perceptual fluency, research by Im et al. (2010) and Im and Ha (2011) manipulate visual cues such as the picture, background, i.e. colour and contrast as well as the font, which can vary depending on font type and size.
<table>
<thead>
<tr>
<th>Reference</th>
<th>Stimuli</th>
<th>Mediators</th>
<th>Outcomes</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Im et al. (2010)</td>
<td>Online fashion apparel</td>
<td>Perceptual fluency, aesthetic evaluation pleasure</td>
<td>Re-patronage intent, purchase intent</td>
<td>Information higher in quality increases perceptual fluency, which directly affects pleasure and aesthetic evaluation. Both directly influence behavioural intentions.</td>
</tr>
<tr>
<td>Im and Ha (2011)</td>
<td>Online fashion apparel</td>
<td>Perceptual fluency, enjoyment, situational involvement</td>
<td>Cognitive effort, purchase intention</td>
<td>Increasing perceptual fluency resulted in higher levels of enjoyment, which directly influenced situational involvement cognitive effort and purchase intentions.</td>
</tr>
<tr>
<td>Cho and Schwarz (2010)</td>
<td>Online shopping</td>
<td>Virtual mirror technology</td>
<td>Aesthetic appeal, person familiarity</td>
<td>Product &amp; purchase recommendation</td>
</tr>
<tr>
<td>Hermann et al. (2013)</td>
<td>In-store shopping</td>
<td>Scent</td>
<td>Scent complexity, familiarity, store congruity, cognitive task performance</td>
<td>Number of anagrams sorted, expenditure, number of products chosen</td>
</tr>
<tr>
<td>Orth and Wirtz (2014)</td>
<td>Interior service environments</td>
<td>Digital photos of a deli</td>
<td>Processing fluency, attractiveness, pleasure</td>
<td>Response behaviours</td>
</tr>
<tr>
<td>Mosteller et al. (2014)</td>
<td>Online shopping website</td>
<td>Verbal information</td>
<td>Perceptual fluency, cognitive effort, positive affect</td>
<td>Choice satisfaction</td>
</tr>
<tr>
<td>Wu et al. (2016)</td>
<td>Online advertising</td>
<td>Product pictures</td>
<td>Perceptual fluency, conceptual fluency</td>
<td>Pleasantness</td>
</tr>
<tr>
<td>Sohn (2017b)</td>
<td>Mobile shopping experience</td>
<td>Mobile websites</td>
<td>Visual complexity, congruence, processing fluency, shopping touchpoint</td>
<td>Satisfaction</td>
</tr>
</tbody>
</table>

Table 4.3 demonstrates a fluency theory approach allows for a broader understanding of how sensory cues within the retail environment can influence consumers’ cognitive processing. Since olfactory cues cannot be seen, Hermann et al. (2013) argue the usefulness of fluency theory as it is otherwise difficult to understand the influence of
particular scent attributes on consumer behaviour. In terms of online visual cues, results also confirm the importance of visual quality that results in an enjoyable shopping experience. Positive affect (Im et al., 2010), and enjoyment (Im and Ha, 2011) moderate the relationship between perceptual fluency and behavioural intentions. High visual quality when shopping online can also facilitate an engaging experience with higher levels of involvement (Im and Ha, 2011). Conversely, shopping environments that are visually complex can lead to a decrease in attractiveness (Orth and Wirtz, 2014). In sum, findings reveal visual stimuli that is less visually complex can lead to greater processing fluency. How consumers feel via processing-induced affect plays an important role in mediating the relationship between visual complexity and attractiveness.

4.5.1 Information Processing Styles

There are also different processing styles. In terms of product information, it is important to distinguish between imagery processing and information processing, whereby the ‘information structure is viewed as distinct from processing model’ (MacInnis and Price, 1987, p.474). Thus, there are two different types of information processing styles: discursive processing and imagery processing (Kim, 2018; Bettman, 1979). MacInnis and Price (1987, p.473) describe imagery as ‘a presentation mode in which multisensory information is represented in a gestalt form in working memory’. This suggests imagery processing may also include previous tactile experiences. Unlike discursive processing that is associated with particular elements of a stimulus and its message, imagery processing is associated with multi-sensorial experiences (Flavian et al., 2017). Kim (2018) evaluate both processing styles as the intervening states in a SOR model. Research posits the use of concrete verbal information can enhance visual information by increasing perceptual fluency. Specifically, they argue concrete verbal information positively influences imagery processing, which makes it easy to imagine and visualise information (Kim and Lennon, 2008).
4.6 Theory of Visual Marketing

Research in visual marketing has sparked a huge interest in recent years. Due to technological innovations, an increasing number of consumer behaviour papers are studying the influence of atmospheric cues on consumers’ visual attention (Chandon et al., 2009; Wedel and Pieters, 2008; Menon et al., 2016). To understand visual attention requires collecting data on eye movements via eye tracking technology, which are quantified to reveal the type of eye movements (Wedel and Pieters, 2008; Duchowski, 2007). Research posits a strong indication of a participant’s visual attention is associated with fixations, and so this eye movement is widely measured and analysed (Huddleston et al., 2015; Ho, 2014). A fixation is a state when the eyes remain stationary and can last from milliseconds to several seconds (Holmqvist et al., 2011). This allows an individual to ‘visually encode spatially distributed information’ (Just and Carpenter, 1976, p.444). The other common eye movements are saccades, which are rapid eye movements and occur when the eye moves from one fixation to another, which usually last between 30 and 80 milliseconds (Holmqvist et al. 2011). In order words, a saccade occurs when eyes glance towards a new area.

Visual attention can occur at a high or a low-level processing. This is also loosely referred to as voluntary and involuntary attention. Mostly, research refers to dual attentional mechanisms that affects how information is processed (Wedel and Pieters, 2008). Gaze may be evaluated by a bottom-up (i.e. stimulus driven) or top-down (i.e. goal-oriented) approach (Duchowski, 2007). For example, if conditions are timed, this approach becomes top-down instead, whereby eye movements are voluntary. In experiments where participants are not told or asked to look at specific stimuli, this is classified as bottom-up approach since eye movements are involuntary (Duchowski, 2007; Holmqvist et al. 2011). Bottom up factors are widely studied in marketing literature where visual stimuli are manipulated to test the effects of a particular stimuli. Examples of stimuli may include the use of colour, image, text and advertising banners (Wedel and Pieters, 2008; Li et al., 2016a; Huddleston et al., 2015). Top-down factors include ‘memory, involvement, attitudes, processing, states, emotions, goals and expertise’ (Wedel and Pieters, 2008, p.142).
While both approaches are attention mechanisms, top-down factors are less well understood. Top-down processing, which is goal-directed, requires effort and is slower (Wedel and Pieters, 2008). It is also possible to use both attention mechanisms with bottom-up and top-down processing combined in facilitating attention (Wedel and Pieters, 2008). As a visual stimulus that provides graphic and pictorial product information, understanding the influence of product images and product visualisation tools on a fashion retail website by measuring visual attention may reveal useful insights.

4.7 Research Framework Adopted

Of the theoretical frameworks outlined in the sections above, the combination of fluency theory with SOR alongside the theory of visual marketing as an underlying framework was considered the most fitting. There has been extant research conducted on online flow, but research has not really concentrated on how certain informational aspects of online shopping influence cognitive processing and its effect on consumers’ perceptions (Mosteller et al., 2014). Although newer research has explored the influence of product presentation videos on imagery fluency, this is focussed on the ease of imagining the product (Flavián et al., 2017; Orús et al., 2017) rather than the ease of processing details, such as product attributes. In contrast to other consumer products, enabling consumers to acquire product details online via product images and product presentation tools is particularly important for fashion apparel retailers (de Klerk et al., 2015; Kim and Lennon, 2008). Fluency has been applied to fashion e-commerce research with a focus on understanding the influence of atmospheric cues (Im et al., 2010; Im and Ha, 2011), which furthers knowledge of the theory and its relevance to online visual stimuli.

Accordingly, the application of fluency theory will broaden this understanding on how consumers process visual product presentation on fashion apparel websites. Specifically, whether the use of product visualisation tools that vary in interactivity facilitates ease of processing towards product information. This is also stated as research gap in literature (Song and Kim, 2012; Yoo and Kim, 2014; Kim and Lennon, 2008). These papers argue there is a need to study visual fluency towards product presentation and that fluency is an underlying theory that explains the way products are presented (i.e. different types and different levels of image interactivity) in certain conditions may be received more or less
positively. However, it is important to acknowledge this research gap was implied towards e-commerce. There is also a research gap in identifying how consumers process information on mobile devices (Sohn, 2017b). Due to the differences that exist between online and mobile that include screen size and the interface, understanding how consumers process product information from a m-commerce perspective and its effects on behavioural outcomes may be even more important (Kahn, 2017, Sohn, 2017b; Cano et al., 2017).

The SOR paradigm is consistently used in consumer research to understand the influence of particular atmospheric cues on consumers’ behaviour aspects. Using approach and avoidance as a basis also enables encapsulation of all three types of responses, i.e. cognitive, affective, conative (Park et al., 2008). As shown in Table 4.1, product presentation influences different types of consumer responses. Other product presentation literature also incorporates approach and avoidance behaviour, which is related to SOR, in their overall conceptual framework (Kim et al., 2007; Park et al., 2008; Fore and Jin, 2003; Park et al., 2005). Additionally, SOR is often combined with additional theories and concepts (Kim, 2018; Mosteller et al., 2014). This demonstrates the versatility of this framework in applying a relevant theory in conjunction. For example, Kim (2018) applies SOR with dual coding theory to understand the influence of image size and product description. Fluency theory has also been studied in relation to the SOR model (Mosteller et al., 2014; Wu et al., 2016) as shown in Figure 4.6.

Figure 4.6 Integration of SOR with Fluency Theory in E-Commerce Research

(Source: Mosteller et al., 2014, p.2487)
Studying SOR in relation to fluency theory is suitable given that the antecedents studied in perceptual fluency research are also studied in environment psychology, i.e. consumers online and offline environment (Sohn, 2017b). Since both Mosteller et al. (2014) and Wu et al. (2016) focus on online shopping and atmospheric cues, this further confirms the suitability of this approach for this study. This framework may also help to clarify earlier findings. For example, Song and Kim (2012) found one large product image is superior to four smaller product images. The authors posit visual fluency may explain why one large product image can lead to a lower level of mental intangibility as well as higher levels of perceived information.

As well as subjective measures, the use of objective measures, such as understanding the influence of stimuli on eye movements can provide further support of the measures outlined above. An eye tracking measure also enables a greater understanding of human-computer interaction (Duchowski, 2007). Recently, visual attention has been studied in relation to retail store environments. Observations can be formed at the macro-level, such as store navigation as well as the micro-level (Klingensmith, 2013; Otterbring et al., 2016; Huddleston et al., 2015), which includes examples such as the use of product packaging and fashion apparel mannequins (Lindström et al., 2016; Klingensmith, 2013). In the study by Chandon et al. (2009), results confirm shelf positioning has an important influence on consumers’ visual attention that is associated with positive brand evaluation. Research confirms the usefulness of studying visual attention towards online atmospherics. Examples of specific stimuli studied online include product reviews (Luan et al., 2016), the use of a human brand (Wook Chae and Lee, 2013) as well as a general evaluation of online atmospherics (Djamasbi et al., 2011). Typical eye tracking measures used in marketing literature are presented in Table 4.4.
Table 4.4 Examples of Eye Tracking Measures in Literature

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Aim/ Stimulus</th>
<th>Eye tracking measures</th>
</tr>
</thead>
</table>
| Ho (2014)        | To understand the importance of displaying a product on visual attention in an effectual manner. Pictures of handbags were used as the stimulus. | • Regions of interest (ROI)  
• Duration of first fixation (DFF)  
• Latency of first fixation (LFF)  
• Number of fixations (NOF)  
• Total contact time (TCT) |
| Li et al. (2016a) | To study the effects of static and dynamic advertising banners on eye movements. Due to the type of eye tracker used, contacts were measured instead of fixations. | • Average contact duration  
• Number of contacts  
• Areas of interest (AOI) |
| Ozcelik et al. (2010) | To understand the influences of signalling when using multimedia to learn. | • Fixation count  
• Total fixation time  
• Areas of interest  
• Mean fixation duration |
| Huddleston et al. (2015) | To compare visual attention towards in-store displays. This focused on price and display information to test the effectiveness of signage when a product is displayed in-store. | • Fixation count  
• Total visit duration  
• Areas of interest |

This has also been observed in online shopping studies using pictures of handbags. With relevance to this study, findings from Ho (2014) confirm the importance of a zoom function enabling e-consumers to obtain greater detail and process information as handle and strap features were attractive to participants. Findings can reveal what information (whether it is branding, colour, size etc...) of a stimulus is visually stimulating. To determine the influence of product presentation on consumers’ visual attention, measuring eye movements via eye tracking technology was considered a suitable approach.

4.8 Research Hypotheses and Propositions

Using SOR as a basis, research hypotheses were developed and guided by theory and relevant literature. In line with previous fluency, e-commerce and product presentation literature, this section outlines hypothesised relationships between processing fluency and other constructs related to emotional and behavioural responses. A separate set of hypotheses and propositions were developed to understand the influence of different levels of product presentation on visual attention, perceptual fluency, purchase intentions as well as behavioural differences.

Although online visual salience affects both types of fluency (Wu et al., 2016), only perceptual fluency was assessed since psychology and consumer research emphasise the importance of consumer perceptions that are built on automatic processing, which can
influence decision making as well as approach and avoidance behaviours (Fitzsimons et al., 2002; Ferraro et al., 2009; Mosteller et al., 2014). This type of fluency is also considered useful in determining the influence of online visual quality on consumer responses (Im et al., 2010) that ‘could explain immediate attraction to a website’ in a casual browsing scenario (Im and Ha, 2011, p.346). Although Wu et al. (2016) state there is a positive correlation between processing fluency, i.e. both forms of fluency, and pleasantness, Im, et al. (2010, p.283) argue ‘pleasure induced by the perceptual fluency is at a perceptual level which is considered as a lower level than deliberate thinking’. Since this study aims to study the influence of product presentation on consumers’ emotions and behaviour, focusing on perceptual fluency is supported in literature. Thus, research hypotheses are outlined as follows:

4.8.1 Product Presentation as “Stimuli” of Fluent Processing

Online shopping stimuli are described as ‘contextual cues external to an individual that attract his or her attention, and manifest themselves in several forms, for instance, as various website characteristics’ (Fang et al., 2018, p.450). A properly designed website via cues such as colour and images can shape consumers’ online shopping experience (Ettis, 2017; Lee et al., 2010). Informativeness is an important aspect of website atmospherics that is considered as a strategic marketing tool (Hsieh et al., 2014; Manganari et al., 2009). Providing information enables consumers to make an informed choice (Dörnyei et al., 2017; Kim and Lennon, 2008).

As a salient atmospheric cue, visual product presentation displayed on fashion apparel websites is identified as a suitable antecedent of fluent processing (Im et al., 2010). Specifically, this type of online merchandise cue provides an indispensable role in displaying product information visually, either through static product imagery or dynamic visualisation tools, such as video and 3D rotation (Roggeveen et al., 2015; Choi and Taylor, 2014). According to Song and Kim (2012), visual quality and size of stimuli are influential considerations. For online fashion retailing, recognition of this cue is often highlighted as such tools are important in communicating visual and tactile information that may otherwise be challenging to obtain from a non-physical environment (McCabe and Nowlis, 2003; de Klerk et al., 2015; Ashman and Vazquez, 2012). The use of SOR in
product presentation literature confirms the applicability of product presentation as appropriate stimuli (Table 4.1)

By manipulating the size of fashion apparel images as well as the text and background, Im and Ha (2011) demonstrate online visual quality results in higher levels of perceived perceptual fluency (Figure 4.7). Although Mosteller et al. (2014) manipulate verbal information online, results are also consistent; clarity of textual information can ease processing and results in higher levels of perceptual fluency. Findings by Wu et al. (2016) confirm the importance of providing clear images to help consumers acquire product information. Complex product images online can overwhelm the online shopper as less visual attention paid to the image resulting in negative fluency (Wu et al., 2016). By providing detailed product information, research confirms advanced product presentation can ease imagery processing, which is associated with the ease of imagining the product (Kim, 2018). Thus, this study posits advanced product presentation tools, such as catwalk video, zoom function and 3D product rotation, which provide more detail if required, should also assist consumers in processing product information with ease. By maintaining visual quality with the use of clear and good quality images as well as product visualisation tools, should ease processing and help consumers acquire more detailed product information.

**Figure 4.7** Difference in Perceptual Fluency of Visual Information Quality

The need to access and acquire product information on mobile device appears to be greater due to changes in consumer shifts (Pantano and Priporas, 2016; Faulds et al., 2018). With
smaller screen sizes and other issues, such as the ‘fat-finger’ problem, shopping on mobile devices may be more challenging (Wang et al., 2015), and may therefore affect consumers’ ability to process information with ease (Kahn, 2017). Although processing fluency on mobile devices is a new research area, current findings confirm visual complexity on mobile devices can also have a detrimental effect on consumer behaviour with lower levels of processing fluency (Sohn, 2017b).

In general, 3D product presentation tools are considered more effective than 2D static imagery in providing sensory information (Choi and Taylor, 2014). Coupled with haptic touch capabilities when shopping on mobile devices, this effect may be amplified. By using gestural interactions, consumers can simulate life-like interactions that result in higher levels of tactile and visual experiences with fashion apparel products online (Cano et al., 2017; Overmars and Poels, 2015a). Rather than just visual simulation, these interactions result in a multi-sensorial experience, which is shown to positively influence product evaluations (Balaji et al., 2011).

4.8.2 “Organism” Effects of Product Presentation

As well as providing instrumental value, empirical research reveals product presentation technology is also associated with experiential value; using an advanced level of product presentation can increase positive emotions experienced during the shopping process (Cano et al., 2017; Jai et al., 2014; Jeong et al., 2009; Fiore et al., 2005a; Fiore et al., 2005b; Lee et al., 2006; Kim et al., 2007). These tools are considered to be entertaining and explorative. Using the four experience realms, results by Jeong et al. (2009, p.119) show image enlargement and a model view are more likely to result in ‘entertainment, educational, escapist, and aesthetic experiences’. Apart from educational experiences, all other experiences were found to be positively related to pleasure and arousal.

However, this may depend on the presentation format (Roggeveen et al., 2015) as particular product presentation tools may be more influential. For example, Jai et al. (2004) compare image enlargement and rotation videos; the latter generated greater levels of pleasure in the brain. Using these tools via gestural interactivity on a mobile device demonstrates greater hedonic value. In terms of information, tools such as fabric scrunch
encourage learning about hedonic attributes (Overmars and Poels, 2015b). Although literature demonstrates these stimuli have a direct or indirect impact on consumers’ emotions, the influence of these tools on affective responses via perceptual fluency has not been confirmed. Research on perceptual fluency and the mere exposure effect illustrate fluency is hedonically marked, and as processing fluency increases positive evaluations also increase towards the stimulus (Reber et al., 2004a; Lee and Labroo, 2004; Winkielman et al., 2003). This is also confirmed with websites atmospherics; by increasing visual quality or decreasing visual complexity, perceptual fluency directly influences pleasure (Wu et al., 2016; Im et al., 2010) or positive affect (Mosteller et al., 2014).

In comparison to PCs, however, shopping on mobile devices is mostly associated with utilitarian value (McCLean et al., 2018; Raphaeli et al., 2017; Singh and Swait, 2017; Gao et al., 2015; Pantano and Priporas, 2016). Hence, using advanced product presentation via gestural interactivity may amplify the hedonic value of shopping for fashion on m-commerce websites and apps.

**H1:** Increasing perceptual fluency via product presentation technology will have a positive influence on affective responses.

Initially, interactivity creates an experiential effect when engaging the consumer, but too much can result in counterproductive processing with negative effects towards the stimulus (Jiang and Benbasat, 2007; Rose et al., 2012; Mosteller et al., 2014). Online shopping studies validate product presentation as important visual stimuli that can lower cognitive processing when shopping online. For example, visual product presentation formats can help to lower mental intangibility (Song and Kim, 2012) and increase mental imagery, which is useful for future consumption (Yoo and Kim, 2014). In line with task complexity and cognitive demands, care should be taken not to overwhelm the perceiver with too many functions that processing ability is hampered. This was found when presenting products online with a video and narration format (Jiang and Benbasat, 2007). If the level of information is too high this increases the complexity of processing a stimulus as well as time taken to process the stimulus (Song and Schwarz, 2008).

Thus, in line with fluency theory, perceptions of cognitive effort are lower if individuals are able to access and visualise the information more easily (Song and Schwarz, 2008;
Mosteller *et al.*, 2014). Shih (1998) also advised against incorporating high levels of interactivity as well as vividness; the latter can lower an individual’s ability to interact with the site. Inversely, Gabarino and Edell (1997) state increasing cognitive effort increases negative affect and can lead to consumers choosing alternative options, thereby influencing choice. However, they note this is likely to be exaggerated under time constraints. In comparison to the positive link between perceptual fluency and affect, studies by Mosteller *et al.* (2014) and Im and Ha (2011) establish a negative relationship between perceptual fluency and perceptions of cognitive effort when shopping online; by increasing the ease of processing, this negatively influences cognitive effort experienced towards online shopping atmospherics.

**H2:** An increase in perceptual fluency will decrease cognitive effort experienced towards the stimulus.

As an outcome, positive affect may also influence judgment towards cognitive processing. Mosteller *et al.* (2014) also demonstrate an inverse relationship; increasing positive affect and fluency during online shopping can offset consumers’ level of cognitive processing. If consumers enjoy shopping online, their affective response can have a negative impact on cognitive effort. Hence, retailers should assess levels to avoid negative effect experienced when shopping on a mobile device.

**H3:** An increase in positive affect will decrease cognitive effort experienced towards the stimulus.

Whether the stimulus is fluent or disfluent can affect aesthetic evaluation (Cho and Schwarz, 2010; Graf and Landwehr, 2015). Reber *et al.* (2004a) assert aesthetic responses towards a stimulus are more likely to be positive if the stimulus is processed fluently. However, they acknowledge affective responses mediate the influence of fluency on aesthetic responses. This is consistent with results from Orth and Wirtz (2014), who demonstrate affective responses mediated by high processing fluency can generate higher levels of attractiveness towards the store environment. These findings suggest positive affective responses towards fashion apparel products, which are displayed using product presentation tools online, may play a mediating role on aesthetic evaluation.
It is also important to note that consumers are likely to have prior affective responses with the stimuli (Cho and Schwarz, 2010), as they may have already engaged with the product presentation tool or the product image before. Hence, consumers may already possess high aesthetic appreciation towards the stimuli (Im et al., 2010). In comparison to findings by Orth and Wirtz (2014), Im et al. (2010) found that the relationship between pleasure and aesthetic evaluation was weak for online shopping websites. Compared to pleasure, perceptual fluency had a greater influence on aesthetic evaluation when shopping for fashion online, Im et al. (2010) posit this is due to the fact that fluency is expected; a more pleasurable effect is likely to be experienced if the fluency is unexpected (Lee and Labroo, 2004).

**H4:** An increase in perceptual fluency will have a positive influence on aesthetic evaluation.

### 4.8.3 "Response" Effects of Product Presentation

Empirical data confirms emotional responses positively facilitate behavioral outcomes, such as willingness to purchase (Donovon and Rossiter, 1982). The relationship between affective responses and positive behavioural intentions is well documented in m-commerce literature (Lu and Su, 2009; Kim et al., 2009a; Gao et al., 2015; Agrebi and Jallais, 2015). This relationship is also confirmed in product presentation literature (Yoo and Kim, 2012; Yang and Wu, 2009; Jeong et al., 2009; Kim et al., 2007; Kim and Forsythe, 2007; Lee et al., 2006; Fiore et al., 2005a; Fiore et al., 2005b).

Not only does perceptual fluency have an influence on positive affect, the affective response itself is found to have a significant mediating role on perceptual fluency in generating favourable behavioural intent towards fashion apparel websites (Im et al., 2010). Although aesthetic evaluation is considered an organism construct according to the SOR model used by Im et al. (2010), findings demonstrate a weak relationship between aesthetic evaluation and purchase intention. Hence, a relationship between aesthetic evaluation and purchase intentions was not proposed in this study. Results from Im and Ha (2011) also demonstrate enjoyment mediates the effect between perceived perceptual fluency and purchase intentions. These findings are also consistent with Winkielman et al. (2003).
H5: An increase in positive affect will have a positive influence on purchase intentions.

4.8.4 Visual Attention Towards Product Presentation

By using the same fashion product category, measuring eye movements can determine if there is a difference in visual attention. Analysis of fixation data can determine whether an online atmospheric cue is an area of interest (Djamabsi et al., 2011; Luan et al., 2016). In the online shopping experiment, Ho (2014) first mapped out particular areas of interest of all handbag images used. A feature has a strong AOI if metrics such as the number of fixations are high. Thus, a high number of fixations indicates attractiveness towards an area of interest (Ho, 2014).

This is consistent with other eye tracking research. Research indicates there is more emphasis and attention towards hedonic elements online; Cyr and Head (2013) found the length of eye-fixations were more significant towards these areas. Other metrics that illustrate high attraction include the length of first fixations and total contact time (Ho, 2014). By comparing different online stimuli, fixation data indicates images on webpages are highly appealing and attractive (Djamasi et al., 2010; Djamasi et al., 2011). Since advanced product presentation are considered to be more useful in helping consumers to obtain product information of fashion apparel online (Lee et al., 2006; Song and Kim, 2012), this suggests the use of high product presentation with good quality static and dynamic imagery are more likely to be fixated on. Conversely, literature demonstrates the importance of verbal data when there is low visual information (Kim and Lennon, 2008; Li et al., 2016b).

In summary, metric data such as number of fixations, is indicative of high visual attention and implies there is attraction towards product presentation, which according to e-commerce literature is regarded as an area of interest.

H6: There is a higher number of fixations (NOF), average fixation duration (AFD) and total fixation duration (TFD) towards fashion products with a high level of product presentation than fashion products with a low level of product presentation.
**H7:** There is a significant difference in the metric data towards the visual data between low and high product presentation.

**H8:** There is a significant difference in the metric data towards the verbal data (i.e. product description) between low and high product presentation.

However, it is important to note that whilst a high fixation duration is indicative of interest and attraction, it may also imply that the AOI is confusing and was not easily processed cognitively. As a result, fixations are described as ambiguous. This is also known as a reverse inference problem and is a problem in eye tracking research (Holmqvist *et al.*, 2011). An example of this could occur when looking at heat maps and scan paths, which can lead to false positives and false negatives (Holmqvist *et al.*, 2011). Although data collected from eye movements using eye tracking technology is considered an objective approach, such process measures lack the depth of subjective measures, for example whether consumers are satisfied or like the stimulus (Duchowski, 2007). An area of interest with a high number of fixations may not necessarily equate to attraction; it may be that the stimulus is complex (Holmqvist *et al.*, 2011). This is considered a limitation of visual attention research. However, using additional measures can help to establish meaning behind visual attention data (Duchowski, 2007).

Despite abundant research relating fluency to visual salience, e-commerce research has not examined perceptual fluency in relation to eye tracking in an academic paper. Using eye tracking with a post-study survey, Otterbring *et al.* (2016) demonstrate it is possible to evaluate navigational fluency with eye tracking when shopping for groceries in a supermarket; findings confirmed gaze behaviour was positive associated with navigational fluency. It is therefore helpful to use this approach to confirm higher visual attention towards a high level of product presentation is related to fluent processing.

**H9:** There is a significant difference in perceptual fluency when shopping for fashion on a mobile website with different levels of product presentation.

By comparing eye tracking data towards price and product information on a display signage, findings by Huddleston *et al.* (2015) confirm the influence of relevant product information on purchase behaviour. Specifically, a higher number of fixations towards
product information was positively related to purchase behaviour. Lindström et al. (2016) obtain similar findings with fashion mannequins but find factors such as fashion knowledge to be influential.

**H10**: There is a significant difference in purchase intentions when shopping for fashion on a mobile website with different levels of product presentation.

Due to limitations in eye tracking, a suitable approach would be to confirm whether high or low level of visual attention is due to cognitive effort or interest towards the product image. Retrospective verbalisations are a complimentary aid in understanding visual attention (Holmqvist et al., 2011). This would also extend and broaden an understanding towards mobile shopping and how and why consumers use product presentations tools on mobile devices. These propositions are outlined below:

**P1**: To understand behavioural differences towards low and high product presentation using retrospective verbalisations.

**P2**: To understand perceptions and attitudes towards product presentation on mobile devices including the influence of gestural interactivity.

A visual model further aids and explains how the theory is related to each of the constructs graphically (Creswell, 2009). For hypotheses 1-5, a framework based on the SOR model is presented in Figure 4.8 along with a summary of the hypotheses.
**Figure 4.8** Proposed Theoretical Model for Hypotheses 1-5

<table>
<thead>
<tr>
<th>STIMULUS</th>
<th>ORGANISM</th>
<th>RESPONSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Presentation</td>
<td></td>
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<tr>
<td>Product views</td>
<td></td>
<td></td>
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<tr>
<td>Image size and quality</td>
<td></td>
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<tr>
<td>Visualisation tools</td>
<td></td>
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<td></td>
<td>Perceptual Fluency</td>
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<tr>
<td></td>
<td>Cognitive Effort</td>
<td>(-)</td>
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<tr>
<td></td>
<td>Positive Effect</td>
<td>(+)</td>
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<td></td>
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<td>((+)</td>
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</tbody>
</table>

**H1**: Increasing perceptual fluency via product presentation technology will have a positive influence on affective responses.

**H2**: An increase in perceptual fluency will decrease cognitive effort experienced towards the stimulus.

**H3**: An increase in positive affect will decrease cognitive effort experienced towards the stimulus.

**H4**: An increase in perceptual fluency will have a positive influence on aesthetic evaluation.

**H5**: An increase in positive affect will have a positive influence on purchase intentions.

In answering whether the hypotheses outlined with visual attention influence cognitive and behavioural responses, a separate series of relationships were proposed (H6-H10) in line with visual marketing theory (Figure 4.9). The addition of P1-P2 provided greater clarity towards high fixation data and broadens understanding on perceptions and attitudes towards different levels of product presentation.
**Figure 4.9 Proposed Theoretical Model for Hypotheses 6-10**

**H6:** There is a higher number of fixations (NOF), average fixation duration (AFD) and total fixation duration (TFD) towards fashion products with a high level of product presentation than fashion products with a low level of product presentation.

**H7:** There is a significant difference in the metric data towards the visual data between low and high product presentation.

**H8:** There is a significant difference in the metric data towards the verbal data (i.e. product description) between low and high product presentation.

**H9:** There is a significant difference in perceptual fluency when shopping for fashion on a mobile website with different levels of product presentation.

**H10:** There is a significant difference in purchase intentions when shopping for fashion on a mobile website with different levels of product presentation.

**P1:** To understand behavioural differences towards product presentation using retrospective verbalisations.

**P2:** To understand perceptions and attitudes towards product presentation on mobile devices including the influence of gestural interactivity.

Overall, this study posits increasing visual quality via advanced product presentation technology will increase visual attention and facilitate perceptual fluency, which in turn will lower cognitive effort and increase aesthetic evaluation, as well as purchase intention with positive affect mediating this effect.
### 4.9 Research Framework Measures

Based on the hypotheses listed above, two separate studies were undertaken to understand the overall influence of fashion product presentation on mobile devices. Both studies measured and compared consumers responses towards different fashion apparel websites on a mobile device, which differed in product presentation.

The level of product presentation was based on measures used in literature (Table 4.5). A fashion website with a high level of product presentation features good quality imagery with different product views alongside product visualisation tools, such as product rotation, zoom function and catwalk video. Whereas, a low level of product presentation was considered to have fewer product images and a basic level of image interactivity. An obvious choice would be image enlargement or the zoom function only as this is considered to be low in interactivity (Lee *et al*., 2010).

<table>
<thead>
<tr>
<th>Feature</th>
<th>High Level</th>
<th>Low Level</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product views</td>
<td>A number of different product views. As well as a front view and back view, additional views, such as a magnified view and model view, are available.</td>
<td>Only a front view and back view available.</td>
<td>Song and Kim (2012); Jeong <em>et al</em> (2009)</td>
</tr>
<tr>
<td>Image size and quality</td>
<td>Large images with good quality images.</td>
<td>Smaller images with poorer quality.</td>
<td>Kim (2018); Song and Kim (2012); Im <em>et al</em> (2010); Park <em>et al</em> (2005)</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>Additional visualisation tools are available. This includes a catwalk video and product rotation.</td>
<td>Typically, only image enlargement available.</td>
<td>Beuckels and Hudders (2016); Cano <em>et al</em> (2017); Jai <em>et al</em> (2014); Lee <em>et al</em> (2010)</td>
</tr>
</tbody>
</table>

This approach is consistent with e-commerce literature that has studied fluency. By designing and analysing the effects of two fashion apparel mock websites, Im *et al* (2010) reveal that by manipulating certain characteristics online to create better visual quality, higher levels of perceptual fluency were found.
4.10 Chapter Summary

This chapter confirms the suitability of fluency theory and the SOR model in studying the influence of product presentation on consumers’ behavioural intentions when shopping for fashion apparel on a mobile device. In line with literature, modifications were required to suit the needs of this research in order to confirm relationships between perceptual fluency and affective and behavioural responses towards shopping on mobile devices. The inclusion of visual marketing theory is an appropriate addition in establishing whether advanced product presentation results in higher visual attention. Since mobile devices are smaller, additional measures with perceptual fluency and purchase intentions as well as verbal data were included alongside fixations to corroborate the influence of product presentation on consumers’ cognitive and approach behaviour towards visual display of fashion merchandise items on a mobile interface. Establishing a theoretical basis is important in structuring a suitable methodology that governs data collection and data analysis.
Chapter Five: Research Methodology

5.1 Introduction

In this chapter, a research philosophy, research data approaches, research design, research strategies, data collection and data analysis methods are discussed, selected and justified accordingly. Sampling, research ethics, reliability and validity are also explored in the following sections. For each research phase, separate research design sections are explored in more detail in sections 5.12 and 5.13 respectively.

5.2 Research Philosophy

A research philosophy is considered important for all research disciplines (Deshpande, 1983). Broadly speaking, there is not one way to study natural sciences or social sciences. Philosophical approaches are governed by two underlying assumptions; epistemology and ontology (Easterby-Smith et al., 2015).

Ontology refers to beliefs about reality, i.e. whether there is a single reality or many realities. On a basic level, depending on the belief, ontological considerations are acknowledged as realism or relativism (Easterby-Smith et al., 2015), which are also referred to as objectivism and subjectivism (Bryman and Bell, 2015; O’Gorman and MacIntosh, 2015). An objective or realist lens considers reality ‘as made up of solid objects that can be measured and tested’ that may or may not involve direct experience (O’Gorman and MacIntosh, 2015, p.56). An example includes assessing height of an individual. Conversely, a subjective or relativist lens considers reality based on human insights and interaction. Criticism with the latter states that in order for defensible claims rooted in subjectivism to be valid, a level of objectivism is still required (O’Gorman and MacIntosh, 2015).

Epistemology is referred to as what is regarded as true knowledge; an epistemic position is required to test knowledge claims for validity. Positivism and interpretivism are considered contrasting viewpoints on the philosophical continuum (Easterby-Smith et al., 2015). In social sciences, there has been much debate about the appropriateness of either research
approach. Moreover, there are also different interpretations, which demonstrates the complexity surrounding these worldviews (Hjørland, 2005). But, an understanding of ontological, epistemological and methodological considerations is expected to offer greater clarity towards a particular paradigm (Easterby-Smith et al., 2015). Selecting an underlying research philosophy is important in providing a foundation to make claims on when disclosing findings (O’Gorman and MacIntosh, 2015; Johnson et al., 2007).

5.2.1 Positivism

Social sciences under an epistemological stance argue that social sciences should be considered equivalent to natural sciences and involve a factual basis. Positivism is generally associated with scientific rigor used to establish causality between observed variables with an emphasis on experimentation (Goulding, 1999). Due to replication and robustness of this approach, positivism has proved popular with many researchers (O’Gorman and MacIntosh, 2015) including disciplines such as marketing and consumer research (Goulding, 1999, Hunt, 1991). However, this research approach has been criticised for the lack of personal immersion required to research social sciences and places faith in ‘random assignment and manipulation checks to reveal the true nature of reality’ (Hirschman, 1986, p.241), which subsequently led to paradigm rivalry between this approach and interpretivism wars during the 1980s (Denzin and Lincoln, 2011). Despite revisions and adjustments to traditional positivism, such as logical positivism, there was also confusion and misuse surrounding this approach. As a result, there were calls to view positivist research with critical pluralism, i.e. not only should there be open-mindedness towards newer revisions and different philosophical approaches, researchers should critically evaluate them (Hunt, 1991). Nevertheless, this approach remains influential. Hjørland (2005, p.133) explains alternatives ‘have yet been able to establish a strong position in the practical guidance of the research process’.
5.2.2 Interpretivism

Conceptually, interpretivism is less rigid than positivism. In marketing, an interpretivist approach involves understanding consumers and their patterns of consumption behaviour by analysing a particular phenomenon under a subjective basis rather than focusing on reasons of such behaviour (Goulding, 1999; Holbrook and O’Shaughnessy, 1988; O’Gorman and MacIntosh, 2015). This research philosophy does have many benefits in providing richness and detail, as well as developing a gestalt view of the research (Szmigin and Foxall, 2000). In some ways, it would be helpful to understand consumer behaviour with an intersubjective reality (Weber, 2004). A similar approach is humanistic inquiry, which is ‘an interpretation of the phenomenon about which one is inquiring’ (Hirschman, 1986, p.240). Thus, this leads to a difference when conceptualising the two main research philosophies (Figure 5.1).

**Figure 5.1 Conceptualisation of Positivist and Humanist Schemas**

![Positivist and Humanist Schemas](source)

Source: Hirschman (1986, p.241)

Figure 5.1 illustrates distinctions between either research philosophy. While a positivistic approach involves establishing causality and/or relationships between X and Y variables, a humanist approach is concerned with meanings, ideas and interpretations that is based on an individual’s constructed reality. Table 5.1 outlines general differences in the type of research associated with each approach. However, validity and reliability are difficult to be determined in interpretivism since data relies upon the subjectivity of the researcher and so research may be prone to bias. While it is possible to capture reality with data, it is difficult to replicate a study with an interpretive stance (Weber, 2004). Nevertheless, it is possible to argue that it is only reasonable from the perspective of the researcher. Others question
the integrity of interpretive research as knowledge that is generated is done so by the researcher and it is not tested as a matter of confirmation or rejection (Belk, 1986, Szmigin and Foxall, 2000).

<table>
<thead>
<tr>
<th>Positivist</th>
<th>Interpretivist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantitative</td>
<td>Qualitative</td>
</tr>
<tr>
<td>Objectivist</td>
<td>Subjectivist</td>
</tr>
<tr>
<td>Scientific</td>
<td>Humanistic</td>
</tr>
<tr>
<td>Experimentalist</td>
<td>Phenomenological</td>
</tr>
<tr>
<td>Traditionalist</td>
<td>Revolutionist</td>
</tr>
</tbody>
</table>

Source: Malhotra et al. (2012, p.195)

There have been many disagreements between the two approaches displayed in Table 5.1. Initially, there was a greater preference towards a positivist approach in consumer research. Although adoption of interpretivism philosophy rose in the 1980s and 1990s (Goulding, 1999), which is evident with a greater number of consumer research papers favouring interpretive methods, such as interviews and focus groups, findings reveal there is still greater focus on using an empirical approach (Kenworthy and Sparks, 2016). However, it is important to recognise that although there is rhetoric, Weber (2004) states these differences are shallow. Additionally, Weber (2004) argues there are similarities between both approaches and that individuals should not treat the other less favourably. This is echoed by Szmigin and Foxall (2000) who argue for a more inclusive approach towards consumer research. By comparing theory testing in marketing research, Kenworthy and Sparks (2016) assert that whilst this research discipline has been progressive in developing and testing theories, such as information processing theory and the SOR paradigm, other theories are only tested once and not as broadly.
5.2.3 Critical Realism

There is an alternative argument with elements of both positivism and interpretivism, including both types of ontologies: subjectivism and objectivism, called realism, which proposes that it is possible to understand social sciences and human behaviour with an objective viewpoint (Kenworthy and Sparks, 2016). In other words, human behaviour can be better understood in the context of science. Unlike positivism, realism also considers what is unobservable and is also referred to as post-positivism (Hunt, 1991; Hyde, 2000). Initially, there was contention and different revisions of scientific realism (Hunt, 1992). Subsequently, there are many versions of realism including critical realism. This branch of philosophy has surged in popularity in many social sciences disciplines including marketing and is arguably considered to be more coherent or better understood than others such as positivism (Easton, 2002; Miller and Tsang, 2010).

Coined by Roy Bhaskar in his work *A Realist Theory of Science* (1975), critical realism is a philosophical branch concerned with human and cognate sciences. It was born out of transcendental realism with an ontological stance (Archer *et al*., 1998). A realist believes the world would exist with or without the absence of human beings (Mingers, 2004). In other words, there is a belief in an external reality, but that there is criticism in ‘our ability to access and measure it’ (O’Gorman and MacIntosh, 2015, p.61). Critical realism also challenges the positivist stance on science as positivism does not account for non-deductive theory. This has led to an anti-positivist movement as well as the changes occurring in the scientific community (Archer *et al*., 1998; Easton, 2002). While positivism and interpretivism appear to be contrasting arguments, each approach ‘reduces reality to human knowledge, whether that knowledge acts as lens or container for reality’ (Fletcher, 2017, p.182). In comparison, critical realism uses theory to ‘engage in explanation and causal analysis (rather than engaging in thick empirical description of a given context)’ (Fletcher, 2017, p.182). Based on the ontological stance of social reality, critical realism can be conceptualised into 3 levels (Figure 5.2).
Fletcher (2017) uses an iceberg analogy to explain this ontological stance. At the tip of the iceberg is the empirical level, which is based on events that are observable and can therefore be measured. It is important to note that human experience and interpretation can play a mediating role in reaching conclusions. Fletcher (2017) emphasises the possibility of establishing causality of these events. The second level is the actual level, which states events are possible with or without human observation, while the third level is acknowledgment of causal mechanisms, which are ‘inherent properties in an object or structure that act as causal forces to produce events (i.e. those appearing at the empirical level)’ (Fletcher, 2017, p.183).

Although there are certain attributes on natural sciences that can be measured, there are also human attributes that can also be measured that are of importance within a certain context (Archer et al., 1998; Mingers, 2004). Relationships between casual powers and events are based on a set of conditions and not just discrete events; ‘objects may be anything that can be said to have causal powers. They may be simple or complex, social or material, abstract or concrete, and are characterised by their relationships’ (Easton, 2002, p.105). This would allow constructs such purchase intentions in this study to be measured under a factual basis.
5.2.3 Research Philosophy Adopted

Most research analysed in the literature appears to adopt a positivistic stance in deriving and testing hypotheses based on theory and previous literature. However, a critical realist considers such theory to be initial theory, which ‘facilitates a deeper analysis that can support, elaborate, or deny that theory to help build a new and more accurate explanation of reality’ (Fletcher, 2017, p.184).

As outlined in previous chapters, a theory suggested to understand the influence of product presentation is perceptual fluency. Hypotheses state by using an advanced level of product presentation, i.e. that is dynamic and interactive, will increase the ease of visualising the product image generating more positive responses towards the product presentation and the fashion website. In e-commerce literature, online atmospheric stimuli that include graphics and images generate high levels of visual attention towards a webpage, which has been confirmed using eye tracking technology with an experimental method. By measuring and testing both research approaches with an objective viewpoint, how consumers perceive fashion product presentation is reviewed through a critical lens. From an ontological perspective, it is possible to demonstrate causal relationships with a social reality based on human experience that is independent of the researcher (Fletcher, 2017). Along with understanding attitudes and perceptions towards product presentation, this approach helps to establish a causal relationship between fluency and attention experienced towards product presentation in providing a deeper understanding of how and why product presentation influences consumers’ emotional and behavioural responses towards fashion m-commerce.

5.3 Research Data Approaches

An important aspect to consider is the role of theory in research. Application of theory may be used to frame research questions as well as subsequent steps of the research process, such as data collection and data analysis. A dichotomous approach involves the use of theory after data collection and data analysis (Bryman and Bell, 2015). There are two approaches of reasoning that can result in knowledge creation: deduction and induction
(Hyde, 2000). Like research philosophies, the use of research approaches in marketing and consumer research has also been debated.

5.3.1 Deduction

Of the two approaches, a deductive strategy has been more popular (Bryman and Bell, 2015; Deshpande, 1983). To pursue a deductive approach would be to generate a list of hypotheses based on established theory in literature, whereby theory is tested to determine the confirmation or rejection of hypotheses leading to a review of the theory in question (Hyde, 2000) (Figure 5.3). To implement a deductive strategy, there is a ‘need to specify how data can be collected in relation to the concepts that make up the hypothesis’ (Bryman and Bell, 2015, p.23).

Figure 5.3 Steps in a Deductive Approach

From a consumer research perspective, the over-use of this approach led to criticism towards this type of reasoning. This includes ‘a lack of richness in theorising, a lack of theory testing in naturalistic settings, the continued dominance of one-shot investigations, and the use of sophisticated correlational methods to imply causality’ (Hyde, 2000, p.83). By distinguishing between information and knowledge extending outcomes, Skipper and Hyman (1990) acknowledge that while deduction may not increase information, they
disagree with the notion that deduction does not lead to knowledge extension. This reasoning approach is widely used in relevant literature (Kim, 2018; Roggeveen et al., 2015).

### 5.3.2 Induction

In an inductive approach, conclusions are generalised and drawn from observations after data analysis (Bryman and Bell, 2015). An inductive approach appears to be less structured as there is emphasis on theory building rather than on theory confirmation. In other words, reality is conveyed based on its own terms and not on predefined theory. This approach is particularly useful when it may not be appropriate to answer the research question using a set of preconceived notions (Gummesson, 2005; Hyde, 2000). While there is a plethora of papers using a deductive strategy in marketing, inductive is considered an important approach for this discipline (Skipper and Hyman, 1990) including consumer research (Holbrook and O'Shaugnessy, 1988). Researchers advocate the use of both approaches in research; the inductive component could help to analyse a particular phenomenon as it is not possible to develop new theory with a deductive approach (Hyde, 2006; Thomas, 2006). However, research generally recommends using a deductive strategy after an inductive one in order to gain validity checks (Skipper and Hyman, 1990).

### 5.3.3 Research Data Approach Adopted

The role of theory, and its application in theory generation of theory confirmation in research is indicative of either approach (Hyde, 2000). Evaluation of relevant literature demonstrates a preference towards a deductive approach. Most papers that review product presentation on online shopping websites do so with a deductive strategy that involve hypotheses testing (Jai et al., 2014; Yoo and Kim, 2012; Fiore et al., 2005a; Beuckels and Hudders, 2016; Kim, 2018). For this study, a deductive approach was also considered appropriate. With the exception of understanding attitudes and perceptions towards product presentation on fashion m-commerce, majority of the hypotheses outlined are based on Figure 5.3 where the aim is to test hypotheses for confirmation or rejection. According to Hyde (2000, p.82), it is also possible to also pursue deductive reasoning in qualitative
research, which ‘can represent an important step towards assuring conviction in qualitative research findings’ (Hyde, 2000, p.82).

5.4 Research Design

In order to conduct research in a timely and effectual manner, a research design provides a necessary foundation. Specifically, a research design ‘represents a structure that guides the execution of a research method and the analysis of subsequent data’ (Bryman and Bell, 2015). It is useful for the researcher as it provides clarity over what choices are necessary in the research process, such as collecting data (Malhotra et al., 2012; Bryman and Bell, 2015). This is displayed in Table 5.2. It is important to note the influence of a research paradigm; depending on whether research employs a positivist or interpretivist methodology can determine the type of research design selected (Easterby-Smith et al., 2015). Broadly speaking, there are different types of research designs (Table 5.2). A good research design should encompass a quality criterion in ensuring results and findings are reliable, replicable and valid (Bryman and Bell, 2015). This is explained in more detail in section 5.10 and 5.11.
Table 5.2 Summary of Different Research Designs

<table>
<thead>
<tr>
<th>Design Type</th>
<th>Description</th>
<th>Importance and Usage</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experimental</td>
<td>Use of laboratory or field experiments. Involves manipulation of an independent variable, which is tested using different conditions, which also includes a control treatment or condition.</td>
<td>Considered a robust design in demonstrating causality. Experimental design is common in psychology and consumer research, while field research is common in business and management research.</td>
<td>Simulated online website (Ballantine, 2005), simulated product presentation (Kim, 2018; Lee et al., 2010; Jai et al., 2014), fluency research (Mosteller et al., 2014)</td>
</tr>
<tr>
<td>Cross-sectional</td>
<td>Research is conducted at the same time and generally involves a larger sample. Also referred to as social survey research. While this method does use a cross-sectional design, so do other methods such as structured observations. Consistency is key. Hence, a standardised method is required.</td>
<td>By comparing cases, it is possible to generate patterns and inferences in the dataset. While it possible to determine relationships, it is not possible to establish causality between variables; an experimental design is required for this.</td>
<td>Survey research on online shopping (Gefen et al., 2003; Chiu et al., 2009)</td>
</tr>
<tr>
<td>Longitudinal</td>
<td>Change is an important aspect of this design, as research is carried out at different points in time. Often, the same participants are used. This design is also described as “contextualist” research.</td>
<td>Used to document and understand changes or shifts in a particular phenomenon in social research. Due to time constraints, it is not used often and also suffers from a lack of causality. It is more useful in proving relationships between constructs than cross-sectional design.</td>
<td>Online information search (Gallant and Arcand, 2017), continued online shopper behaviour (Hsu et al., 2006) and online shopping adoption in rural areas (Lennon et al., 2007)</td>
</tr>
<tr>
<td>Case study</td>
<td>Research of a particular phenomenon is analysed in depth, often with multiple cases. Commonly applied in business research. For example, a case study could be based on a particular organisation.</td>
<td>This design is used on a specific basis to examine various aspects of cases and therefore may not be generalisable. It may also involve a longitudinal design. Qualitative approaches are often applied, such as interviews.</td>
<td>Examples include eye tracking research (Oliveira et al., 2016),</td>
</tr>
<tr>
<td>Comparative</td>
<td>Different cases are analysed and compared using similar research methods. For example, this may include analysing similarities and differences of a particular phenomenon between different countries.</td>
<td>This design is suitable in highlighting differences in social research. This approach may involve the use of quantitative and/or qualitative methods. It may be difficult in obtaining data.</td>
<td>Cultural differences (Sheldon et al., 2017), the influence of different store atmospheres and interactions (Ballantine et al., 2010).</td>
</tr>
</tbody>
</table>

Adapted from: Bryman and Bell (2015); Creswell (2009); Chiu et al., (2009)

The research design adopted for this study includes both experimental and cross-sectional design. A cross-sectional research design was implemented by gathering consumer responses towards current fashion retail websites accessed on a mobile device to determine whether the relationships proposed in the SOR framework concerning fluency processing and approach responses are related and involved the use of a large sample to do so. A
5.5 Research Strategies

Otherwise referred to as strategies on inquiry, data collection approaches are known as quantitative, qualitative or a mixed-methods design. Due to IT advances in computer programs, there are a number of strategies that can be applied to either research approach (Creswell, 2009). Hanson and Grimmer (2007) assert the importance of selecting either approach as a foundation for academic research.

5.5.1 Qualitative Research

Otherwise known as an exploratory strategy, this approach requires an ‘understanding of the social world through an examination of the interpretation of that world by its participants’ (Bryman and Bell, 2015, p.392). In other words, qualitative research uses a subjective lens to reveal the world through the eyes of people, which can typically provide data that is richer and experiential in nature. By studying human behaviour through this lens, it is possible to attach meanings within findings (Calder, 1977, Bryman and Bell, 2015). With an emphasis on interpretation rather than outcomes, interpretation is considered an essential part of qualitative research (Gummesson, 2005). Calder (1977, p.359) states there are three approaches within qualitative research: clinical, exploratory and phenomenological, of which the latter is a strong and distinctive form as the aim is to ‘attempt to experience a set of actors and to describe that experience’.

From a philosophical perspective, this approach is typically correlated with an interpretivist approach in business and marketing research (Bryman and Bell, 2015, Holbrook and O’Shaugnessy, 1988), but can also be adopted under a realist stance (Fletcher, 2017). It is also generally associated with inductive reasoning (Gummesson, 2005). In comparison to quantitative research, a qualitative approach is less structured. Grounded theory is an example of a qualitative strategy that places weight on this approach.
(Creswell, 2009). Other qualitative strategies include ethnography, narrative research, case studies and phenomenological research (Creswell, 2009). Popular qualitative approaches in consumer research include focus groups (Calder, 1977) and interviews. Table 5.3 demonstrates adoption of a qualitative approach in relevant literature.

**Table 5.3 Qualitative Approach in Retail Consumer Research**

<table>
<thead>
<tr>
<th>Example of References</th>
<th>Research context</th>
<th>Method(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pantano and Priporas (2016)</td>
<td>To understand how mobile retailing affects consumption behaviour, i.e. to provide detailed insight.</td>
<td>Open-ended interviews (face to face and Skype)</td>
</tr>
<tr>
<td>McCormick and Livett (2012)</td>
<td>To understand the influence of how online fashion websites are presented, specifically towards product viewing and fashion information.</td>
<td>In-depth interviews that also included photo-elicitation and projective measures</td>
</tr>
<tr>
<td>Ballantine et al. (2010)</td>
<td>To holistically understand what effect store atmospherics have on consumers’ hedonic shopping experience.</td>
<td>In-depth interviews with protocol analysis.</td>
</tr>
<tr>
<td>Piotrowicz and Cuthbertson (2014)</td>
<td>To identify the role of IT and its application to omni-channel retailing.</td>
<td>Focus groups sessions</td>
</tr>
<tr>
<td>Siddiqui et al. (2003)</td>
<td>To identify retailer and consumer views towards fashion websites with an emphasis on design</td>
<td>In-depth interviews</td>
</tr>
<tr>
<td>Demangeot and Broderick (2006)</td>
<td>Consumers’ perceptions towards their online shopping experience when navigating a website</td>
<td>In-depth interviews with think-alouds</td>
</tr>
</tbody>
</table>

Ballantine et al. (2010, p.642) advocate a qualitative approach in understanding the influence of multisensory cues on shoppers’ behaviour due to the ‘extensive set of interactions that need to be examined’. As a dynamic research area, Pantano and Priporas (2016) state this approach is more suitable in exploring how developments in technology have led to shifts in consumption behaviour towards m-commerce.

**5.5.2 Quantitative Research**

This type of research approach is typically associated with positivism, in which reality is considered as a single reality through an objective lens, with a deductive approach that generates hypotheses based on theory. Hence, a quantitative approach is defined as a ‘strategy that emphasises quantification in the collection and analysis of data’ (Bryman and Bell, 2015, p.37). This approach commands data to be tested rigorously as measurement is necessary in transforming theoretical ideas into real world data. For example, to determine causality between a set of defined variables (Gummesson, 2005). In other words, it is possible to test relationships between constructs in a proposed or
hypothesised research model by using a multivariate statistical technique such as structural equation modelling (Hair et al., 2014). Quantitative research requires concepts and constructs to be measured via indicators that depend on the nature of the method and data (Bryman and Bell, 2015).

A quantitative approach is generally not suited in studying the social sciences and understanding consumers; the everyday context is removed. In trying to attain accuracy, measurement can create a false sense of consumer behaviour (Bryman and Bell, 2015). Although quantitative research is rigorously tested, data is still subject to judgment from the researcher (Gummesson, 2005). An issue may also arise at the data analysis stage where researchers may misapply a statistical analysis technique, such as factor analysis (Stewart, 1981). Nevertheless, the researcher is a particular issue in qualitative research as insight is subjective; the researcher can emphasise what is important or not important depending on their view. Other issues include data loss, lack of generalisability. Additionally, it may not be clear how findings are generated. This also makes it harder to repeat the research, which can affect the reliability (Bryman and Bell, 2015; Gummesson, 2005). As this approach is exploratory, it can be difficult to find an appropriate structure to conduct research (Creswell, 2009). Based on aspects described for quantitative and qualitative strategies, general assumptions are summarised in Table 5.4.
### Table 5.4 General Assumptions in Qualitative and Quantitative Research

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Qualitative</th>
<th>Quantitative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Philosophy</td>
<td>Interpretivism with an inductive approach</td>
<td>Positivism with a deductive approach</td>
</tr>
<tr>
<td>Rationale</td>
<td>Details and insight of phenomenon. To understand and explain a phenomenon within a given context. This approach requires interaction with individuals.</td>
<td>Description of phenomenon. To establish correlation and/or causality between a set of constructs in a given context, which are pre-determined.</td>
</tr>
<tr>
<td>Data generation</td>
<td>Data collection followed by interpretation and compared with existing theory. This requires the use of open-ended research question.</td>
<td>Data is collected based on a theory-driven approach, which is structured. This uses specific research questions.</td>
</tr>
<tr>
<td>Role of researcher</td>
<td>The researcher is an instrument that guides data collection and analysis.</td>
<td>The researcher remains objective and is not an instrument.</td>
</tr>
<tr>
<td>Approaches</td>
<td>Usually, exploratory approach that is descriptive. Interpretation is required to make sense of data.</td>
<td>This can be descriptive or scientific. These approaches are systematic.</td>
</tr>
<tr>
<td>Strategies of inquiry including methods</td>
<td>Grounded theory, ethnography, narrative research, focus groups, interviews and structured observations.</td>
<td>Experimental research and non-experimental research. For example, survey research and structured observation.</td>
</tr>
<tr>
<td>Association</td>
<td>Emphasis on words and insight.</td>
<td>Emphasis on numbers, critical verification and rigour.</td>
</tr>
<tr>
<td>Sample</td>
<td>Due to richness of data, a smaller number of participants is sufficient.</td>
<td>A larger, representative sample used generalise findings on a larger population.</td>
</tr>
<tr>
<td>Analysis</td>
<td>Large amounts of data with a high level of detail. Thus, data needs to be condensed.</td>
<td>Using computer programs such as SPSS, data is typically analysed using statistical analysis.</td>
</tr>
</tbody>
</table>

Adapted from: Bryman and Bell (2015); Calder (1977); Gummesson, (2005); Creswell (2009); Hyde (2000)

Despite the differences outlined in Table 5.4, there is some ambiguity over each approach. Research can be employed in various ways. For example, a qualitative approach is not just associated with words; photo-elicitation technique, which is based on visual images, is also adopted in qualitative research to capture richer detail (Bryman and Bell, 2005; McCormick and Livett, 2012). There may be some numerical measurement in a qualitative approach, while an experimental design may not use a sample size that is usually required in survey research. An example is eye tracking and EEG research, which typically use smaller sample sizes than surveys (Duchowski, 2007). Consequently, researchers state the need to exercise caution when defining either data collection approaches as a distinct strategy (Silverman, 1993; Calder, 1977; Gummesson, 2005; Bryman and Bell, 2015).

In marketing, quantitative approaches dominate academic research and are well established. By evaluating marketing papers between 1993 and 2002, Hanson and Grimmer (2007) reveal majority of papers feature this approach. They argue there can be
too much data when using a qualitative approach, which can be an issue when publishing due to word constraints. They may also be dominating in certain research contexts. Despite the plethora of research, most consumer research on store atmospherics had previously focussed on a quantitative approach (Ballantine et al., 2010). This also appears to be the case with newer research such as m-commerce (Pantano and Priporas, 2016). Although there is a preference for this approach in marketing in which hypotheses testing is ‘placed on the highest level of scientific excellence in social sciences’, Gumnesson (2005, p.317) argues a quantitative approach in marketing lacks insight and a lack of abstraction in understanding phenomenon and advocates a mixed approach in marketing that encapsulates synergy between both strategies.

5.5.3 Mixed Methods Research

Johnson et al. (2007, p.129) describe a mixed methods strategy as an ‘intellectual and practical synthesis based on qualitative and quantitative research’. This strategy is argued to be a methodological orientation in its own right and is considered one of the main research paradigms alongside qualitative and quantitative research. It is important to note that there are different mixed methods designs, which also includes different forms of triangulation, i.e. concurrent or sequential. Emphasis may be on either qualitative or quantitative research or may carry equal weighting (Johnson et al., 2007; Creswell and Plano Clark, 2011) (Figure 5.4). Reasons for doing a mixed method approach include limitations or inadequacies of using one research approach only, to further understand initial results, to first explore research qualitatively, a need to use a second approach to develop greater insight, for theoretical reasons, and the need to use several studies to answer research questions (Creswell and Plano Clark, 2011; Creswell, 2009).
The use of mixed method approaches has increased over the last 50 years (Johnson et al., 2007). A review of top marketing journals between 1993 and 2002 found only 8.8% of papers adopted this approach, of which only 13.3% were considered to be triangulated. Of the mixed method papers, weighting was given towards quantitative research (Hanson and Grimmer, 2007). According to Figure 5.4, this is described as “quantitative dominant”. Harrison and Reilly (2011) establish mixed methods feature in many journals including marketing research, suggesting its approach as an acceptable one. However, there have been disagreements over this approach, its definition and the benefits this strategy provides (Denzin, 2012).

Until recently, mixed methods research was not mixed at all stages of the research process (Creswell and Plano Clark, 2011). There are philosophical differences, which may make it inopportune to combine; paradigms associated with qualitative and quantitative research strategy are based on different ontological and epistemological orientations. However, Bryman and Bell (2015) argue they can be combined in a technical sense that can help compare and support findings from one research approach. While it is possible to compare data, ‘data can reside side by side as two different pictures that provide an overall composite assessment of the problem’ (Creswell, 2009, p.214). Findings of different research strategies may be triangulated where one research method is used to validate the findings from another method to ‘capture a more complete, holistic and contextual portrayal of the unit(s) under study’ (Jick, 1979, p.603). Although this may help to confirm
findings, problems may arise if the findings are not congruent (Bryman and Bell, 2015; Jick, 1979).

5.5.4 Research Strategy Adopted

Ultimately, choosing a research strategy is dependent on the research questions and problems (Creswell and Plano Clark, 2011). For a number of reasons, a mixed methods approach was selected as the most appropriate research strategy. One of the main reasons is that different research questions were best answered with different research strategies, as demonstrated in Table 5.5. Of the research philosophies, a critical realist perspective is considered suitable for conducting mixed method research (Shannon-Baker, 2016). This philosophical approach ‘validates and supports key aspects of both quantitative and qualitative approaches’ (Creswell and Plano Clark, 2011, p.44). As well as determining the underlying mechanisms of fluency and visual attention towards cognitive processing of product images and visualisation tools and its influence on emotional and behavioural outcomes, adopting a critical realist stance can enhance understanding towards contextual factors, i.e. consumer perceptions towards product presentation on mobile devices. Unlike positivism, fluency and visual attention are therefore considered initial theories in critical realism as ‘theories cannot offer an all-encompassing or complete view of a phenomenon’ (Shannon-Baker, 2016, p.329).
Table 5.5 Suitable Strategies for Research Questions

<table>
<thead>
<tr>
<th>Research Questions</th>
<th>Strategy</th>
<th>Rationale</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1-H5</td>
<td>Quantitative</td>
<td>A quantitative strategy is suitable to confirm relationships (i.e. correlation) between constructs in this multi-dimensional framework.</td>
</tr>
<tr>
<td>H6-H8</td>
<td>Quantitative</td>
<td>A quantified measure via statistical analysis can determine this difference. Answering this research questions involves an experimental design. Hence, it is possible to infer causality.</td>
</tr>
<tr>
<td>H9-H10</td>
<td>Quantitative</td>
<td>Based on literature and visual attention theory. A quantified measure via statistical analysis can determine this difference.</td>
</tr>
<tr>
<td>P1-P2</td>
<td>Qualitative</td>
<td>To provide a deeper and richer analysis of product presentation in a mobile context. Using this strategy is beneficial in revealing consumer perceptions and responses towards gestural interactivity. This measure has not been conceptualised and tested as a construct in previous literature.</td>
</tr>
</tbody>
</table>

To verify the statements H1-H5, the constructs and relationships in the framework are specific and based on fluency theory found in relevant literature, i.e. product presentation and atmospherics on online shopping websites (Im et al., 2010; Im and Ha, 2011, Mosteller et al., 2014). Therefore, it was appropriate to also test hypotheses on already established measures rather than adopt a qualitative measure, where there is little guidance from relevant literature. The majority of product presentation studies pursue a quantitative approach (Kim, 2018; Orús et al., 2017; Cano et al., 2017; Jai et al., 2014; Choi and Taylor, 2014), which justifies this approach in testing H1-H5 with the use of quantitative research. Only Kim and Forsythe (2007, 2009) adopt focus group interviews alongside survey methods. Although it is possible to analyse eye movement data qualitatively (Djamasbi et al., 2010), hypotheses were aligned with research on eye-tracking papers that ran statistical analysis to confirm the influence of a visual stimuli in a retail environment (Huddleston et al., 2015; Lindström et al., 2016). The use of mixed-methods in eye tracking research is also confirmed; Cyr and Head (2013) who use eye tracking to measure the effects of e-commerce task framing also use multi-methods as well as a questionnaire.

Using qualitative research in this way can provide subsidiary support and develop further understanding of relationships tested with a quantitative strategy (Bryman and Bell, 2015).
For example, the relationship between product presentation and visual attention, i.e. when and why do participants focus on the product image and how does the level of product presentation influence this relationship. It would also help to understand if and how the screen size and interface influences interaction with product presentation as well as shopping on fashion websites via a mobile interface in general. As m-commerce is a dynamic field that is continuing to change consumption behaviour (Pantano and Priporas, 2016; Faulds et al., 2018), a qualitative research approach would provide a different perspective. Specifically, it would offer a deeper insight and a more rounded analysis of consumers’ behaviour towards this stimulus within a mobile shopping context. Although there are a number of ways and reasons to conduct a mixed methods approach, it is important to explain why. Table 5.6 explains what type of mixed methods design was used in this study.

<table>
<thead>
<tr>
<th>Definition</th>
<th>Application</th>
<th>Rationale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timing</td>
<td>Sequential and concurrent</td>
<td>To confirm relationships based on established theory, testing H1-H5 was conducted first. As part of an experimental design, the other hypotheses and propositions were conducted using a convergent parallel design, i.e. at the same time.</td>
</tr>
<tr>
<td>Weighting</td>
<td>Equal emphasis on quantitative and qualitative</td>
<td>Weighting is given to both strategies in line with a critical realist perspective. While relationships are confirming using a quantitative approach, it is also important to acknowledge the contextual factors surrounding product presentation on mobile devices.</td>
</tr>
<tr>
<td>Mixing</td>
<td>Mixing will occur during the data analysis and interpretation stage</td>
<td>While a qualitative approach is used in a supportive role to eye tracking, all methods provide a different perspective of product presentation on fashion retail websites on mobile websites.</td>
</tr>
<tr>
<td>Theorising</td>
<td>Explicit</td>
<td>Due to a deductive approach, fluency is considered explicit. There is application of fluency theory in the first research phase and partly in testing H9, but this theory does not govern other measures necessarily.</td>
</tr>
</tbody>
</table>

Adapted from: Creswell (2009, p.206)

Due to equal weighting, this strategy adopts a middle ground between the two research strategies, which is reflected on the continuum as displayed in Figure 5.4. Depending on whether the ‘phasing of data collection may be simultaneous or sequential’ (Bryman and
Bell, 2015, p.646), can determine the type of mixed method design. However, this study incorporates within-methods in terms of quantitative research as well as between-methods. This two-phase study is illustrated in Figure 5.5.

**Figure 5.5 Multi-Phase Mixed Method Design Adopted in This Study**

Specifically, this study encapsulates both convergent parallel design as well as explanatory sequential design as part of a two-phase study. Data collection on research based on hypotheses 1-5 was collected and analysed first to assess the influence of product presentation on fluent processing. This was followed by a convergent parallel design to collect data based on an experimental design with participants shopping on mobile devices. At this stage, qualitative data was collected at the same time as quantitative data to converge findings from both approaches as well as to expand on qualitative aspects concerning mobile shopping and contextual factors. Hence, eye movement data, as well as data concerning hypotheses H8-H9 and P1-P2 were collected simultaneously, analysed separately and interpreted together.
5.6 Data Collection Methods

There are a variety of data collection methods. Based on the requirements of this mixed-methods study, particular data collection methods were selected for the two-phase study, which were collected at different points in time. The first phase involved an online survey based on a cross-sectional research design. Survey data was collected and analysed before the second phase. Based on an experimental design, an eye tracking study was conducted. This phase also included a pre and post experiment survey as well as a post-experiment interview for each participant that took part in the eye tracking study. The following sections explain these methods in more detail. Benefits and limitations of each approach are also outlined. In both phases, the participants used a particular mobile device to shop from i.e. a smartphone or tablet.

5.6.1 Online Survey

A popular quantitative tool featured in many scholarly journals is survey research (Creswell, 2009; Casey and Poropat, 2014). As a method, a survey design ‘provides a quantitative or numeric description of trends, attitudes, or opinions of a population by studying a sample of population’ (Creswell, 2009, p.145). There are different ways to administer and collect survey data, such as postal distribution, over the phone, face to face with the interviewee or over the internet, all of which offer different advantages and disadvantages (Easterby-Smith et al., 2015; Stieger and Reips, 2010).

To examine relationships between constructs, an online survey was selected for this study as survey websites, such as Qualtrics and Survey Monkey, are considered a convenient data collection method of creating a survey, distributing, collecting and exporting data (Easterby-Smith et al., 2015). Unique aspects of online surveys include customisation and interactivity. Depending on the responses selected, it is possible to screen or re-direct participants to another page by using conditions such as skip-logic (Easterby-Smith et al., 2015). Interviewer effects are not an issue and the participant can complete the survey at their own convenience (Bryman and Bell, 2015).
Structured question surveys are often used to test hypothesised or proposed relationships in a multi-dimensional framework, which includes the principle that ‘each item should express only one idea’ (Easterby-Smith et al., 2015, p.232). An important consideration is the response format, which can impact statistical analysis (Pallant, 2013). To understand attitudes and opinions that provide participants with a range of responses from one extreme to another including a midpoint, scales such as Likert scales and Semantic Differential scales are often used (Pallant, 2013; Easterby-Smith et al., 2015). The survey design adopted is discussed in more detail in Section 5.12.

5.6.2 Eye Tracking Study: Eye Tracking Experiment

Usage of this technology is adopted to detect eye movements and measure visual attention. From a consumer retail perspective, understanding visual attention can help reveal insights on consumers’ browsing and choice behaviour (Otterbring et al., 2016; Luan et al., 2016; Behe et al., 2015; Huddleston et al., 2015). Application of eye tracking is common under experimental conditions whereby participants are subjected to a visual source of information, which is encoded by the participant. This information is then subjected to computation to reveal the meaning of the eye movement (Just and Carpenter, 1976). Of the different eye movements, fixation data is commonly analysed to reveal a greater understanding of how internal cognitive systems may be affected by visual stimuli (Just and Carpenter, 1976; Duchowski, 2007).

Russo (1978) describes how the use of eye tracking to understand cognitive processing is only the tip of the iceberg. While using eye tracking can provide some understanding on information acquisition, i.e. what individuals look at and focus on, Russo (1978) argues internal processing is not observable. Thus, visual attention cannot explain consumer behaviour in its entirety. For example, Chandon et al. (2009) found attention towards shelf positioning in store does not necessarily yield equal effects in evaluation. This demonstrates out-of-store factors do have a strong impact on evaluation. Nevertheless, using this technology does provide insight on consumers’ decision-making, that would not be possible with other methods, such as surveys, which rely on verbal recall (Chandon et al., 2009; Li et al., 2016a). While some studies only use eye tracking as a singular data collection method (Li et al., 2016a; Ho, 2014), eye tracking is often used in conjunction
with other methods such as surveys (Pan et al., 2004; Lindström et al., 2016; Otterbring et al., 2016; Djamasbi et al., 2010; Djamasbi et al., 2011; Luan et al., 2016; Chae et al., 2013; Behe et al., 2015) and interviews (Cyr and Head, 2013; Benn et al., 2015). For example, Liu et al. (2016) ask questions regarding cognitive load in relation with eye tracking.

With a bottom-up approach, where eye movements are stimulus-driven, it is important to not divulge what the stimulus is as this can affect participants’ eye movements. Hence, a cover story is used (Otterbring et al., 2016). Eye fixations are only relevant if a particular group(s) of eye fixations are isolated and interpreted. Individual fixations will not adequately reveal the level of information required to understand information processing (Russo, 1978).

While it is important to ensure there is high accuracy and precision when collecting eye tracking data (Nyström et al., 2013), Holmqvist et al. (2011) assert the significance of precision in measuring fixation data. Factors such as mascara and glasses can impact data quality. To maintain data quality the researcher is able to watch the recording of the eye movements on a separate screen during the experiment as conducted by Djamasbi et al. (2010). Important steps included in eye tracking include calibration to avoid fixation errors as well as mapping fixation data. Although more than one dependent measures, i.e. eye tracking measures, can be collected, Holmqvist et al. (2011) states this may convert the study into a more exploratory study instead of a confirmatory one. Visual attention via eye tracking technology was chosen as a method in this study to understand the influence of product presentation on visual attention.

5.6.3 Eye Tracking Study: Pre and Post Experiment Survey

Participants were asked to complete two surveys for the eye tracking study: demographic survey (about the participant) and a post survey based on their shopping experience. A demographic survey was considered appropriate to confirm the suitability of the sample. These includes questions such as frequency of shopping (online or in-store). Research confirms the use of this approach as part of an experimental design featuring eye tracking (Otterbring et al., 2016; Huddleston et al., 2015; Luan et al., 2016). To infer causality
between product presentation and the outcomes perceptual fluency and purchase intentions, a post survey was considered an appropriate option according to eye tracking literature, which included the use of single-item measures. For example, Huddleston et al. (2015) used a single-item question to determine consumers’ likelihood to buy after engaging with the eye tracker. Similarly, Otterbring et al. (2016) also used a single-item measure survey questions for store familiarity and navigational fluency. Participants were asked to complete these questions on paper to avoid interviewer effects of a verbal survey that is conducted as part of face to face interviewing situation (Bryman and Bell, 2015).

5.6.4 Eye Tracking Study: Post Experiment Interview

Recognised as a well-known qualitative measure, interviews are employed to find out information that centres around a particular topic or phenomenon (Easterby-Smith et al., 2015). Rowley (2012, p.261) states interviews are utilised to gain ‘insights into or understanding of opinions, attitudes, experiences, processes, behaviours, or predictions’. There is evidence of this approach in understanding consumer behaviour online and on mobile devices (McCormick and Livett, 2012; Jiang and Yang, 2013; Kim et al., 2016; Parker and Huang, 2016) including product presentation technology (Kim and Forsythe, 2007, 2009). In comparison to surveys, a smaller sample is used due to time constraints. As a result, there are concerns of generalising findings to the wider population. However, unlike surveys, interviews are exploratory and can provide richer detail with a deeper understanding of a given phenomenon (Rowley, 2012).

Interviews can be structured differently. For example, they may be structured or semi-structured (Bryman and Bell, 2015). Structured interviews are likened to surveys with the exception that the interview is conducted face to face. Unstructured interviews are described as the opposite where only a few questions are asked, and the interview is guided by what is said by the participant. This type of interviewing, however, is more advanced as experience is required (Rowley, 2012). Semi-structured interviewing adopts the middle ground, there is flexibility in modifying questions to pursue a line of questioning guided by what the participant said (Bryman and Bell, 2015). Since questions were based on what the participant chose to focus on or did not focus on in terms of product presentation, there was a preference in selecting this style of interviewing.
Verbal data collected with eye tracking experiments are referred to as concurrent or retrospective verbalisations. The latter requires asking the participants their thoughts about the stimulus after the experiment, while the former occurs when the participant is encouraged to think out loud while their eye movements are collected simultaneously (Holmqvist et al. 2011). Benn et al. (2015) also adopted retrospective verbalisation to understand visual attention towards information on online grocery websites. It is also important to note concurrent verbalisation may influence individual’s eye movements that can otherwise result in biased verbalisations (Holmqvist et al., 2011).

A post experiment interview was selected for several reasons. Firstly, verbal data was included at the end of the eye tracking experiment as a methodological triangulation to compensate the disadvantages of either method in clarifying the ambiguous nature on fixation durations. In other words, this data was used to cross-validate the analysis of the eye tracking measures. Retrospective verbalisation was selected to avoid biased verbalisation. Secondly, this method was selected to understand participants perceptions and attitudes towards product presentation. With the exception of Kim and Forsythe (2007, 2009), a post interview approach has not been used to specifically study the influence of product presentation. Given that mobile devices utilise a different interface to PCs, interviews can offer exclusive insights of fashion product presentation on mobile devices.

5.6.5 Limitations of Data Collection Methods

For the online survey, limitations include lack of clarity when answering questions as well as lack of detail with open-ended questions and a low retention rate (Bryman and Bell, 2015). For this reason, questions and responses in an online survey should be easy to read and understand. The phrasing of the question is also important as leading questions can introduce bias in the dataset (Easterby-Smith et al., 2015). Since no open-ended questions were required, the lack of detail with such answers was not a concern. When completing online surveys, participants may also omit the truth when asked if they fit the sample criterion (Bryman and Bell, 2015). Therefore, a panel website, i.e. Critical Mix, was selected to distribute the online survey to participants who met the sample requirements.
Eye tracking is also not without limitations. Technology cannot observe visual attention that may occur at the “corner” of the eye. The general assumption of eye tracking is that it does in all gazes, but this may not always be the case (Duchowski, 2007). Eye fixations only serve to process visual information. This is also a limitation as we cannot understand other types of cognitive processing (Russo, 1978). Findings can be influenced by certain constraints, such as time. Hence, experiments were kept short so that participants did not get bored, as this can influence eye movements (Duchowski, 2007). To avoid bias, the selection of products looked at when shopping on the mobile device was also controlled. Naturally, there is some bias; participants know they are being observed so may not act as they normally would.

While a field setting may be preferable, using a lab-setting is more likely to yield higher data quality than a field setting (Holmqvist et al., 2011). Whether the experiment is task-free or task-dependent may also affect results (Duchowski, 2007). Since the aim is to understand the effects of visual stimuli on cognitive processing from a bottom-up perspective, timed conditions or task-driven shopping would alter this to a top-down analysis where the system is not expected to interfere with eye movement. It would influence natural human behaviour (Duchowski, 2007). For this reason, participants were not given a specific task except to browse on the website or told how long to browse the mobile device. To compensate for limitations of either method, data collected from the second research phase (i.e. eye tracking experiment, post survey and interview data) were converged to understand the overall effect of product presentation technology on consumers’ perceptual fluency, purchase intentions and visual attention.

One of the disadvantages of qualitative data collection is to know when the amount of data collection is adequate (Bryman and Bell, 2015). Pilot studies were used to assess the length of the interview and the depth required to acquire information about participants’ attitudes and perceptions towards how fashion apparel is visually displayed on a mobile device. Pilot studies confirmed an in-depth style of interviewing was not necessary as the data collected revealed similar themes with enough information to analyse data qualitatively.

Another disadvantage of conducting interviews is that it is often based on verbal recall. The length of time is also an important consideration as participants may not recall their thoughts towards the stimuli if the experiment is long (Holmqvist et al. 2011). To limit this
issue, participants’ browsing time was limited to 90 seconds. In both eye tracking and online surveys, consumers’ purchase decisions may already be pre-determined when evaluating the influence of visual stimuli within a shopping context (Chandon et al., 2009). Hence, interviews are an important method in helping to provide further information and clarity regarding the impact of using low or high product presentation on fashion m-commerce sites, which is not afforded by eye tracking or online surveys.

5.7 Data Analysis Methods

Once data is collected, both qualitative and quantitative data require different data analysis methods. Based on the three methods explained above, the following section outlines data analysis methods required for both phases.

5.7.1 Online Survey: Statistical Analysis

Once data is exported from the survey website, the next step involves preparing a codebook using software, cleaning up the data and running the appropriate statistical analysis technique (Pallant, 2013). Since the goal of the online survey was to examine the proposed relationships between the constructs perceptual fluency, positive affect, cognitive effort, aesthetic evaluation and purchase intentions, suitable statistical techniques included a reliability analysis and Exploratory Factor Analysis (EFA) followed by Structural Equation Modelling (SEM).

To run statistical analysis, software programs IBM SPSS 23 and the add-on AMOS 22 were selected. A reliability analysis is also known as Cronbach’s Alpha. Field (2013, p.706) describes reliability as a measure that ‘should consistently reflect the construct it is measuring’. Such a measure would help to determine whether the online survey items in each of the scales or the scale as a whole is reliable (Field, 2013). Conducting an EFA allows the researcher to find out the degree to which the observed scale items are related to their respective constructs, which are represented by factor loadings (Byrne, 2010). Since this stage is exploratory, SEM was required to determine how well the hypothesised model corresponds to the sample data (Byrne, 2010). Steps are outlined in Figure 5.6.
This first stage of SEM is therefore known as Confirmatory Factor Analysis (CFA), which requires the development of a path diagram. In CFA, the goal is to ensure there is good model fit and construct validity before proceeding onto the next stage of testing structural theory. The final stage of SEM evaluates the relationships between the constructs with an emphasis on structural relationships. SEM is considered a reliable multivariate technique; since the measurement error is accounted for in SEM, only the common variance is examined (Hair et al., 2014).

A benefit of SEM is model complexity can be analysed, while multiple regression is more suited to simpler models. However, there is a need to develop a model before SEM analysis. In other words, it is necessary to ensure there is a theoretical basis for the model before running analysis between the scale items. There are also many factors to consider such as the sample size (Tabachnick and Fidell, 2013).

A demographic analysis is also a useful way to support the suitability of a sample as well as providing an overview of the sample. By selecting descriptive statistics on SPSS,
variables such as age, internet usage and online shopping can be represented graphically or numerically via frequencies and percentages (Pallant, 2013).

5.7.2 Eye Tracking Experiment Data: Statistical Analysis

There are a variety of measures that can be analysed, which exemplifies the strength and usefulness of collecting eye tracking. A common method is to depict the intensity of the fixations in the form of heat maps or gaze plots. Areas that are more intense indicate a high level of fixations (Klingensmith, 2013; Holmqvist et al., 2011). Another way to analyse eye tracking data is to analyse data quantitatively (Duchowski, 2007). From the Analyser software, metric data can be exported as an Excel file and then imported into SPSS for statistical analysis (Holmqvist et al., 2011).

Since participants looked at different products, which vary according to the shape of the fashion apparel and the way the model is posing, generating a heat map with the aggregated data across all participants was not considered a suitable analysis technique. Analysing quantitative indicators, such as fixation duration and number of fixations, is more appropriate in assessing significant differences between two treatment groups: metric data from the control group (low level of product presentation) and metric data from the non-control group (high level of product presentation). Since the eye tracking experiment involves manipulation of one independent variable: product presentation, with two levels, an independent samples $t$-tests was considered appropriate in comparing sample means for each metric between the two groups. Put simply, a $t$-test detects if there is a large enough difference between the two sample means for there to be a significant difference (Field, 2013).

To determine the suitability of a $t$-test instead of its non-parametric equivalent, i.e. Mann-Whitney U test, the dataset would be plotted to check the shape of the distribution curve. If there is a normal shaped curve, data would be labelled as parametric while an abnormal shaped curve is labelled as non-parametric test. However, Duchowski (2007, p.168) argues eye tracking metric data is parametric data ‘because related metrics can be represented by a uniform (equal distance) interval/ratio scale’. For this reason, a $t$-test was selected.
Using standard error, a *t*-test is based on the null hypothesis, i.e. there is no difference. An appropriate level of confidence is 95%. Thus, the results being due to chance is set at less than 5%. This is the confidence level in the results if the experiment was to be repeated by different individuals (Field, and Hole, 2003). With a larger difference, there is more confidence in determining a significant difference in the dataset. SPSS outputs include group mean, the overall mean and the difference between each variable and group mean. In a *t*-test, testing the null hypothesis i.e. there is no difference between groups is done using Levene’s test and is also known as homogeneity of variance (Pallant, 2013).

5.7.3 Pre and Post Eye Tracking Survey: Statistical Analysis

Unlike the online survey, multivariate statistics are not required to analyse survey responses pre and post eye tracking experiment. However, both the online survey and the pre-eye tracking experiment survey feature demographic questions, in which descriptive statistics was considered a suitable analysis (Pallant, 2013).

In a separate study to the eye tracking, Djamabsi *et al.* (2010) conducted a survey and asked participant to rate different websites according to visual appeal. By grouping these scores into two a low and high group, paired *t*-tests were used to determine a difference between these two groups. Like the eye tracking metric data, the use of an independent samples *t*-tests would help to compare sample means for perceptual fluency and purchase intentions.

5.7.4 Post Eye Tracking Interview: Thematic Analysis

In comparison to other qualitative data analysis methods, i.e. grounded theory, discourse analysis and phenomenology, a thematic analysis (Bryman and Bell, 2015) is based on the ‘core meanings evident in the text, relevant to evaluation or research objectives’ (Thomas, 2006, p.241). The process of analysing verbal data began with transcribing recorded data (Figure 5.7). An important factor is to listen and write up the transcript accurately (Bryman and Bell, 2015). Hence, the transcripts were written exactly as the words were said and expressed. Information is more likely to be retained when an interview has been conducted. Therefore, interviews were transcribed as soon as possible rather than after all
the interviews were concluded. This analysis also required reading the transcripts a few times in order to establish the main codes of themes present in the verbal data (Thomas, 2006). According to Rowley (2012, p.268), themes may be ‘‘facts’, experiences, processes, actions, behaviours, views, influencing factors, interactions, or something else’. Once established, the next step was to assign sections of the transcripts to the relevant theme or sub-theme.

As established earlier, findings derived from this approach are not based on a model with pre-conceived theory; they are derived from the raw data (Thomas, 2006). Some revision may be required as some text may be associated with two codes or there may be data that is not relevant to any categories that relate to the objectives. Unlike grounded theory, this data may not be included in order to reduce the number of categories and codes as only the most important are required in the overall framework (Thomas, 2006).

**Figure 5.7 Processes in Qualitative Research**

![Diagram showing processes in qualitative research]

Adapted from: Thomas (2006, p.237)

This type of analysis was used to attach meanings to findings. It may be conducted using software, such as NVivo, or manually (Rowley, 2012). Since the dataset was not particularly large, the latter approach was preferred.
5.8 Sampling

Since is not possible to test the whole population, a sample is required. A sample is defined as a ‘segment of the population that is selected for investigation. It is a sub-set of the population’ (Bryman and Bell, 2015, p.187). This step in a research process is important as it can affect the credibility of the data collected. By selecting an appropriate sampling unit, the aim is to make claims and draw inferences based on the sample to a wider population. According to Easterby-Smith et al. (2015), this is achieved by using a representative and precise sampling design. The former relates to a need to select a sample that is representative of the population and includes selecting parameters of a sampling frame as an unrepresentative sample leads to bias. For example, if relevant groups of people are excluded (Bryman and Bell, 2015). The latter is concerned with ‘how credible a sample is’ in terms of the sampling proportion and sample size (Easterby-Smith et al., 2015, p.79).

While large samples have greater precision, it is necessary to consider an adequate sample size to draw inferences. Increasing sample size may not necessarily lead to a precise sample. However, the sampling error is more likely to be lower (Bryman and Bell, 2015). Of the two issues considered (precision and representation), Easterby-Smith et al. (2015, p.80) argue representation is more important; it is ‘preferable to have a sample size that properly represents the population even if the precision is lower because of a small sample’. There are two types of sampling techniques: probability and non-probability sampling. Based on these sampling techniques, there are different types of sample designs (Figure 5.8).
The most basic form of probability sampling is random sampling, which is based on the fact that every member of a population has a known and equal chance of being selected. It allows a sample to be a true representative of the population, while other types are variations of random sampling (Malhotra et al., 2012). Using this type of sampling for finding sample sizes means that it is possible to employ statistical techniques like confidence intervals and margins of error to validate the results (Malhotra et al., 2012). It is also based on ‘theoretical distributions of observations’ (Teddle and Yu, 2007, p.79).

Obtaining a large sample size can be affected by factors, such as time and cost restraints. Non-response is also an issue (Bryman and Bell, 2015).

In addition to a lack of resources, these factors can otherwise lead to the adoption of non-probability sampling. This type of sampling entails different variations of sampling techniques that are not part of probability sampling. Precision is a key factor; the most important aspect of favouring non-probability sampling is to obtain a particular sample size. For example, a convenience sample is considered the easiest route in obtaining a high response rate and is often applied in research. This involves participants being chosen by
the researcher. In comparison, purposive and quota samples are more selective, whereby recruiting individuals is based on the sample category, such as participant characteristics. A snowball sample is considered when obtaining a specific sampling unit that may be difficult to obtain (Bryman and Bell, 2015; Easterby-Smith et al., 2015).

5.8.1 Sample and Sampling Technique Adopted

Selecting a sample with participants who were UK females and aged between 18-24 with experience of shopping for fashion online was suitable given the research objectives and nature of this study. Since the context of this research is based on fashion retailing, the use of a female sample was appropriate. UK female consumers purchase more fashion items than their male counterparts online (Mintel, 2017). The use of female sample only is consistent with studies that analyse fashion apparel product presentation (Kim, 2018; Jai et al., 2014; Yoo and Kim, 2012; Yoo and Kim, 2014; Kim and Lennon, 2010). Fiore and Jin (2003) compared male and female participants in their product presentation study and found female participants answered approach responses positively, whereas this result was not true for male consumers.

Given that this study is based on mobile shopping, using a young consumer sample is suitable. Young consumers, i.e. Millennials and Generation Z, are mobile obsessed with high levels of mobile usage (The Business of Fashion and McKinsey & Company, 2017). According to Mintel (2017), half of young consumers use their smartphone to purchase fashion items. Although consumers aged between 25-34 constitute part of the Millennial and Generation Y age group (Lissita and Kol, 2016), female consumers aged between 18-24 spend more on fashion apparel than their female 25-34 counterparts (Mintel, 2017). Data was only collected from UK shoppers as cultural differences may have an impact; consumers in one country may shop and behave differently to shoppers in a different country (Mazaheri et al., 2014; Clemons et al., 2016).

Since a particular sampling unit had already been identified and is required for a particular purpose, a purposive sampling technique was considered the most appropriate. This type of sampling is ‘designed to generate a sample that will address research questions’ with emphasis on the depth of information obtained from the sample rather than using a large
sample size for representativeness (Teddlie and Yu, 2007, p.84). In this case, participants were selected and recruited on the basis that they met the sample criterion. Participants that did not meet this criterion were rejected from either phase of the study. Creswell and Plano Clark (2011, p.173) also describe this approach as purposeful sampling in which participants are recruited on the basis they have ‘experienced the central phenomenon or the key concept of being explored in the study’. As the sample selected are proficient users of mobile devices and demonstrate high online shopping experience, a purposive sample was appropriate.

5.9 Research Ethics

Since data is collected from people, it is important to consider potential ethical issues. It is essential to follow an approved code on conduct during a study. Not only should ethical issues be considered at all stages of a research project, there is an emphasis on protecting participants as it helps to ‘develop trust with them, promote the integrity of research, guard against misconduct and impropriety that might reflect on their organisations’ (Creswell, 2009, p.87).

Additionally, ethical principles are important in protecting the integrity of the study within academia (Easterby-Smith et al., 2015). For the purposes of this study, the main ethical issues included consent, confidentiality and data storage. Before collecting data, it is vital to ensure there is informed consent (Creswell, 2009). For this reason, participants were provided with a participant information sheet or a webpage with the information for the online survey outlining the research, how the experiment will be conducted, the task itself as well as a consent form that must be signed if the participant agrees to take part. In order to protect the privacy of participants, highly personal information such as names and email addresses were not recorded or stored to ensure anonymity of all participant data. To protect the data and results, files were stored in a password protected folder and backed up on the researcher’s university computer. It is advisable to send a research plan to an Institutional Review Board to minimise risk (Creswell, 2009). Therefore, a research ethics application form was submitted describing the research plan and ethical considerations. Ethical approval was granted by The University of Manchester’s Ethics Committee (Ref 16357).
5.10 Research Reliability

There is a need to be detailed and unambiguous about how the study was carried out. This enables the research to be replicated if necessary and maintains validity of the results. Field and Hole (2003) stipulate that it is important to measure the dependent variable accurately. This aspect evaluates findings against reality and whether the same results would be reached by others if the study was replicated (Easterby-Smith et al., 2015). It is important to note a mixed methods approach is also subject to ‘similar constraints and considerations as research relying on a single method or research strategy’ (Bryman and Bell, 2015, p.659). For the online survey, constructs and scale items were adapted from relevant literature that included product presentation, fluency and online shopping. Measures were also evaluated against the original paper to ensure relevant scales had internal reliability. Additionally, it is possible to do a split-half test, whereby correlation is carried out between two sets of indicators to indicate consistency between data and is otherwise known as internal consistency (Field, 2013; Pallant, 2013). An example of a split-half test is Cronbach’s alpha. This test was applied to quantitative data as a test for internal validity where 0.7 is the cut off point for validity (Pallant, 2013).

To ensure there was reliability with the second phase, measures were based on previous literature. Specifically, the experimental design was aligned with other studies that also measure visual attention in a retail environment. Detail is also important in an experimental design (Bryman and Bell, 2015). Hence, each step of the eye tracking experiment was recorded to ensure accuracy and replicability of the study. The software analysis was used carefully to ensure fixations were mapped onto the screenshots as accurately as possible. Epistemological and ontological orientations can affect the validity and reliability as Easterby-Smith et al. (2015) demonstrates opposing views on validity and reliability. For qualitative research, replicability and reliability is challenging given that these terms are usually associated with measurement. In comparison to quantitative research, data collection and analysis in qualitative research is subjective and may not yield the same conclusions if replicated (Bryman and Bell, 2015).
5.11 Research Validity

Reliability alone is not enough; measures need to be valid as well as reliable. To ensure research is internally valid and that any findings are due to manipulations, Field and Hole (2003) recommend a good experimental design. Influences on internal validity include group threats, regression to the mean, time threats, history, maturation, instrument change, differential mortality, reactivity and experimenter effects (Field and Hole, 2003). To increase internal validity, Easterby-Smith et al. (2015) assert this requires ‘the elimination of plausible alternative explanations for any differences observed between groups’. This is consistent with online shopping studies as Hong et al. (2004, p.174) emphasise the importance of an experimental design to control influences such as ‘knowledge of particular products, familiarity with particular Web sites, brand preferences, price sensitivity, downloading speed, etc.’ as well as the website design that can affect interval validity. However, an experimental design that may require a lab set-up may not be representative of reality. Hence, external validity is also referred to as ecological validity. This type of validity is influenced by over-use of particular participant cohort and a limited number of participants (Field and Hole, 2003).

Research validity in survey research relates to the extent the survey measures the right elements that need to be measured. In simple terms, validity refers to how well an instrument measures what it is intended to measure (Field and Hole, 2003). For this reason, a pre-testing stage was implemented to ensure the accuracy of constructs and scale items. EFA was helpful during the pilot stage as well as the actual data analysis in determining if the respective scale item was associated with a particular construct (Pallant, 2013).

To demonstrate the difference in product presentation, the online survey was based on attitudes and perceptions towards two fashion retail websites that differed in product presentation. While using actual fashion websites may lack internal validity as it is not possible to control for other variables that can influence responses, the survey is likely to have higher ecological validity as it is based on actual websites where participants are asked to shop from their mobile device rather than taking part in an experimental study that may not be reflective of behaviour towards actual m-commerce. Many papers who use an experimental design to understand online shopping behaviour acknowledge this approach
as a limitation of external validity (Kim, 2018; Beuckels and Hudders, 2016; Yang and Wu, 2009). Additionally, the online survey study is based on a cross-sectional design. Unlike experimental design, where manipulation of an independent variable is required, accounting for alternative hypotheses is less of an issue since relationships proposed are associative rather than causal relationships.

Conversely, an experimental design was adopted for the eye tracking study. Duchoswki (2007) argues that although a lab setting may not reflect a real-life setting, the researcher has more control over the experiment in collecting valid data. There is a problem of causality if eye tracking measures are not tightly controlled (Holmqvist et al., 2011). Other variables that may influence eye movements towards fashion retail websites were limited since only the product presentation was manipulated. In order to do so, a mock website was devised to facilitate a low level of product presentation while an actual fashion website (i.e. ASOS) was selected as a website with a high level of product presentation. As participants are shopping on a mobile device during the experiment, this creates a more natural setting than using images of websites or product pictures as conducted by Ho (2014).

Due to technological barriers as well as time and cost constraints, it was not possible to create a mock website with a high level of product presentation that featured visualisation tools such as catwalk video and product rotation. This approach is therefore a balance of internal and external validity and was also adopted by Beuckels and Hudders (2016) in testing the influence of product presentation on luxury fashion websites. While both research phases of this study did not inform participants about the actual stimuli (i.e. product presentation) being studied as this can lead to bias, this was particularly important for the eye tracking experiment. Awareness can influence eye movements and transform a bottom-up approach to a top-down approach instead (Wedel and Pieters, 2008). This helps to maintain internal validity.

Calder (1977) states validity is also a big issue for interviews in qualitative research. Due to the fact that qualitative research is viewed with the lens of social reality that is comprised of multiple realities, other researchers recommend alternative criteria that includes trustworthiness and authenticity (Guba and Lincoln, 1994). Since this study used a mixed methods approach, triangulation of the online survey with the eye tracking survey
with behavioural responses, such as purchase intentions, can be assessed. Essentially, the use of a mixed-methods approach can help the lack of validity as Calder (1977, p.363) summarises ‘validity can be best assessed with multiple methods’.

5.12 Research Design: Online Survey

Once the research philosophy and research methods were known, this helped to effectively decide what research design was ideal to implement before proceeding onto data collection. Based on the mixed-methods strategy outlined above with a two-phase approach, the online survey was conducted as part of the first research phase.

5.12.1 Survey Design

The survey was set up and designed using the website Surveygizmo.com (Appendix 1). When designing a well-structured survey, Easterby-Smith et al. (2015) state there are a number of principles and considerations for a good design that help to increase the quality of data collection. These are discussed in Table 5.7. Based on multi-dimensional measures, i.e. constructs, questions outlined in the online survey are otherwise referred to as scale statements or scale items (Pallant, 2013). It is essential to select the order of questions carefully as this may have an effect on completed responses (Marshall, 2005). A series of steps were taken to ensure high levels of retention rate and to ensure questions were read and answered with ease and clarity.
Table 5.7 Rationale of Survey Design Adopted

<table>
<thead>
<tr>
<th>Consideration</th>
<th>Chosen design</th>
<th>Rationale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Introduction text</td>
<td>Text was kept concise</td>
<td>To decrease cognitive load, thereby making it easier for the participants to answer. To also increase retention rate.</td>
</tr>
<tr>
<td>Order of questions</td>
<td>Demographic questions followed by actual survey questions. Behavioural questions were asked at the end.</td>
<td>It is also ideal to ask the factual questions before proceeding with attitudes and opinions. Known as “priming”, asking questions about whether they think product presentation is favourable beforehand may cloud the participants’ thinking.</td>
</tr>
<tr>
<td>Number of questions</td>
<td>A maximum of four scale statements per construct.</td>
<td>To keep the survey succinct and easy to answer, it was helpful to use fewer questions. Four scale statements per construct are also considered adequate for SEM analysis.</td>
</tr>
<tr>
<td>Grouping of questions</td>
<td>Questions were asked on separate pages as a set of matrix questions.</td>
<td>Questions of a similar topic should be grouped together.</td>
</tr>
<tr>
<td>Design</td>
<td>Questions should be aesthetically easy to read.</td>
<td>Questions should be presented simply in an understandable manner to avoid confusion.</td>
</tr>
<tr>
<td>Response arrangement</td>
<td>Vertical arrangement</td>
<td>This format is preferable to avoid mistakes. It is also easier to code afterwards.</td>
</tr>
<tr>
<td>Type of question</td>
<td>Closed questions</td>
<td>It is straightforward. Ease of drawing comparisons between answers. This format also allows the respondent to answer the question with ease and the likelihood of variability is lower.</td>
</tr>
<tr>
<td>Participation uptake level</td>
<td>Incentive provided</td>
<td>Compared to no incentives, an incentive helps to entice a higher number of respondents to complete the survey.</td>
</tr>
</tbody>
</table>

Adapted from: Easterby-Smith *et al.*, 2015; Pallant, 2013; Bryman and Bell, 2015; Steiger and Reips, 2010)

Demographics were asked at the beginning to enable filtering of participants who did not comply with the survey criteria. To do this, page conditions with skip logic were applied on questions such as consent, age, gender. As questions should follow an order of events (Easterby-Smith *et al.*, 2015), the first set of questions required the participant to answer questions about themselves as well as their fashion consumption and attitudes towards mobile shopping in general.

There was no need to design an aesthetically high-quality survey as Casey and Poropat (2014) reveal this is not an important aspect for individuals who are heavy internet users. Since the survey was aimed at young consumers who typically spend many hours online (Mintel, 2017; PwC, 2015), this was considered unnecessary, and so the survey design was kept simple. It is important to note there may be advantages to different approaches. For example, the use of abbreviations in a horizontal format can free up space particularly for
closed ended questions. However, a vertical arrangement was given priority as it was more important for the survey to be easy to read and understand (Bryman and Bell, 2015).

5.12.2 Stimuli

To test the influence of product presentation and the difference between low and high product presentation, a decision was made to test two retailers with different levels of product presentation for fashion apparel. A fashion retailer considered to have a high level of product presentation is ASOS (Ashman and Vazquez, 2012). As well as selling their own brand of apparel and accessories, ASOS sell a variety of other brands, such as Boohoo and Miss Selfridge. The opposing website selected that featured a lower level of product presentation was Amazon as they also sell the same fashion brands as ASOS, such as New Look, in addition to their own clothing brands. Essentially, both of these online retailers sell products with a similar selection of products and brands, i.e. high-street fashion apparel.

However, there are differences between ASOS and Amazon. Both websites differ in terms of design and other atmospheric variables. Since this study was based on a cross-sectional design, the aim was to establish relationships between constructs and not causality as there may be other influential elements. Previous shopping experience and exposure to website may also be an issue. However, these websites were chosen on the basis of ecological validity. For ASOS, the main emphasis is on fashion goods. However, they do sell beauty and other miscellaneous gifting products (Fletcher, 2018), while Amazon is a giant retailer that also sells other type of products, albeit with a bigger variety from books to fashion to electronics (Cronin, 2014). Both retailers are described as pure-play retailers (Jayawardhena and Wright, 2009; Ashman and Vazquez, 2012). Key differences concerning the level of product presentation between ASOS and Amazon are displayed in Table 5.8.
Table 5.8 Product Presentation Differences Between ASOS and Amazon

<table>
<thead>
<tr>
<th>Product Presentation</th>
<th>ASOS</th>
<th>Amazon Fashion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of product views</td>
<td>Four product views: front, back, close up and full model view</td>
<td>Two product views: front view and back view</td>
</tr>
<tr>
<td>Quality of images</td>
<td>Higher quality; clear to see</td>
<td>Lower quality images, detail not clear</td>
</tr>
<tr>
<td>Styling of model</td>
<td>High fashion pose</td>
<td>Basic pose</td>
</tr>
<tr>
<td>Product visualisation tools</td>
<td>Zoom function</td>
<td>Zoom function</td>
</tr>
<tr>
<td></td>
<td>Catwalk video</td>
<td></td>
</tr>
</tbody>
</table>

*Differences noted in April 2017

Since this survey was an online survey where consumers would be asked to shop on a mobile device, smartphones were selected instead of tablet devices as the device required to shop from. As reiterated in Chapter 2, these devices are considered personal devices are more likely to be commonplace. It is also important to note both ASOS and Amazon have an optimised mobile website and a mobile app. To increase the ease of the browsing activity, the product category selected was dresses. As displayed in Figure 5.9, the link to dresses was located at the top of women’s product category page and was therefore more likely to be noticeable.

Figure 5.9 Fashion Apparel Category Page
5.12.3 Online Survey Sample

The sample criterion considered for the online survey were females aged between 18-24 who have experience of shopping for fashion online. McDonald and Adam (2003) argue that a survey that is answered online differs demographically than a traditional postal survey. This is relevant, as the sample group for this survey are more inclined to answer a survey online. Since a student sample is often considered a limitation (Hooghe et al., 2010) and may not be representative of all females between the ages of 18-24, participants were also asked if they were a student. Online usage tends to be higher for this demographic cohort, particularly for mobile devices (PwC, 2015). Thus, it was necessary to ask demographic questions about the participants at the beginning of the survey to infer generalisations about the population group studied. Thus, the results can only be generalised to this particular demographic cohort.

As a survey is usually a quantitative method, a high number of responses is needed to obtain a representative sample (Bryman and Bell, 2015), so inferences can be drawn in terms of behavioural intent. Higher number is helpful if there are irregularities within the dataset, such as outliers (Pallant, 2013), as well as a low response rate (Fan and Yan, 2010). More detail on the suitability of the sample size selected for SEM is provided in sections 6.6.1.1. and 6.7.1.1.

5.12.4 Online Survey Procedure

For the online survey, sets of surveys were devised. Each survey was based on a different online fashion retailer (ASOS or Amazon) with the same set of questions and responses. A between-subject design was implemented to not only confirm relationships in the theoretical framework, but to also compare the relationships towards cognitive, emotional and behavioural outcomes. A between-subject approach is well established in product presentation literature (Fiore et al., 2005a; Fiore et al., 2005b; Park et al., 2005; Lee et al., 2006; Park et al., 2008; Yang and Wu, 2009; Lee et al., 2010; Song and Kim, 2012). In earlier research, Fiore and Jin (2003) used repeated measures and acknowledge this approach as a limitation; exposure to same stimuli twice can create bias.
The online surveys designed on SurveyGizmo.com were circulated by Critical Mix to their panel of survey members. Only participants who met the sample criteria were sent a link to the survey. Once selected, participants were asked to read information about the survey, which included information on the research aim, the browsing activity, participation, data confidentiality and who to contact for enquires. This page was followed by consent. If agreed, participants were directed to a series of screening questions on the next page about their age, gender, nationality and online shopping experience.

The following page included questions about their mobile shopping usage. Participants were then asked to browse for dresses on a specific fashion website (ASOS or Amazon) for more than 5 minutes using their smartphone device. In order to answer questions about product presentation, participants were also asked to view at least one dress in detail. This activity is task-dependent to ensure consumer responses reflect thoughts and attitudes towards how fashion images are displayed on a smartphone device as well as their overall shopping experience. As it was not possible to determine if participants did or did not do this at this stage of the survey, a checking question was asked following the shopping task page to ascertain if they had spent at least five minutes browsing before answering the following questions on perceptual fluency, cognitive effort, positive affect, aesthetic evaluation and purchase intentions. A final question about access was inquired at the end; whether the participant had accessed the survey via a mobile app or website.

5.12.5 Demographics and Scale Item Development

Demographic analysis helps to corroborate the suitability of the sample as well as an understanding of participants’ shopping behaviour and their mobile shopping usage. Many of the scale items for the online survey were adapted from recent journal papers that are relevant to the subject area. Table 5.9 shows each construct employed and the respective scale items.
### Table 5.9 Demographic Questions and Adapted Scale Items

<table>
<thead>
<tr>
<th>Type of Item</th>
<th>Item</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEMOGRAPHICS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.</td>
<td>Student number check</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Are you a student?</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Yes</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• No</td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>Frequency of shopping for fashion</td>
<td>Wang et al. (2011)</td>
</tr>
<tr>
<td></td>
<td>On average, how often do you shop for fashion clothing? (This includes shopping from a PC, laptop, smartphone, tablet and/or in-store shopping)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• At least once a day</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Several times a week</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Several times a month</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Several times a year</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Rarely</td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>Mobile shopping usage</td>
<td>Lee et al. (2010)</td>
</tr>
<tr>
<td></td>
<td>• I am familiar with mobile shopping.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• I frequently use mobile devices to shop from.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• I visit mobile websites/apps to gather product information.</td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>(7-point Likert scale)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CONSTRUCTS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>Perceptual Fluency</td>
<td>Pak et al. (2016)</td>
</tr>
<tr>
<td>8.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9.</td>
<td>(7-point S-D scale)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PF1: The product picture attracts my attention instantly</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PF2: The product picture stands out on the product page</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PF3: Information presented in the product picture is easy to view</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PF4: It is easy to identify information (such as quality and fit)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>from the product picture</td>
<td></td>
</tr>
<tr>
<td>10.</td>
<td>Cognitive Effort</td>
<td>Mosteller et al. (2014)</td>
</tr>
<tr>
<td>11.</td>
<td></td>
<td>*Hong et al. (2004)</td>
</tr>
<tr>
<td>12.</td>
<td>(7-point Likert scale)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• CE1: Looking at an individual product required time</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• CE2: Looking at an individual product required effort</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• CE3: Looking at an individual product was complex</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• CE4: Looking at an individual product was frustrating</td>
<td></td>
</tr>
<tr>
<td>15.</td>
<td></td>
<td>*Novak et al. (2000)</td>
</tr>
<tr>
<td>16.</td>
<td>(7-point S-D scale)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PA1: While visiting this website/app, I felt… happy-unhappy</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PA2: While visiting this website/app, I felt… pleased-annoyed</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PA3: While visiting this website/app, I felt… satisfied-unsatisfied</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PA4: While visiting this website/app, I felt… contented-melancholic</td>
<td></td>
</tr>
<tr>
<td>18.</td>
<td>Aesthetic Evaluation</td>
<td>Im et al. (2010)</td>
</tr>
<tr>
<td>20.</td>
<td>(7-point Likert scale)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• AE1: The product pages look attractive</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• AE2: The product pages look organised</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• AE3: There is proper use of graphics (i.e. product pictures)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• AE4: There is proper use of visualisation tools (examples include zoom or catwalk video)</td>
<td></td>
</tr>
<tr>
<td>22.</td>
<td>Purchase Intentions</td>
<td>Im and Ha (2011)</td>
</tr>
<tr>
<td>23.</td>
<td></td>
<td>*Dodds et al. (1991)</td>
</tr>
<tr>
<td>24.</td>
<td>(7-point Likert scale)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PI1: It is likely that I would purchase fashion clothing from this mobile website or app</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PI2: At the price shown, I would consider buying fashion clothing at this mobile website or app</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PI3: It is probable that I would consider buying fashion clothing from this mobile website or app</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• PI4: I am willing to buy fashion clothing from this mobile website or app</td>
<td></td>
</tr>
<tr>
<td>26.</td>
<td>Access to ASOS/Amazon</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>• Mobile app</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Mobile optimised website</td>
<td></td>
</tr>
</tbody>
</table>

*original source of scale item

Since there are a total of five constructs, the number of scale statements were kept to four scale items as a minimum of three scale items are recommended by Hair et al. (2014) for SEM and to also avoid the online survey becoming too long. It is important to note that the scale statements found in relevant journal papers are often not the original scale statements, so the journal paper indicated with an asterix displays the original source of the scale statements.
Likert scales are common in research and are used to assess attitudes towards a topic or phenomenon (Friborg et al., 2006). Semantic differential scales are defined as a ‘series of bipolar, seven-step scales defined by verbal opposites (e.g. good-bad, strong-weak, fast-slow, hot-cold, fair-unfair etc.)’ (Osgood, 1964, P.173). There are advantages and disadvantages to both types of scale items. In terms of psychological constructs, Friborg et al. (2006) find questions set up under semantic differential scales create less bias than Likert scales. While it is possible to reduce bias for Likert scales by introducing reverse statements, this can create errors. However, a disadvantage of the semantic differential scale is that greater cognitive effort is required to answer questions using this format (Friborg et al., 2006). In line with the original scale of the scale items and to minimise error from using either format only, a combination of Likert scales and semantic differential scales were employed.

### 5.12.6 Online Survey Pilot Test

A pilot test was designed on a website using Select Survey and tested on postgraduate fashion students studying International Fashion Retailing at The University of Manchester. This was appropriate given that many students fit the sample criterion: female, aged between 18-24 with online shopping experience. Before sending out the official survey, piloting is a crucial step in ensuring the reliability and reliability of the online survey (Pallant, 2013). This step also helped to refine the survey; the way the statements were phrased, and the order of questions were also re-drafted as a result of feedback during the piloting stage.
5.13 Research Design: Eye Tracking Study

The second phase adopted a mixed-method concurrent approach with quantitative and qualitative data collected at the same time. The following sections outline the research design of the following research phases. The aim of using eye tracking technology is to assess the influence of product presentation when shopping for fashion products. Most research on this topic area have used surveys to examine the influence of product. Visual attention research on this particular online stimulus has not been previously analysed.

5.13.1 Experimental Design

A basic experimental design is two levels with control verses experimental level (Field and Hole, 2003). To test the effects of low product presentation vs. the effects of high product presentation, participants were split into two treatment groups, whereby the product presentation was manipulated. When stimuli are manipulated in eye tracking experiments and the aim is to analyse the influence of the stimuli on eye movements, this approach is considered a bottom-up approach (Wedel and Pieters, 2008).

To test a high level of interactivity, the online fashion retailer ASOS was selected, while a mock website was created on Wix. Based on the eye tracking experimental design by Molina et al. (2014), experimental design for this study was adapted accordingly (Figure 5.10). In terms of image interactivity, ASOS offers visualisation tools such as zoom function for all products, catwalk video for clothing and shoes, and 360° product rotation for handbags. ASOS also uses a high level of product imagery that includes high quality images and several product views. A similar approach was implemented by Beuckels and Hudders (2016) who manipulated images from an existing luxury fashion website, i.e. Saks Fifth Avenue, to create a control website. Similarly, Huddleston et al. (2015) manipulated signage information so that the signs either displayed price information or product information in their study.
Figure 5.10 Eye Tracking Experimental Design Overview

As catwalk video and 360° product rotation were not available together on a particular product category, there were two browsing conditions for each group. The first condition is to browse for Women’s Tops. On ASOS, participants have the opportunity to use the zoom function and catwalk video when viewing product pages. Unlike product categories such as dresses, which already showcase the whole outfit in the front image, there are additional images of tops worn as a whole outfit with trousers, shorts or a skirt. To evaluate product presentation on information processing, Kim (2018) also used product images of tops. The second condition is to browse for Women’s Handbags. On ASOS, participants have the opportunity to use the zoom function and 360° product rotation.

Since there are many products and many different brands featured on ASOS, the product selection was refined by using one brand for Tops: Pimkie. When this study was conducted, ASOS offered 23 Pimkie tops. For consistency, a similar number of products were required for the handbags condition. Since there was a limited number of handbags
under this brand, products for the handbag condition included brands such as Pimkie, Glamorous and Marc B. For the control, a website was developed on Wix.com ([https://sobiakhan-6.wixsite.com/mysite](https://sobiakhan-6.wixsite.com/mysite)) using an e-commerce fashion template and was given the name Pretty Gal. While using a simulated website may lack ecological validity, it was essential to ensure that the product images on Pretty Gal were the same as ASOS to maintain experimental validity (Field and Hole, 2003). The website had two links to assortment pages at the top of the page: one for Tops and one for Handbags. Pages that were set up on Wix included a homepage, assortment pages for both tops and handbags (Figure 5.11), and individual product pages (Figure 5.12).

**Figure 5.11 Product Assortment Pages of Handbags**

For validity, images of the tops and handbags were downloaded and saved as well as the associated product information from ASOS. While the textual product information was kept exactly the same, images were manipulated for the product presentation condition. Using Paint, image quality and size were lowered from approximately 1006 x 1160 pixels to 700 x 807 pixels. Product views were also limited to front view and back view only on the product pages for the Pretty Gal website.
There is a problem of causality if measures are not tightly controlled, which explains the need for a controlled experimental design (Field and Hole, 2003). This study is a 2-factorial between-subject and within-subject design as there are two conditions in the experiment and two groups of participants. Multi-method approach involving eye tracking has been used in marketing (Cyr et al., 2010; Pieters et al., 2002). While there is greater sensitivity in a within-group design, there may be carry-over effects (Field and Hole, 2003). Since there are two groups and each participant are tested a second time, the type of design for this study is also a hybrid (‘mixed’) designs where ‘each participant is exposed to all of the conditions of the experiment’ (Field and Hole, 2003, p.70). To avoid systematic bias, it is important to randomise effects; participant randomisation to experimental conditions as well as the order of experimental conditions (Field and Hole, 2003). This was implemented using a tool on Randomizer.org (Research Randomizer, 2018).

5.13.2 Apparatus

The most common eye tracking method involves video-based pupil and corneal reflection. Video-based eye trackers capture eye movements in real-time respective to point of regard. There are further types of eye trackers that use video-based technology with infrared illumination (Holmqvist et al. 2011). These include a static eye tracker (also known as
remote system), head-mounted eye tracker (helmet, glasses for example) and a head eye tracker, which is used additionally to the head-mounted eye tracker 'in order to calculate the position of the head in space' (Holmqvist et al., 2011, p.51). The main differences between a static system and a head-mounted system are discussed in Table 5.10.

**Table 5.10 Summary of the Main Types of Video-Based Eye Trackers**

<table>
<thead>
<tr>
<th></th>
<th>Static Eye Tracker</th>
<th>Head-Mounted Eye Tracker</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Set-up</strong></td>
<td>Eye camera on table. Eyes are illuminated; stimuli is usually shown on a monitor device. Eye tracker can be built into a device or integrated (i.e. a portable eye tracker used on a laptop).</td>
<td>Eye-tracker may be in a helmet or a pair of glasses for example. The eyes are illuminated. There are cameras on the device as well as a scene camera, which captures a video of the live view.</td>
</tr>
<tr>
<td><strong>Sub-Types</strong></td>
<td>Tower-mounted systems with forehead/ chin rests</td>
<td>No sub-types but a head tracker can be used additionally to determine the location of the head in space</td>
</tr>
<tr>
<td><strong>Advantages</strong></td>
<td>Due to head restriction, data quality is higher than remote system</td>
<td>There are no restrictions. Devices are usually lightweight. Possible to observe real-life settings. Offers greater versatility than a static eye tracker. Easy calibration process.</td>
</tr>
<tr>
<td><strong>Disadvantages</strong></td>
<td>Participant’s head is restricted; more obtrusive</td>
<td>Limitation in lab-based conditions. It is difficult to have the same frame of reference. Aggregating the data can be time-consuming</td>
</tr>
</tbody>
</table>

Adapted from: Holmqvist et al. (2011) and He et al. (2014).

A static eye tracker that is integrated with a device stand to collect eye movements is the Tobii Mobile Device Stand (TMDS) (Figure 5.13). It involves both the infrared (illumination) and an eye camera up front and close to the participant. This particular apparatus has also been used by Molina et al. (2014) in a study to evaluate the effectiveness of mobile devices for learning. The apparatus is embedded with an eye tracker and provides a pad for a smartphone or tablet device. It is connected to a computer so that the researcher is able to see what the participant is paying attention to on the screen. The eye tracker itself in unobtrusive as there no need to wear anything on the head. In terms of a mobile eye tracker, this is a head-mounted eye tracker which requires the eye-tracking glasses to be connected to a portable recorder (Holmqvist et al., 2011; He et al., 2014) (Figure 5.13). Mobile eye trackers are particularly useful if an experiment requires an individual to move. An example of this is when doing an eye tracking study in a supermarket (Holmqvist et al., 2011; He et al., 2014).
Selection of eye tracker should match the needs of a study as each type of eye tracker has its advantages as well as its shortcomings (Holmqvist et al., 2011). Pre-testing was conducted with both types of eye trackers. Although the process of aggregating data is simpler using the TMDS, there was often a loss of data collection with slight head movements, and the eye movements needed to be re-calibrated. This was not an issue when using Tobii Glasses, which was also found to be easier to operate. In addition, asking participants to hold the iPad for the shopping activities is more natural than browsing on the iPad using a mobile device stand (He et al., 2014). Thus, the Tobii Pro Glasses 2 was selected in favour of the TMDS. Details involving the eye tracker and set-up are provided in Table 5.11.

<table>
<thead>
<tr>
<th>Consideration</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking method</td>
<td>Corneal reflection, dark pupil</td>
</tr>
<tr>
<td>Gaze Sampling rate</td>
<td>50 Hz or 100 Hz</td>
</tr>
<tr>
<td>Calibration</td>
<td>1 point for calibration procedure</td>
</tr>
<tr>
<td>Tablet with Analyzer software</td>
<td>Dell Windows 10</td>
</tr>
<tr>
<td>Tablet used by participants</td>
<td>iPad</td>
</tr>
<tr>
<td>Size of the iPad</td>
<td>9.50 × 7.31in</td>
</tr>
</tbody>
</table>

Source: Tobii Technology (2016a)

A natural setting is ideal in collecting data that is reflective of reality. Hence, this type of setting is more likely to have higher ecological validity (Field and Hole, 2003). Conducting the eye tracking in a quiet room with the Tobii Pro Glasses 2 helped to create more natural
conditions than using a TMDS, which requires a lab-based set up (Holmqvist et al., 2011). Since the online survey was based on responses towards smartphones, a tablet device was selected for the eye tracking study to understand the overall influence of product presentation on smartphone and tablet devices. During the pilot study, mapping fixations with either set-up on a smartphone device was also found to be more challenging. It is important to map fixations clearly and accurately as this can affect the overall data validity (Holmqvist et al., 2011). More information regarding the set-up is explored in the following sections.

5.13.3 Eye Tracking Study Sample

Like the online survey, the participant criterion for this study were 18-24-year-old females who have experience of shopping online. Literature confirms the use of a female sample for online shopping (Kim and Lennon, 2010; Kim, 2018). This also extends to eye tracking research with a female sample used to study the in-store fashion environment (Linström et al., 2016; Ho, 2014) as well as the online fashion environment (Cyr and Head, 2013; Menon et al., 2016).

Due to variations in sample size, there appears to be a lack of consensus on the appropriate sample size for eye tracking. A large sample size is advocated for eye tracking research. However, this depends on the experimental design. Specifically, if there is more than one group (Duchowski, 2007). The suitability of this sample size was based on similar research areas, such as marketing papers based on web design. For example, Djamasi et al (2011) divided participants into two groups, i.e. baby boomers and Gen Ys, with 22 participants in each group. In the study by Liu et al. (2016), 16 participants were employed to study online multimedia with a repeated measures design, while Pan et al. (2004) used 30 participants in their 2x2x2x4 design to study webpage viewing behaviour. In line with this, a sample size of 15 participants in each group was originally proposed. This would provide an overall sample size of 30 participants.

Using a purposive sampling approach, students from The University of Manchester were asked to take part. Specifically, this included students from the Design and Fashion Business department. The study was introduced at the beginning of lectures and posters
were placed in strategic areas such as the students’ common room in Sackville Street Building. With a higher level of awareness, this student group are more likely to shop for fashion (Auty and Elliot, 1998). If interested, students were encouraged to type the web address or click on the link to the Eventbrite page where they could find out more information and select a suitable date and time slot to take part in the study. Although many students signed up initially and selected a slot, there was a no-response from some participants, which impacted the overall sample size to 24 participants instead. Data was also excluded from one participant due to bad calibration. De Winter (2013) states it is possible to use a smaller sample for t-test analysis provided there is a large effect size.

Whilst factors such as mascara and contact lenses can affect eye tracking (Holmqvist et al., 2011), this did not seem to be an issue during the pilot test. In comparison to static eye trackers, head-mounted eye trackers provide the most versatility when using eye trackers on participants with conditions listed above. However, head-mounted eye trackers such as Tobii Glasses require an additional set of snap-on corrective lenses for participants who wear glasses. For this reason, Lindström et al. (2016) who used Tobii Glasses excluded participants who wore glasses in their study. Since the eye tracker did not contain a set of corrective lenses, participants who wore glasses were also excluded from this study.

5.13.4 Eye Tracking Study Procedure

As experimental conditions were required, a field study was not an option. Hence, the eye tracking experiment took place in a quiet room at Sackville Street Building, The University of Manchester, where the researcher was based. Once the participant arrived, they were given a brief with the eye tracking activity (participant information sheet). After reading the information and agreeing to take, participants were asked to sign the participant consent form.

Similar to Ho (2014), the aim of the research was kept broad in terms of the subject area: how website design influences the shopping experience on a tablet device. Prior to the experiment, each participant completed a short demographic survey to provide insights on their shopping behaviour and online usage. To avoid bias effects like Ozcelik (2010), participants were randomly assigned participants to either condition (high product
presentation website ASOS vs low product presentation Pretty Gal). Using the tool on Research Randomizer (2018), Participants were randomly assigned into one of two groups. Even numbers were assigned the non-interactive images condition while odd numbers were assigned the interactive images condition.

Subsequently, the Tobii Glasses 2 was placed on the participant’s head. For data quality purposes, a strap was also used to secure the eye tracker. Participants were informed there were two different product categories (tops and handbags) to browse from on the iPad i.e. there were two webpages set up on the Safari app of the iPad, as soon as the calibration was successful. The order of the conditions was also randomised. Participants were permitted to click on any of the products on the assortment page to go to the product page.

With the setup ready, eye movements were calibrated using the Controller software via the Dell tablet. This step was vital to ensure there were no focussing errors (Duchowski, 2007). Each video was captured and paused after 90 seconds of browsing. The process was then repeated with the other condition i.e. product category (tops or handbags) for the same amount of time. The recording was stopped after 90 seconds to avoid accumulation of too much data, which would require a significant amount of time to assign each fixation of the video to an image. In the study by Djamasbi et al (2010), participants were asked to look at different webpages for a minimum of 10 seconds. Ozcelik et al (2010) used a fixed total duration of 91s. Duchowski (2007) advises to keep the experiment short and simple as not only does data accumulate in an eye tracking study, it also permits frequent calibration during the experiment. Pilot studies also confirmed the suitability of the set-up and procedure for the actual data collection. The percentage of eye tracking data quality was also checked on the Controller software via the Dell tablet to ensure there was limited data loss throughout the experiment.

Following the eye tracking experiment, participants were asked to answer two questions based on perceptual fluency and purchase intentions on paper. This was followed by a short semi-structured interview about what they looked at when they shopped on either website (ASOS or Pretty Gal) on the iPad. Participants were asked to discuss their thoughts towards the use of or lack of product presentation as well as their general attitudes and perceptions towards these tools on mobile devices. A few notes were taken as a reminder if key words were mentioned, but this was limited as taking notes can be distracting (Bryman
and Bell, 2007). In line with Fusch and Ness (2015), interviews were conducted until there was enough data regarding product presentation on mobile devices and no more questions could be asked. After the interview, participants were thanked for their time and participation. Each participant was also given a £5 shopping voucher in exchange for their participation.

5.13.5 Eye Tracking Study Pilot Test

Holmqvist et al. (2011) advocate a mini explorative pilot study before collecting actual data for an eye tracking stage in order to gain familiarity with the set-up, data collection and data analysis. Hence, the pre-pilot stage was tested on friends and colleagues. Ho (2014) used 10 participants for pilot study. Chae et al (2013) used 11 participants for their pre-test that was based on a two factor within-subject design. For this reason, 12 participants for the pilot study was considered appropriate. Although it is a good idea to be aware, Holmqvist et al. (2011, p.65) state that it is not important to run statistical analysis during the explorative stage ‘since the goal of the pilot study is to generate testable hypotheses and not a p-value’. Nonetheless, it was ideal to conduct a small pilot study initially to understand what data is being collected and to increase familiarity with either type of eye tracker as well the technology itself. Thus, the pilot tested the website ASOS as well as a simulated website featuring the same products i.e. Wix website.

5.14 Chapter Summary

Overall, the research methodology undertaken in this study included a two-phase mixed methods strategy. Based on a cross-sectional design, the first phase involved an online survey to confirm relationships proposed in the theoretical framework. This was sequentially followed by the second phase, which adopted a concurrent experimental design in conducting an eye tracking experiment alongside a survey and an interview at the same time. A critical realist stance under an inductive approach was suitable in examining the underlying mechanisms of cognitive processing and visual attention towards product presentation, whilst also understanding the influence of this online stimuli from a contextual perspective, i.e. on mobile devices. Results and data analysis of each research phase are presented in the next two chapters.
Chapter Six: Online Survey Data Analysis and Results

6.1 Introduction

The subsequent sections outline the steps of the multivariate statistical analyses applied to both ASOS and Amazon quantitative datasets. The next steps included reliability testing for scale items, exploratory factor analysis and structural equational modelling. Not only were scale items assessed to determine the underlying factor structure and how well they represent the construct, structural relationships in the theoretical model were also tested. To validate the appropriateness of the sample from both datasets, analysis using descriptive statistics was also conducted.

6.2 Codebook Preparation and Data Screening

Firstly, the data from the online survey was exported as raw data in the form of an Excel spreadsheet. This spreadsheet was modified, and responses were coded numerically. For example, the 7-point Likert scale used with responses that ranged from strongly agree to strongly disagree were coded from 1-7. This spreadsheet was imported into SPSS version 23.

Initially, a total of 514 responses (ASOS: 255, Amazon: 259) were collected. Pallant (2013) advises inspecting the dataset for errors by examining scores that are out of range as well and removing or modifying the error. It is also important to locate missing responses as this affects SEM (Hair et al. 2014). Since participants completed the browsing task remotely, several formulas were inserted in the Excel workbook to detect missing responses, unengaged responses and responses that were completed in less than 5 minutes. As a result, 30 cases were removed from the ASOS dataset and 14 were removed from the Amazon dataset.
6.3 Sample Descriptive Analysis

As a result of data screening, there were 225 complete responses for the ASOS survey. For the Amazon survey, there were 244 complete responses. There were 469 combined responses across the two surveys. Table 6.1 provides a snapshot of the demographic data. The table reveals that at least 83% of the sample shop several times month whether this is online shopping from a desktop or a laptop, from a mobile device such as a smartphone or tablet or in-store shopping. Nearly 8% of respondents shop at least once a day.

<table>
<thead>
<tr>
<th>Questions</th>
<th>Responses</th>
<th>Frequency</th>
<th>Valid %</th>
<th>Cumulative %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student</td>
<td>No</td>
<td>232</td>
<td>49.5</td>
<td>49.5</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>237</td>
<td>50.5</td>
<td>100.0</td>
</tr>
<tr>
<td>Frequency of shopping for fashion</td>
<td>At least once a day</td>
<td>35</td>
<td>7.5</td>
<td>7.5</td>
</tr>
<tr>
<td></td>
<td>Several times a week</td>
<td>112</td>
<td>23.9</td>
<td>31.3</td>
</tr>
<tr>
<td></td>
<td>Several times a month</td>
<td>246</td>
<td>52.5</td>
<td>83.8</td>
</tr>
<tr>
<td></td>
<td>Several times a year</td>
<td>66</td>
<td>14.1</td>
<td>97.9</td>
</tr>
<tr>
<td></td>
<td>Rarely</td>
<td>10</td>
<td>2.1</td>
<td>100.0</td>
</tr>
<tr>
<td>MS1 I am familiar with mobile shopping</td>
<td>Strongly Agree</td>
<td>352</td>
<td>75.1</td>
<td>75.1</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>88</td>
<td>18.8</td>
<td>93.8</td>
</tr>
<tr>
<td></td>
<td>Somewhat Agree</td>
<td>19</td>
<td>4.1</td>
<td>97.9</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>7</td>
<td>1.5</td>
<td>99.4</td>
</tr>
<tr>
<td></td>
<td>Somewhat Disagree</td>
<td>2</td>
<td>0.4</td>
<td>99.8</td>
</tr>
<tr>
<td></td>
<td>Disagree</td>
<td>1</td>
<td>0.2</td>
<td>100.0</td>
</tr>
<tr>
<td>MS2 I frequently use mobile devices to shop from</td>
<td>Strongly Agree</td>
<td>287</td>
<td>61.2</td>
<td>61.2</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>110</td>
<td>23.5</td>
<td>84.6</td>
</tr>
<tr>
<td></td>
<td>Somewhat Agree</td>
<td>42</td>
<td>9.0</td>
<td>93.6</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>14</td>
<td>3.0</td>
<td>96.6</td>
</tr>
<tr>
<td></td>
<td>Somewhat Disagree</td>
<td>10</td>
<td>2.1</td>
<td>98.7</td>
</tr>
<tr>
<td></td>
<td>Disagree</td>
<td>4</td>
<td>0.9</td>
<td>99.6</td>
</tr>
<tr>
<td></td>
<td>Strongly Disagree</td>
<td>2</td>
<td>0.4</td>
<td>100.0</td>
</tr>
<tr>
<td>MS3 I visit mobile websites/app to gather product information</td>
<td>Strongly Agree</td>
<td>225</td>
<td>48.0</td>
<td>48.0</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>152</td>
<td>32.4</td>
<td>80.4</td>
</tr>
<tr>
<td></td>
<td>Somewhat Agree</td>
<td>59</td>
<td>12.6</td>
<td>93.0</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>23</td>
<td>4.9</td>
<td>97.9</td>
</tr>
<tr>
<td></td>
<td>Somewhat Disagree</td>
<td>7</td>
<td>1.5</td>
<td>99.4</td>
</tr>
<tr>
<td></td>
<td>Disagree</td>
<td>3</td>
<td>0.6</td>
<td>100.0</td>
</tr>
<tr>
<td>Access to Retailer</td>
<td>App</td>
<td>150</td>
<td>32.0</td>
<td>32.0</td>
</tr>
<tr>
<td></td>
<td>Mobile optimised website</td>
<td>319</td>
<td>68.0</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Majority of the sample is familiar with mobile shopping with more than 97% agreeing with this statement on some level. 75% strongly agree with this statement, which indicates mobile shopping habits are habitual to this sample. 93% agree on some level that they frequently use mobile shopping. 93% also agree on some level with the MS3 question i.e. they visit mobile website/apps to gather product information. This information indicates that mobile shopping is not a new phenomenon to the respondents in this survey and that their devices are used at the browsing stage. In terms of access for the browsing activity,
more than two-thirds (68%) used the mobile optimised website, while 32% accessed ASOS or Amazon using the retailer’s app downloaded on their smartphone. 50.5% of respondents in the sample are students, while 49.5% are not.

### 6.4 Demographic Sample Validity

Overall, this analysis confirms the suitability of this sample in answering the survey as well as the suitability of the sample criterion i.e. females between the ages of 18-24 who have experience of shopping online. Respondents shop for fashion products frequently and display habitual shopping habits towards mobile shopping. The analysis also shows they shop on mobile devices regularly. Comparing the demographic information and shopping habits with a sample of older respondents would help to validate the sample further. Since there is an equal number of student and non-student responses, the sample is reflective of the consumers between the ages of 18-24 as a student sample is often considered a limitation (Hooghe et al., 2010) and may result in coverage error as a sample that is unrepresentative of 18-24-year-old females (Gideon, 2012). The total sample size (469 responses) is a similar size to other sample sizes in product presentation research whereby surveys were also used to collect data (Fiore et al., 2005b; Park et al., 2005; Lee et al., 2006; Park et al., 2008; Yang and Wu, 2009).

### 6.5 Reliability Statistics for Scale Items

Table 6.2 displays the reliability values for the constructs via the scale items. All constructs display good reliabilities with Cronbach’s Alpha values above the 0.7 minimum across ASOS and Amazon surveys. Although values above 0.7 are acceptable, values above 0.8 are preferred (Pallant, 2013).

<table>
<thead>
<tr>
<th>Construct</th>
<th>Number of Items</th>
<th>Cronbach’s Alpha for ASOS</th>
<th>Cronbach’s Alpha for Amazon</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceptual fluency (PF)</td>
<td>4</td>
<td>0.771</td>
<td>0.751</td>
</tr>
<tr>
<td>Cognitive effort (CE)</td>
<td>4</td>
<td>0.795</td>
<td>0.759</td>
</tr>
<tr>
<td>Positive affect (PA)</td>
<td>4</td>
<td>0.917</td>
<td>0.917</td>
</tr>
<tr>
<td>Aesthetic Evaluation (AE)</td>
<td>4</td>
<td>0.810</td>
<td>0.763</td>
</tr>
<tr>
<td>Purchase intentions (PI)</td>
<td>4</td>
<td>0.892</td>
<td>0.919</td>
</tr>
<tr>
<td>All constructs</td>
<td>20</td>
<td>0.802</td>
<td>0.847</td>
</tr>
</tbody>
</table>
Majority of the values are above 0.8, except for aesthetic evaluation for Amazon as well as perceptual fluency and cognitive effort across both surveys. To interpret the data further, the Inter-Item Correlation Matrix for each construct was evaluated for any negative values. No negative values were found, suggesting variables for each construct account for the same characteristics. Since these items were taken from an established scale, Pallant (2013) advises against deleting items to make results comparable to other studies using the same scale.

6.6 Data Analysis and Results for ASOS

Since the surveys were based on different websites, there may be differences in the way participants answered either survey. Hence, there may be differences in the underlying structure (Schumacker and Lomax, 2016). For this reason, both ASOS and Amazon datasets were treated separately. Data analysis based on ASOS is evaluated and explained in the following sections.

6.6.1 Exploratory Factor Analysis

An EFA was conducted on the 20 items used in the online surveys that are made up of five different scales (i.e. perceptual fluency, aesthetic evaluation, cognitive effort, positive affect and purchase intentions) using SPSS version 23.

6.6.1.1 Suitability Criterion for EFA

To establish the suitability criterion of a sample for EFA involves evaluating the sample size. Although a high sample size is ideal (Pallant, 2013), there are inconsistencies in sample size recommendations. Shumacker and Lomax (2016) refer to Costello and Osborne (2005) who recommend 20 cases per variable. Nunnally (1978) recommend 10 cases per variable. Whereas, Hair et al. (2014) and Tabachnick and Fidell (2013) suggest a minimum of 5 cases per variable.
Since there were 20 variables in the survey (from perceptual fluency to purchase intentions), there should be a minimum of 100 cases based on the criterion from Tabachnick and Fidell (2013), or a minimum of 200 cases based on the recommendation from Nunnally (1978). With a sample size of 225 cases for ASOS, this sample size is considered satisfactory for EFA based on both recommendations. Pallant (2013) states an evaluation of how strongly the items inter-correlate should also be evaluated. There are two statistical measures: the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett’s test of sphericity. The initial values extracted are shown in Table 6.3.

<table>
<thead>
<tr>
<th>KMO Measure of Sampling Adequacy</th>
<th>0.872</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bartlett’s Test of Sphericity</td>
<td></td>
</tr>
<tr>
<td>Approx. Chi-Square</td>
<td>2684.837</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>190</td>
</tr>
<tr>
<td>Significance</td>
<td>.000</td>
</tr>
</tbody>
</table>

Tabachnick and Fidell (2013) states the KMO value should be greater than 0.5, and that the Bartlett’s test of significance should have a p value less than 0.05. The figures above show this is met with an extracted KMO value of 0.872 and a significance of 0.000. Linearity is also important to ensure that correlations between the variable are linear (Tabachnick and Fidell, 2013). As this can be difficult to assess, Pallant (2013) states that linearity can be assumed if the sample size meets the requirements and there are enough cases to variables. Overall, all measures of the suitability criterion confirm EFA is an appropriate statistical technique to apply to the ASOS dataset.

### 6.6.1.2 Factor Extraction

EFA was conducted using maximum likelihood extraction method since this method is the favoured estimation method for SEM (Blunch, 2008), which was applied to the dataset after EFA. According to Field (2013), this factor extraction method is the most appropriate, given that results were to be generalised to the wider population of the sample criterion. A total of 4 factors were extracted with eigenvalues greater than 1 and a cumulative shared variance of 58.343% (Table 6.4). The first factor extracted 32.534% of the variance, which is lower than the 40% guideline as stated by Blunch (2008). This implies that the scale is not one-dimensional and that variables are not measuring the same
According to theory and the observed variables used, there are 5 latent variables. Therefore, 5 factors were expected to be extracted.

**Table 6.4 Initial Total Variance Explained: ASOS**

<table>
<thead>
<tr>
<th>Factor</th>
<th>Initial Eigenvalues</th>
<th>Extraction Sums of Squared Loadings</th>
<th>Rotation Sums of Squared Loadings*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>% of Variance</td>
<td>Cumulative %</td>
</tr>
<tr>
<td>1</td>
<td>7.416</td>
<td>37.078</td>
<td>37.078</td>
</tr>
<tr>
<td>2</td>
<td>2.271</td>
<td>11.356</td>
<td>48.434</td>
</tr>
<tr>
<td>4</td>
<td>1.532</td>
<td>7.658</td>
<td>65.847</td>
</tr>
<tr>
<td>5</td>
<td>0.973</td>
<td>4.863</td>
<td>70.711</td>
</tr>
<tr>
<td>6</td>
<td>0.905</td>
<td>4.535</td>
<td>75.335</td>
</tr>
<tr>
<td>7</td>
<td>0.691</td>
<td>3.403</td>
<td>78.689</td>
</tr>
<tr>
<td>8</td>
<td>0.587</td>
<td>2.937</td>
<td>89.625</td>
</tr>
<tr>
<td>9</td>
<td>0.496</td>
<td>2.476</td>
<td>84.602</td>
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<tr>
<td>10</td>
<td>0.461</td>
<td>2.305</td>
<td>86.907</td>
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<td>11</td>
<td>0.421</td>
<td>2.100</td>
<td>89.513</td>
</tr>
<tr>
<td>12</td>
<td>0.399</td>
<td>1.944</td>
<td>90.457</td>
</tr>
<tr>
<td>13</td>
<td>0.349</td>
<td>1.732</td>
<td>92.189</td>
</tr>
<tr>
<td>14</td>
<td>0.303</td>
<td>1.513</td>
<td>93.702</td>
</tr>
<tr>
<td>15</td>
<td>0.244</td>
<td>1.411</td>
<td>95.173</td>
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<tr>
<td>16</td>
<td>0.267</td>
<td>1.334</td>
<td>96.507</td>
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<td>17</td>
<td>0.217</td>
<td>1.083</td>
<td>97.590</td>
</tr>
<tr>
<td>18</td>
<td>0.210</td>
<td>1.064</td>
<td>98.654</td>
</tr>
<tr>
<td>19</td>
<td>0.179</td>
<td>0.905</td>
<td>99.549</td>
</tr>
</tbody>
</table>

*Extraction Method: Maximum Likelihood.

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

Factor 1 also appears to have the most variance with 32.534%, while factors 2, 3 and 4 have variance values of 10.091%, 9.167% and 6.551% respectively. With a significant majority, factor 1 accounts for the most variance overall. Another way to represent factor extraction is to use Catell’s scree plot (Figure 6.1). This is useful in determining the number of factors extracted by examining the ‘factors above the elbow, or break in the plot’ (Pallant, 2013, p.191).

**Figure 6.1 Initial Scree Plot: ASOS**
As shown in Table 6.5, the scree plot in Figure 6.1 confirms only 4 factors were extracted as there is a break in the plot with factor 4. Since the first extraction % is lower than 40%, Blunch (2012) advises using Principal Component Analysis (PCA) instead of Factor Analysis (FA). Initially, both techniques were applied to the dataset and revealed similar results. However, on balance, using FA was preferred because the measurement model in FA is more in line with the measurement model used in CFA (Gaskin, 2016), which is the next stage of data analysis. FA is also preferred over PCA if the goal is to examine correlations in a dataset with the use of factors (Blunch, 2012).

6.6.1.3 Factor Rotation

Factor rotation plays an important part in interpreting the correlation matrix and the reproduced correlation matrix (Tabachnick and Fidell, 2013). Unlike orthogonal rotation, oblique rotations are selected if the factors are correlated with each other (Tabachnick and Fidell, 2013). Pallant (2013, p.192) advises to start with Oblique rotation to ‘check the degree of correlation between your factors’ as well as comparing data with orthogonal rotation. Both factor rotations were compared with the ASOS data; the Orthogonal rotation led to a messier pattern matrix. Oblique rotation is also recommended if factors are highly correlated, i.e. greater than 0.3 (Pallant, 2013). The final factor correlation matrix confirmed the use of oblique rotation. Within this type of factor rotation, there are different types of rotational techniques: direct oblimin and promax (Field, 2013). According to Pallant (2013) direct oblimin is the most commonly used and was therefore selected.

6.6.1.4 Factor Loadings

Factor loadings of the rotated solution i.e. the pattern matrix, are presented in Table 6.5. In terms of significant factor loadings, values should be 0.5 or higher. Values between 0.3 and 0.4 are considered the minimum to allow interpretation of loadings (Hair et al. 2014). Tabachnick and Fidell (2013) state that variables with loadings of 0.32 and higher should only be interpreted. Based on the guidelines provided by Hair et al. (2014), factor loadings should exceed 0.4 to be significant if the sample size is between 200 and 250. All factor loadings shown below meets this guideline. While PA has large loadings with similar values, PI and CE have marker variables, i.e. PI4, PI3 and CE2, which have the largest
loadings and account for the most correlation in the factor (Tabachnick and Fidell, 2013). It is a relatively simple pattern matrix except there is one main issue. Variables associated with a particular construct load on their respective factor except for variables on factor 4. Specifically, there is a multicollinearity issue with PF variables and AE variables loading on the same factor. Further modifications were therefore required.

Table 6.5 Initial Pattern Matrix: ASOS

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Factor 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>PA1</td>
<td>.841</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA2</td>
<td>.816</td>
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<td></td>
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<tr>
<td>PA3</td>
<td>.897</td>
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<td></td>
</tr>
<tr>
<td>PH4</td>
<td></td>
<td>- .926</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PH3</td>
<td></td>
<td>- .916</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PH2</td>
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<td></td>
</tr>
<tr>
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<td>- .038</td>
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</tr>
<tr>
<td>CE2</td>
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<tr>
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</tr>
<tr>
<td>PF4</td>
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</tr>
</tbody>
</table>

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
* Rotation converged in 7 iterations.

This issue is also confirmed by examining the communalities. This determines how much shared variance a variable has. Variables with a communality lower than 0.3 indicates that these variables do not share enough variance. In other words, these variables do not relate well with the other variables in the same construct and may be candidates for deletion (Field, 2013; Pallant, 2013). In the communalities table (Appendix 3), all the variables were above the threshold of 0.3 except for PF4, which has a communality value of 0.272.

6.6.1.5 EFA Modifications

The pattern matrix and the communality values confirmed PF4 should be removed. Upon removal, the KMO value decreased from 0.872 to 0.869, but remained higher than the threshold value of 0.5. Communalities were inspected again, and all variables values exceeded 0.3. A pattern matrix is displayed in Figure 6.6. Again, 4 factors were extracted.
with 59.930% shared variance. After the removal of PF4, the same issue persisted with aesthetic evaluation and perceptual fluency variables loading on the same factor.

Table 6.6 Modified Pattern Matrix (1): ASOS

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Factor 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>PA1</td>
<td>.862</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA2</td>
<td>.827</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA3</td>
<td>.817</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA4</td>
<td>.805</td>
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</tr>
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</tr>
<tr>
<td>PF3</td>
<td></td>
<td></td>
<td>.449</td>
<td></td>
</tr>
</tbody>
</table>


*Rotation converged in 7 iterations.

In such cases, Pallant (2013) advises loading the variables on a different number of factors. To identify which variable may be causing an issue, only perceptual fluency and aesthetic evaluation variables were subjected to EFA with a deliberate extraction of 2 factors instead of the default setting of extracting factors with an eigenvalue more than 1 (Table 6.7). For this reason, PF4 was included back into factor analysis.

Table 6.7 Pattern Matrix with AE and PF Variables Extracted (1): ASOS

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>PF1</td>
<td>.510</td>
<td></td>
</tr>
<tr>
<td>PF2</td>
<td>.842</td>
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</tr>
<tr>
<td>PF3</td>
<td>.433</td>
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</tr>
<tr>
<td>AE1</td>
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<td>.385</td>
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<td>PF4</td>
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</tr>
<tr>
<td>AE3</td>
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<tr>
<td>AE2</td>
<td>.679</td>
<td></td>
</tr>
<tr>
<td>AE4</td>
<td>.647</td>
<td></td>
</tr>
</tbody>
</table>


*Rotation converged in 10 iterations.
Table 6.7 shows perceptual fluency and aesthetic evaluation do load on separate factors except for AE1 cross-loading on both factors. As expected, PF4 has a low loading (i.e. below 0.4). Therefore, a decision was made to remove both AE1 and PF4. A new pattern matrix is presented in Table 6.8.

Table 6.8 Pattern Matrix with AE and PF Variables Extracted (2): ASOS

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>AE3</td>
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</tr>
<tr>
<td>AE4</td>
<td>0.620</td>
<td></td>
</tr>
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<td>0.619</td>
<td></td>
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</tr>
<tr>
<td>PF1</td>
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<td>0.844</td>
</tr>
<tr>
<td>PF3</td>
<td></td>
<td>0.431</td>
</tr>
</tbody>
</table>

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

Table 6.8 shows a clean pattern matrix with perceptual fluency and aesthetic evaluation variables loading on separate factors. The correlation coefficient between the two factors is high at 0.6 (Table 6.9), which implies there is a lot of shared variance between perceptual fluency and aesthetic evaluation (Field, 2013).

Table 6.9 Factor Correlation Matrix between PF and AE variables: ASOS

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.000</td>
<td>0.648</td>
</tr>
<tr>
<td>2</td>
<td>0.648</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

The factor correlation matrix (Table 6.9) also confirmed the use of using Oblique rotation as the correlation between AE and PF exceeded 0.3. Although AE and PF variables have factor loadings on separate factors when two factors are deliberately extracted, the results from the factor correlation matrix indicate that these variables still may not separate as two factors when plugged into the original EFA. Therefore, the results in Table 6.10 were as expected.
Table 6.10 Modified Pattern Matrix (2): ASOS

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>PA1</td>
<td>.859</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA2</td>
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<tr>
<td>PF3</td>
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<td>.458</td>
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<td></td>
</tr>
</tbody>
</table>

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

Even with the removal of AE1 and PF4, both AE and PF still load on the same factor. All variables have factor loading values higher than 0.4. This table and the factor correlation matrix table confirm there is a high shared variance. It was not possible to separate these 2 latent variables in the original EFA unless the variables of either construct are removed. Since perceptual fluency is the only dependent variable in the theoretical framework it was considered detrimental to retain in this analysis. For this reason, the remaining aesthetic evaluation variables were removed from the EFA analyses. The modified pattern is displayed in Table 6.11.
Table 6.1 Final Pattern Matrix: ASOS

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Factor 4</th>
</tr>
</thead>
<tbody>
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<td>PA4</td>
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<td></td>
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</tr>
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</tr>
<tr>
<td>PF3</td>
<td></td>
<td></td>
<td>.457</td>
<td></td>
</tr>
</tbody>
</table>

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

Table 6.11 shows a clean pattern matrix with no cross-loadings. All loadings are above the threshold of 0.4. Factor loadings are questionable if there is only one loading or two loadings that have an average value less than 0.7 (Tabachnick and Fidell, 2013). Since each factor has at least three variables that load only on that factor and the factor loadings are significant, the factor is therefore reliable.

6.6.1.6 EFA Summary

The final factor structure illustrated in the pattern matrix confirms there is overall construct validity with the variables correlating on the relevant factor. The findings support the application of positive affect variables, cognitive effort variables and purchase intentions variables as distinguished scales. However, perceptual fluency variables and aesthetic evaluation variables are not recognised as separate scales by EFA, which suggests there is high shared variance between the two sets of variables. Removing aesthetic evaluation from the analysis produced a clean pattern matrix. While these EFA variables may be used in CFA, Schumacker and Lomax (2016) warn against using the results from EFA and feeding only these variables into CFA and SEM overall. According to Blunch (2012), EFA does not determine the actual structure within the dataset and that CFA is required to determine the overall structure between factors and variables.
6.6.2 Confirmatory Factor Analysis

CFA was applied to the original 20 variables adopted in the online survey to test the measurement model with the ASOS dataset using AMOS version 22. Unlike EFA, the researcher specifies which variables go together in respect to the latent variable or factor (Byrne, 2010). The following sections outline the steps taken in CFA in determining the final measurement model before conducting SEM to establish the structural model, which is otherwise known as the causal model. Theoretical underpinning with the use of hypotheses is explained in Chapter 4.

6.6.2.1 Conceptual Model Development in CFA

Using steps outlined by Hair et al. (2014), CFA was conducted. Since constructs have already been defined prior to EFA using established scales from literature, the first step in CFA was to develop the measurement model. There are different approaches to test the conceptual measurement model. Once developed, this model should be examined for how much common variance each of the variables share and which of the variables account for most of the latent variable (Schumacker and Lomax, 2016). Using AMOS, the measurement model was drawn on the graphical interface using ellipses and arrows. These arrows are used to denote the structural regression coefficients and illustrates the influence of a variable (Hair et al., 2014). There is also an error term associated with each observed variable, which were numbered 1 to 20. These error terms are uncorrelated to each other (Byrne, 2010). The double headed arrows represent the covariances between the factors. It is important to specify the measurement model to assess if the sample data fits with the hypothesised model (Byrne, 2010).

6.6.2.2 Model Specification

Unlike EFA, specifying the measurement model is possible during CFA, whereby an observed variable should only load on one factor (Byrne, 2010). This ensures there is unidimensionality whereby a group of variables only account for one underlying construct (Hair et al. 2014). Hence, it is only these relationships that are estimated. Freeing other paths between a variable and another construct impacts construct validity (Hair et al.
As there were four observed variables per factor, the measurement model meets the three-indicator rule of a minimum of 3 variables per factor (Hair et al., 2014). There are 160 degrees of freedom. Therefore, the order condition to ensure positive degrees of freedom is satisfied.

Based on the scales and hypotheses, the measurement model is a first-order CFA model. It is a five-factor structure. Each of the five factors were abbreviated and had four observed variables each i.e. there were a total of 20 observed variables. A chi-square statistical test and a reasonable model that is valid is required to confirm or reject the conceptual model.

### 6.6.2.3 Model Identification

For model estimation to take place, a model must be identified. The number of data points and parameters should be calculated. Model identification occurs when the parameters of the hypothesised model are consistent with the data (Byrne, 2010). This demonstrates there is adequate information that satisfies structural equations when calculating the covariance matrix (Hair et al., 2014). Information about the model and its identification was obtained from the text output on AMOS.

There are 210 distinct sample moments in total. This includes 50 distinct parameters to be calculated. Degrees of freedom can be calculated by subtracting distinct parameters from the distinct sample moments: 210 – 50 = 160. According to AMOS, a minimum was achieved. Models can be identified on three levels: underidentified, just-identified and overidentified (Hair et al. 2014). An overidentified model, where there are more parameters to be estimated than the variances and covariances, is considered ideal in SEM (Byrne, 2010). It is possible to estimate the number of unique variances with the equation: \( \frac{1}{2} \left[ p(p + 1) \right] \), with \( p \) as the number of observed variables (Hair et al. 2014). In this case, \( p \) is 20. Based on the equation, this confirmed there were 210 unique variances and covariances, which is the same as the number of distinct sample moments calculated by AMOS. With the addition of 20 error variances and 9 covariances to the 20 observed variables, there were a total of 49 parameters to be estimated. Since there are more unique variances and covariances (210) than parameters to be estimated (49), the model meets the identification objective as an overidentified model and so fit values can be calculated.
6.6.2.4 Model Estimation

Once the model is identified, the measurement model is estimated. This stage requires evaluation of the parameter estimates i.e. factor loadings, standard errors and whether the parameter estimates in the model are statistically significant (Byrne, 2010). To establish construct validity of the measurement model, it is important to evaluate path estimates between the observed variables and the factors (Hair et al., 2014). Two outputs were produced on AMOS: one of them included path estimate values on the measurement model (Figure 6.2). The other was a textual output. Hair et al. (2014) state that while standardised values of 0.7 or higher are significant, values of 0.5 and above are the required minimum. Low values indicate the observed variable is not reflecting the scale and may need to be removed (Hair et al. 2014).

Figure 6.2 Initial Measurement Model Estimated: ASOS
In Figure 6.3, majority of the loadings have high values above 0.7. This was found to be true for all variables except for the variables PF3, PF4, CE1, CE4 and AE4, which have loadings of 0.59, 0.50, 0.6, 0.68 and 0.58 respectively. However, all variables exceed the minimum threshold of 0.5. The value for PF4 is particularly borderline and therefore may be an issue later. In a similar fashion to standardised estimates that exceed 1.0, covariance estimates between factors that exceed 1.0 are also an issue (Hair et al. 2014). Although there are no covariance estimates that exceed this threshold, perceptual fluency and aesthetic evaluation share a high covariance of 0.76. In addition to the EFA results, this confirms high shared variance between these two constructs in CFA.

A chi-square test is useful in determining if there are similarities between the sample variance-covariance matrix and the variance-covariance matrix obtained from the theoretical framework (Schumacker and Lomax, 2016). If both matrices are similar this would produce a non-significant chi-square value. The chi-square value obtained is 384.85 with 160 degrees of freedom. However, the chi-square value is sensitive to the sample size. A chi-square can become inflated in a large dataset which is not ideal (Byrne, 2013). The $p$-value for the measurement model is 0.000, which is below the required minimum of 0.05. This indicates that the sample data does not adequately fit the hypothesised model (Byrne, 2010). According to Hair et al. (2014, p.630), this $p$-value is ‘significant using a type 1 error rate’. Nevertheless, Byrne (2010) states that it is impractical to have a good fit between the sample data and hypothesised model based on the chi-square relating to the degrees of freedom as well as issues with testing statistical significance. As well as an insignificant chi-square value, Tabachnick and Fidell (2013) propose the value of the normed chi-square should be less than 2. For this measurement model, the threshold is above 2 at 2.405. Due to these issues, other fit indices are required to assess the goodness of fit of the sample covariance matrix (Hair et al. 2014).

### 6.6.2.5 Model Fit Assessment

The last step of CFA is to assess the model validity. This is important to assess how well the observed data fits with the theory. Model fit is pertinent to this because it compares the covariance matrix of the observed data with the estimated population covariance matrix with the hypothesised paths. However, the rules surrounding which fit indices are
appropriate is often debated (Tabachnick and Fidell, 2013). Model fit values for the initial CFA is provided in Table 6.12.

**Table 6.12 Model Fit of the Initial Measurement Model: ASOS**

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Initial Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>384.85, $p = 0.000$</td>
<td>Small $\chi^2$ and $p &gt; 0.05$ (Hair <em>et al.</em>, 2014)</td>
</tr>
<tr>
<td>Normed Chi-Square ($\chi^2$/df)</td>
<td>2.405</td>
<td>$&lt; 2$ (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>GFI</td>
<td>0.809</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&gt; 0.95 (Hoelter, 1983)</td>
</tr>
<tr>
<td>NFI</td>
<td>0.861</td>
<td>Value close to 1 (Hair <em>et al.</em>, 2014)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&gt; 0.95 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.913</td>
<td>&gt; 0.95 (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.079</td>
<td>$\leq 0.06$ (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$&lt; 0.10$ (Browne and Cudeck, 1993)</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>0.000</td>
<td>$&gt; 0.05$ (Jöreskog and Sörbom, 1996a)</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.809</td>
<td>Value close to 1 (Jöreskog and Sörbom, 1993)</td>
</tr>
<tr>
<td>PGFI</td>
<td>0.651</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.0771</td>
<td>$&lt; 0.10$ (Hair <em>et al.</em>, 2014)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$&lt; 0.05$ (Schumacker and Lomax, 2016)</td>
</tr>
</tbody>
</table>

There are different types of fit indices: absolute fit indices, comparative fit indices, parsimony fit indices and residual-based indices (Tabachnick and Fidell, 2013). Absolute fit indices include the $\chi^2$ statistic, which has been discussed previously, and the Goodness-of-fit Fit Index (GFI). Comparative fit indices include the Normed Fit Index (NFI), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and the Closeness of Fit (PCLOSE). Parsimony fit indices include the Adjusted Goodness-of-Fit Index (AGFI) and the Parsimonious Goodness-of-Fit Index (PGFI). Residual-based indices include Root Mean Square Residual (RMR) and the Standardised Root Mean Residual (SRMR). The following sections analyse the indices in more detail.

**6.6.2.6 Goodness-of-fit Fit Index (GFI)**

It is possible to calculate two types of fit indexes based on a weighted amount of variance in the dataset explained by the estimated sample covariance matrix (Bentler, 1983). This includes the goodness-of-fit index (GFI) and the adjusted goodness-of-fit index (AGFI). The GFI measure was developed to overcome the issues of sample size with the $\chi^2$ statistic (Hair *et al.*, 2014). Values close to 1 indicate a good fit. Some argue that the threshold should be values above 0.9, while others state values should exceed 0.95 (Hoelter, 1983). Since there are other developed fit indices, this measure has been used less often (Hair *et al.*, 2014).
6.6.2.7 Normed Fit Index (NFI)

Bentler-Bonett (1980) developed the NFI to compare the chi-square value of the observed model to the chi-square value of the independent model. It can be calculated using the following equation:

\[ \text{NFI} = \frac{\chi^2_{\text{indep}} - \chi^2_{\text{model}}}{\chi^2_{\text{indep}}} \]  

(Tabachnick and Fidell, 2013).

Values are within 0 to 1. A high NFI reflects a good model fit with values above 0.95 (Tabachnick and Fidell, 2013). However, this value may be under-estimated if the sample is small. Due to adjustments made to NFI, Non-Normed Fit Index was introduced. However, there is an issue with large variability (Tabachnick and Fidell, 2013).

6.6.2.8 Comparative Fit Index (CFI)

Another comparative fit index is the Comparative Fit Index (CFI) (Bentler, 1988) which ‘employs a noncentral \(\chi^2\) distribution with noncentrality parameters \(\tau_i\)’ (Tabachnick and Fidell, 2013, p.772). A \(\tau_i\) value close to 0 implies good model fit.

\[
\text{CFI calculation: } \text{CFI} = 1 - \frac{\chi^2_{\text{indep}}}{\chi^2_{\text{model}}} 
\]

Therefore, a low noncentral parameter \(\tau_i\) is ideal to yield a high CFI value. CFI values that are greater than 0.95 represent a good model fit (Hu and Bentler, 1999). It is also possible to attain good CFI values with a small sample size (Bentler, 1988). A good CFI value is a value greater than 0.95 (Tabachnick and Fidell, 2013; Hu and Bentler, 1999). Another advantage of CFI is that model complexity is not an issue, which is why this fit index is commonly used. The use of CFI is recommended over NFI (Bentler, 1990). The CFI value is 0.913, which is below the recommended minimum of 0.95.
6.6.2.9 Root Mean Square Error of Approximation (RMSEA)

This measure provides useful information about the measurement model by incorporating the error of approximation (Byrne, 2010). Hair et al. (2014) regard this index as an absolute fit index. This measure is also commonly used; it is used to assess how well the measurement model can be generalised to a wider population (Hair et al., 2014). This fit index calculates the fit of the model to a perfectly fitted model (Browne and Cudeck, 1993).

\[
\text{RMSEA calculation} = \frac{\sqrt{\text{F}_0}}{\text{df}_{\text{model}}} \quad \text{where } \text{F}_0 = 0 \text{ in a perfect model.}
\]

RMSEA values that are 0.06 or smaller are indicative of good model fit in terms of the degrees of freedom (Hu and Bentler, 1999). According to Browne and Cudeck (1993), RMSEA values that exceed 0.10 represent inadequate model fit. However, Hu and Bentler (1999) warn against using absolute cut-off value. Unlike the \( \chi^2 \) statistic, the measure tries to compensate for the size of the sample and the number of variables in a model. In small samples, however, this fit index tends to yield a poor RMSEA value. Again, the estimation procedure selected can influence the RMSEA value (Tabachnick and Fidell, 2013). When analysing RMSEA values, a researcher can specify the confidence intervals between a range of values (Hair et al., 2014). The RMSEA value for the initial measurement model is 0.079, which is a mediocre fit value according to MacCallum et al. (1996).

6.6.2.10 Closeness of Fit (PCLOSE)

In relation to the RMSEA and the confidence interval, it is possible to test the closeness of fit on AMOS (Byrne, 2010). This ensures that the RMSEA value is significant. For this to be true, the PCLOSE value should be above 0.05 (Jöreskog and Sörbom, 1996). The confidence interval range increases if there is a small sample and if there are many parameters in the measurement model (MacCallum et al., 1996). In this case, it is necessary to use a large sample size to compensate for a wide confidence interval.
6.6.2.11 Adjusted Goodness-of-Fit Index (AGFI)

AGFI was developed from GFI to account for the number of parameters in the model and therefore the degrees of freedom (Tabachnick and Fidell, 2013). It is usually lower than the GFI value as the index is limited due to model complexity (Hair et al., 2014). Values can range from 0 to 1 with values close to 1 revealing good model fit (Jöreskog and Sörbom, 1993).

6.6.2.12 Parsimonious Goodness-of-Fit Index (PGFI)

Since there is a level of parsimony in the model, it is possible to transform GFI to PGFI. For PGFI values, a high value that is close to 1.00 is desirable in producing a good model fit (Tabachnick and Fidell, 2013). An advantage of PGFI is that it explains model complexity of the hypothesised model against the observed model (Byrne, 2010). As a result, low values are deemed to be acceptable if other fit indices are above 0.9 (Mulaik et al., 1989). In terms of how PGFI is calculated, it is apparent that too many data points would yield a lower PGFI value resulting in a poor fit model (Tabachnick and Fidell, 2013).

6.6.2.13 Root Mean Square Residual (RMR)

To interpret the residual in covariances, analysing Standardised Residuals (SR) are advised. Although useful when comparing individual standardised residuals, SRs do not reveal model fit information (Hair et al., 2014). Therefore, to achieve a more useful figure is to obtain the average value of the residual i.e. the RMR. Small RMR values represent good model fit (Hair et al., 2014).

6.6.2.14 Standardised Root Mean Residual (SRMR)

However, residuals can vary due to the scale used and so a standardised root mean square SRMR is easier to understand and analyse. Similarly, small SRMR values indicate a good model fit; values 0.08 or less are preferred (Tabachnick and Fidell, 2013). Both indices are described as ‘are the average differences between the sample variances and covariances
and the estimated population covariances and covariances’ (Tabachnick and Fidell, 2013, p.775).

6.6.2.15 Summary of Goodness of Fit Statistics

Since smaller values are needed for indices RMR, SRMR and RMSEA, these are described as the badness-of-fit indices (Hair et al., 2014). According to Tabachnick and Fidell (2013) which fit indices to choose is up to the researcher as all the indices will generate similar findings. However, the most widely used fit indices include the CFI and RMSEA (Hair et al., 2014; Tabachnick and Fidell, 2013).

6.6.2.16 Summary of Initial Measurement Model

Most of the model fit values are not within the threshold, which confirms that this model fit is a poor model fit. CFI is 0.913 which is below the desired threshold of 0.95. At this stage, the researcher could either remove a construct that has a high covariance with another construct or create a second-order factor (Byrne, 2010). Based on the pilot results and EFA data, a decision was made to remove aesthetic evaluation from the CFA due to high covariances. This demonstrates that both EFA and CFA regard PF and AE variables to be similar with a shared variance.

6.6.3 CFA Model Modifications (1)

Using other model diagnostic information from AMOS can help to make modifications to the measurement model either to resolve issues or to further support the measurement theory (Hair et al., 2014). Since the measurement model is based on theory, changes based on diagnostic information should be carefully considered. Making changes would result in model re-specification that could affect the validity of the model. Diagnostic information includes standardised residuals, modification indices and specification searches (Byrne, 2010). While Hair et al. (2014) warn against removing a problem variable as this may not improve model fit, this may reveal that there is an underlying larger problem with the measurement model at hand. It is possible to use an approach known as model generating;
this is when initial modification indices are used to improve the model fit. With aesthetic evaluation removed, a modified measurement model was re-estimated in Figure 6.3.

**Figure 6.3 Modified Measurement Model (1): ASOS**

All loadings met the minimum path estimate loading of 0.5 except for PF4. At 0.49, PF4 is a candidate for deletion. Based on the most widely used model fit measures, there is mediocre model fit with the modified (1) measurement model (Appendix 4). Since more paths were freed from removing aesthetic evaluation variables, the degrees of freedom decreased from 160 to 98. Although CFI improved from 0.913 to 0.927, it remained below the 0.95 threshold. While the SRMR value were the same, the RMSEA value slightly worsened from 0.079 to 0.083.

Based on these values, it was necessary to evaluate additional diagnostic information to improve the model. This includes modification indices between the error terms. Modification index values, more than 4.0, indicate a path between a variable and a construct could be freed to improve model fit. By using this diagnostic information, it is possible to correlate error terms within the same construct as well as correlations between constructs (Hair *et al.*, 2014). The largest modification index is displayed in Table 6.13.
Table 6.13 Largest Modification Indices Between Error Terms: ASOS

<table>
<thead>
<tr>
<th>Modification Indices</th>
<th>Modification Index</th>
<th>Par Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>e3 &lt; -- &gt; e4</td>
<td>28.388</td>
<td>0.231</td>
</tr>
</tbody>
</table>

Modification indices are to be added one at a time on AMOS (Byrne, 2010) while inspecting the overall model fit each time. The largest modification index was between e3 and e4 i.e. PF3 and PF4 (M.1. = 28.388), so these error terms were correlated using a double-headed arrow on AMOS. The model was estimated again. While there was an improvement in the normed $\chi^2$ value (cmin/df) from 2.543 to 2.254, the value remained above the threshold of 2. Although the overall model fit remained mediocre, there were improvements in the goodness of fit values. CFI increased to 0.942 but was still below 0.95. Both RMSEA and SRMR values were within their respective thresholds. The modification indices were also analysed. Due to a large modification index, error terms between CE1 and CE2 were correlated on AMOS (M1. = 20.757) (Figure 6.4).

With two sets of error terms correlated on the measurement model, the measurement model was calculated again. The chi-square $\chi^2$ value decreased significantly from 218.642 to 180.025. There were less degrees of freedom due to the two sets of correlated error terms.

Figure 6.4 Modified Measurement Model (2): ASOS
All parameter estimate loadings were above the required threshold of 0.5 except for PF4 and CE1. While the loading remained the same for PF4, the loading for CE1 significantly decreased from 0.62 to 0.43. It appeared there was an underlying issue with these variables that could not be improved with re-specification. The model fit was also observed (Appendix 5). Interestingly, model fit significantly improved while the loadings on the measurement model for the variables that have correlated error terms had worsened. The normed chi-square decreased to 1.875. CFI increased above the minimum threshold to 0.960. Both GFI and NFI had values closer to 1. No further modification indices could be added between error terms. Since there was only miss-specification with the path estimates, validity and reliability of the latent variables were assessed.

### 6.6.4 Construct Validity and Reliability

It is important to ensure the estimated model is valid i.e. the data is accurate and correlates with the hypothesised model drawn from theory. Construct validity ‘is the extent to which a set of measured items actually reflects the theoretical latent construct those items are designed to measure’ (Hair et al., 2014, p.618). In other words, it is an evaluation of how representative the estimated model is of the population. It is comprised of 4 aspects: convergent validity, average variance extracted, reliability and discriminant validity (Hair et al., 2014). Using the Excel Stats Package provided by Gaskin (2016), construct validity and reliability were calculated (Table 6.14).

#### Table 6.14 Construct Validity and Reliability of the Measurement Model (2): ASOS

<table>
<thead>
<tr>
<th></th>
<th>CR</th>
<th>AVE</th>
<th>MSV</th>
<th>MaxR(H)</th>
<th>PosAffect</th>
<th>PerFluency</th>
<th>CogEffort</th>
<th>PurIntent</th>
</tr>
</thead>
<tbody>
<tr>
<td>PosAffect</td>
<td>0.917</td>
<td>0.734</td>
<td>0.384</td>
<td>0.919</td>
<td>0.857</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PerFluency</td>
<td>0.766</td>
<td>0.466</td>
<td>0.384</td>
<td>0.943</td>
<td>0.620</td>
<td>0.683</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CogEffort</td>
<td>0.765</td>
<td>0.459</td>
<td>0.109</td>
<td>0.953</td>
<td>-0.319</td>
<td>-0.330</td>
<td>0.678</td>
<td></td>
</tr>
<tr>
<td>PurIntent</td>
<td>0.903</td>
<td>0.703</td>
<td>0.249</td>
<td>0.974</td>
<td>0.499</td>
<td>0.416</td>
<td>-0.250</td>
<td>0.838</td>
</tr>
</tbody>
</table>

Table 6.14 highlights issues with construct validity. This is explained in the following subsections. Essentially, there were two convergent validity issues; the Average Variance Explained (AVE) values for perceptual fluency and cognitive effort were less than 0.50.
6.6.4.1 Reliability

Calculating reliabilities ensures that there is internal consistency among the variables of a construct. In a previous section, coefficient alpha values were calculated for each of the constructs using Cronbach’s Alpha. Overall, all constructs had reliabilities over the required minimum of 0.7. However, the use of this statistical test has been disputed as a reliability measure since it ‘may understate reliability’ (Hair et al., 2014, p.619). For this reason, Construct Reliability (CR) is used in SEM analyses. This is calculated using the ‘squared sum of factor loadings for each construct and the sum of the error variance terms for a construct’ (Hair et al., 2014, p.619). Values above 0.7 indicate there is adequate reliability. According to Table 6.14, there were no issues with CR: all the latent variables exceed the threshold of 0.7.

6.6.4.2 Convergent Validity

As well as standardised parameter estimates, AVE is also another measure of convergent validity. Hair et al. (2014, p.619) state AVE is ‘calculated as the mean variance extracted for the item loading on a construct and is a summary indicator of convergence’. AVE values more than 0.5 indicate that there is convergence among the variables, while values less than 0.5 indicates the opposite (Hair et al., 2014). The results revealed inadequate convergence among perceptual fluency variables and cognitive effort variables. Since the measurement model already identified PF4 and CE1 as problem variables, this suggested these particular variables account for more error variance in the AVE calculation.

6.6.4.3 Discriminant Validity

Hair et al. (2014, p.619) describe discriminant validity as ‘the extent to which a construct is truly distinct from other constructs’. There are two methods in ensuring there is discriminant validity among the variables. The robust way of calculating this is to examine the AVE values between two constructs with the square value in Table 6.14 (in bold) of the correlation estimate. There is discriminant validity if the square value for each construct is higher than the correlation estimation values between constructs (Hair et al., 2014). For the results in Table 6.14, there were no issues and so no modifications were necessary to improve discriminant validity.
6.6.4.4 Further CFA Model Modifications

Since there were validity concerns, it was necessary to further modify the measurement model. It is plausible to retain a variable that may be problematic if there is overall a reasonable model fit and there is construct validity. However, at other times a problematic variable should be retained to meet CFA criteria such as validity or the number of variables per factor (Hair et al., 2014). Since there were issues with construct validity and there are 4 variables per factor, removing PF4 and CE1 variables was considered a last resort.

6.6.5. CFA Model Modifications (2)

To improve the AVE, the Variance table was analysed to find the error term with the largest error variance. The error term e9 i.e. CE1 had the largest variance and was therefore removed from the measurement model, which was again evaluated for construct validity and reliability. While the model fit was considered adequate, convergent validity issues still remained with perceptual fluency, i.e. the AVE was less than 0.5. As a result, PF4 was deleted and re-estimated (Figure 6.5).

Figure 6.5 Modified Measurement Model (3): ASOS
After the removal of CE1, CE2 was assigned the regression weight of 1. All parameter estimate loadings were higher than 0.5, with the majority above 0.7, which revealed there was construct validity. The model fit was re-analysed (Table 6.15).

**Table 6.15 Model Fit of the Modified Measurement Model (3): ASOS**

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>154.373, p = 0.000</td>
<td>Small $\chi^2$ and p &gt; 0.05 (Hair et al., 2014)</td>
</tr>
<tr>
<td>Normed Chi-Square ($\chi^2$/df)</td>
<td>2.174</td>
<td>&lt; 2 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>GFI</td>
<td>0.913</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>NFI</td>
<td>0.922</td>
<td>Value close to 1 (Hair et al., 2014)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.956</td>
<td>&gt; 0.95 (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.072</td>
<td>≤ 0.06 (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>0.011</td>
<td>&gt; 0.05 (Jöreskog and Sörbom, 1996a)</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.871</td>
<td>Value close to 1 (Jöreskog and Sörbom, 1993)</td>
</tr>
<tr>
<td>PGFI</td>
<td>0.617</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.063</td>
<td>≤ 0.08 (Tabachnick and Fidell, 2013)</td>
</tr>
</tbody>
</table>

CFI remained above 0.95 at 0.956 and SRMR was also within the respective threshold. Other fit indices such as GFI and NFI were above 0.9 and closer to the ideal value of 1. RMSEA is 0.072, which was considered a mediocre value. Compared to the previous measurement model, PLCOSE still remained below 0.05 but had increased from 0.00. Overall, there was adequate model fit. There were no suitable modification index values. Validity and reliability were re-assessed in Table 6.16.

**Table 6.16 Construct Validity and Reliability of the Measurement Model (3): ASOS**

<table>
<thead>
<tr>
<th>CR</th>
<th>AVE</th>
<th>MSV</th>
<th>MaxR(H)</th>
<th>PosAffect</th>
<th>PerFluency</th>
<th>CogEffort</th>
<th>PurIntent</th>
</tr>
</thead>
<tbody>
<tr>
<td>PosAffect</td>
<td>0.917</td>
<td>0.734</td>
<td>0.379</td>
<td>0.919</td>
<td>0.887</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PerFluency</td>
<td>0.787</td>
<td>0.559</td>
<td>0.379</td>
<td>0.942</td>
<td>0.616</td>
<td>0.748</td>
<td></td>
</tr>
<tr>
<td>CogEffort</td>
<td>0.785</td>
<td>0.550</td>
<td>0.110</td>
<td>0.952</td>
<td>-0.319</td>
<td>-0.331</td>
<td>0.742</td>
</tr>
<tr>
<td>PurIntent</td>
<td>0.903</td>
<td>0.703</td>
<td>0.249</td>
<td>0.974</td>
<td>0.499</td>
<td>0.417</td>
<td>-0.249</td>
</tr>
</tbody>
</table>

Table 6.16 demonstrates no issues with construct validity and reliability. It is important to ensure there is reasonable model fit at the CFA stage before proceeding to the structural model in the SEM stage (Hair et al., 2014).
6.6.6 CFA Summary for ASOS

Overall, the values suggest there is a good model fit which implies that the observed covariance matrix is the same as the estimated covariance matrix. In other words, the observed measurement model is calculating values that are expected in line with the theory. Whilst the model fit for the final measurement model was not as good as the model fit for the previous measurement model, there is construct validity.

6.6.7 Structural Equation Modelling (SEM)

This step involved conducting SEM to determine relationships between the constructs. AMOS does not distinguish between exogenous and endogenous constructs as well as relationships between endogenous constructs. Hence, several changes were required to transform the measurement model to a structural model. These included theoretical and notational changes. An adequate sample size and model identification is also important in SEM (Byrne, 2010; Hair et al., 2014).

6.6.7.1 SEM Model Measurement

Specifying the path diagram involves setting up the causal model whereby relationships change from a correlational one to a dependence one. This enables the hypotheses to be tested in order to establish the relationships between the constructs. Perceptual fluency is the only the exogenous latent variable in the causal model. Any construct that is deemed to be an outcome is referred to as an endogenous construct. Positive affect, cognitive effort and purchase intentions are all endogenous constructs, and as such they require an error term (Hair et al., 2014). To assess the SEM model measurement, estimates were calculated in Figure 6.6.
In terms of the $R$ square, there was adequate $R^2$ for all the endogenous variables, which have respective values of 0.13, 0.39 and 0.25. According to Cohen (1988), the effect size for cognitive effort (i.e. 0.13) is a small effect. Evaluating the structural model validity is the last stage in the SEM process. Here, the model fit of the structural model should be compared to the final measurement model (Hair et al., 2014). The model fit of the structural model (Table 6.17) is similar to the final measurement model (Table 6.15).

A SEM assessment should determine the extent of the specified relationships between constructs (Hair et al., 2014). Since this model is recursive, there are less free parameter estimates and therefore the $\chi^2$ value should be less than the $\chi^2$ for CFA. The $\chi^2$ value for the final measurement model is 154.373 while the $\chi^2$ value for the structural model is

### Table 6.17 Model Fit of Structural Model: ASOS

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>151.329, $p = 0.000$</td>
<td>Small $\chi^2$ and $p &gt; 0.05$ (Hair et al., 2014)</td>
</tr>
<tr>
<td>Normed Chi-Square ($\chi^2/df$)</td>
<td>2.102</td>
<td>$&lt; 2$ (Tabachnick and Fidell, 2013), $&lt; 5$ (Kelloway, 1998)</td>
</tr>
<tr>
<td>GFI</td>
<td>0.915</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>NFI</td>
<td>0.924</td>
<td>Value close to 1 (Hair et al., 2014), $&gt; 0.95$ (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.958</td>
<td>$&gt; 0.95$ (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.070</td>
<td>$\leq 0.06$ (Hu and Bentler, 1999), $&lt; 0.10$ (Browne and Cudeck, 1993)</td>
</tr>
<tr>
<td>PCCLOSE</td>
<td>0.019</td>
<td>$&gt; 0.05$ (Jöreskog and Sörbom, 1996a)</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.876</td>
<td>Value close to 1 (Jöreskog and Sörbom, 1993)</td>
</tr>
<tr>
<td>PGFI</td>
<td>0.627</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.0703</td>
<td>$\leq 0.08$ (Tabachnick and Fidell, 2013)</td>
</tr>
</tbody>
</table>
151.329. Since the latter value is similar it is not likely that there will be an improvement in model fit. The model fit of the structural model has a reasonable model fit in terms of the normed chi-square, CFI, RMSEA and SRMR. These model fit values are all above their respective thresholds. Thereby, the model is observing what is expected based on theory.

### 6.6.7.1 Hypotheses Testing

Moderation was not considered necessary to facilitate as there are no moderating latent variables. Direct effects are shown in Table 6.18. The table below shows that most of the paths in the structural model are significant at the 95% confidence level i.e. \( p \)-values were less than 0.05.

<table>
<thead>
<tr>
<th>Table 6.18 Direct Effects of the Structural Model: ASOS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
</tr>
<tr>
<td>PosAffect --- PerFluency</td>
</tr>
<tr>
<td>CogEffort --- PerFluency</td>
</tr>
<tr>
<td>PurIntent --- PosAffect</td>
</tr>
<tr>
<td>CogEffort --- PosAffect</td>
</tr>
<tr>
<td>PF1 --- PerFluency</td>
</tr>
<tr>
<td>PF2 --- PerFluency</td>
</tr>
<tr>
<td>PF3 --- PerFluency</td>
</tr>
<tr>
<td>CE2 --- CogEffort</td>
</tr>
<tr>
<td>CE3 --- CogEffort</td>
</tr>
<tr>
<td>CE4 --- CogEffort</td>
</tr>
<tr>
<td>PA1 --- PosAffect</td>
</tr>
<tr>
<td>PA2 --- PosAffect</td>
</tr>
<tr>
<td>PA3 --- PosAffect</td>
</tr>
<tr>
<td>PA4 --- PosAffect</td>
</tr>
<tr>
<td>PI1 --- PurIntent</td>
</tr>
<tr>
<td>PI2 --- PurIntent</td>
</tr>
<tr>
<td>PI3 --- PurIntent</td>
</tr>
<tr>
<td>PI4 --- PurIntent</td>
</tr>
</tbody>
</table>

Note: *** indicates significance at the 0.001 level.

The results confirm two significant relationships: between perceptual fluency and positive affect as well as affect and purchase intentions. However, the relationships with cognitive effort were found to be insignificant. The standardised regression weights were also summarised in Table 6.19.
Table 6.19 Standardised Regression Weights of Structural Model: ASOS

<table>
<thead>
<tr>
<th>Latent factor</th>
<th>Estimator</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>PosAffect</td>
<td>PerFluency</td>
<td>0.623</td>
</tr>
<tr>
<td>CogEffort</td>
<td>PerFluency</td>
<td>-0.208</td>
</tr>
<tr>
<td>PurIntent</td>
<td>PosAffect</td>
<td>-0.199</td>
</tr>
<tr>
<td>PF1</td>
<td>PerFluency</td>
<td>0.817</td>
</tr>
<tr>
<td>PF2</td>
<td>PerFluency</td>
<td>0.845</td>
</tr>
<tr>
<td>PF3</td>
<td>PerFluency</td>
<td>0.547</td>
</tr>
<tr>
<td>CE2</td>
<td>CogEffort</td>
<td>0.686</td>
</tr>
<tr>
<td>CE3</td>
<td>CogEffort</td>
<td>0.792</td>
</tr>
<tr>
<td>CE4</td>
<td>CogEffort</td>
<td>0.743</td>
</tr>
<tr>
<td>PA1</td>
<td>PosAffect</td>
<td>0.849</td>
</tr>
<tr>
<td>PA2</td>
<td>PosAffect</td>
<td>0.876</td>
</tr>
<tr>
<td>PA3</td>
<td>PosAffect</td>
<td>0.876</td>
</tr>
<tr>
<td>PA4</td>
<td>PosAffect</td>
<td>0.822</td>
</tr>
<tr>
<td>PI1</td>
<td>PurIntent</td>
<td>0.757</td>
</tr>
<tr>
<td>PI2</td>
<td>PurIntent</td>
<td>0.657</td>
</tr>
<tr>
<td>PI3</td>
<td>PurIntent</td>
<td>0.965</td>
</tr>
<tr>
<td>PI4</td>
<td>PurIntent</td>
<td>0.914</td>
</tr>
</tbody>
</table>

Although the regression weights of the structural relationships are of importance, it is still important to analyse the regression weights of the structural covariance matrix. All the regression weights between the variables and the factors exceed the 0.5 minimum required for valid relationships (Hair et al., 2014).

### 6.6.8 SEM Summary for ASOS

Overall, the results show that perceptual fluency has indirect effects on purchase intentions for ASOS. The results also show that positive affect mediates the relationship between perceptual fluency and purchase intentions. However, the relationships involving cognitive effort were not supported. To further support findings of the direct and mediating effects of the hypothesised relationships, a post-hoc statistical power could be used. This would help to establish unsupported direct effects hypotheses. An SEM was conducted with and without the problem variables PF4 and CE1. Both attempts produce insignificant paths between perceptual fluency and cognitive effort as well as positive affect and cognitive effort.
6.7 Data Analysis and Results for Amazon

Like ASOS, the data from the online questionnaire based on Amazon was exported as an Excel Spreadsheet and modified with responses coded numerically. Data analysis based on Amazon was evaluated and explained in the next few sections via the use of EFA, CFA and SEM using SPSS version 23 and AMOS 22.

6.7.1 Exploratory Factor Analysis

Since Amazon is a different retailer and may involve a different shopping experience, it is important not to combine the results from ASOS and Amazon together to generate the underlying factor structure. Tabachnick and Fidell (2013) states that combining EFA data across different samples may not reveal the differences between the two retailers if differences exist. Thus, an EFA was conducted on the 20 items used in the online questionnaire that are made up of five different scales using SPSS version 23.

6.7.1.1 Suitability Criterion for EFA

The sample size for the Amazon analysis was 244 cases based on 20 variables across the five constructs. Like the ASOS sample, the Amazon sample size is considered satisfactory for EFA based on both recommendations from Tabachnick and Fidell (2013) and Nunnally (1978). In order to test whether this dataset is suitable for factor analysis, the KMO of sampling adequacy and Bartlett’s test of sphericity measures were applied (Table 6.20).

<table>
<thead>
<tr>
<th>Table 6.20 Initial KMO values and Bartlett’s Test: Amazon</th>
</tr>
</thead>
<tbody>
<tr>
<td>KMO Measure of Sampling Adequacy</td>
</tr>
<tr>
<td>Bartlett’s Test of Sphericity</td>
</tr>
<tr>
<td>Approx. Chi-Square</td>
</tr>
<tr>
<td>Degrees of freedom</td>
</tr>
<tr>
<td>Significance</td>
</tr>
</tbody>
</table>

Based on the values recommended by Tabachnick and Fidell (2013), both the KMO value and Bartlett’s test of significance (KMO > 0.5; p < 0.05) meet the criteria. At 0.874, the KMO figure is above 0.7 and is therefore considered to be a good initial KMO value. In conclusion, both the sample size and the KMO of sampling adequacy and Bartlett’s test of
sphericity measures confirm EFA is a suitable multivariate test to apply to the Amazon dataset.

6.7.1.2 Factor Extraction

To make the results comparable to ASOS, EFA was conducted using the same extraction method: maximum likelihood. Based on Kaiser’s criterion, Table 6.21 shows how many factors were extracted with eigenvalues of 1 or more and the amount of shared variance (Pallant, 2013).

<table>
<thead>
<tr>
<th>Factor</th>
<th>Initial Eigenvalues</th>
<th>Extraction Sums of Squared Loadings</th>
<th>Rotation Sums of Squared Loadings²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% of Variance</td>
<td>Cumulative %</td>
<td>% of Variance</td>
</tr>
<tr>
<td>1</td>
<td>7.937</td>
<td>37.066</td>
<td>37.066</td>
</tr>
<tr>
<td>2</td>
<td>2.327</td>
<td>11.636</td>
<td>49.702</td>
</tr>
<tr>
<td>3</td>
<td>1.677</td>
<td>8.383</td>
<td>57.875</td>
</tr>
<tr>
<td>4</td>
<td>1.386</td>
<td>6.629</td>
<td>64.504</td>
</tr>
<tr>
<td>5</td>
<td>1.076</td>
<td>5.381</td>
<td>69.985</td>
</tr>
<tr>
<td>6</td>
<td>.910</td>
<td>4.550</td>
<td>74.536</td>
</tr>
<tr>
<td>7</td>
<td>.787</td>
<td>3.933</td>
<td>78.468</td>
</tr>
<tr>
<td>8</td>
<td>.603</td>
<td>3.116</td>
<td>81.584</td>
</tr>
<tr>
<td>9</td>
<td>.570</td>
<td>2.848</td>
<td>84.432</td>
</tr>
<tr>
<td>10</td>
<td>.450</td>
<td>2.250</td>
<td>86.682</td>
</tr>
<tr>
<td>11</td>
<td>.410</td>
<td>2.052</td>
<td>88.935</td>
</tr>
<tr>
<td>12</td>
<td>.364</td>
<td>1.816</td>
<td>90.753</td>
</tr>
<tr>
<td>13</td>
<td>.356</td>
<td>1.760</td>
<td>92.533</td>
</tr>
<tr>
<td>14</td>
<td>.303</td>
<td>1.516</td>
<td>94.049</td>
</tr>
<tr>
<td>15</td>
<td>.285</td>
<td>1.425</td>
<td>95.475</td>
</tr>
<tr>
<td>16</td>
<td>.251</td>
<td>1.253</td>
<td>96.728</td>
</tr>
<tr>
<td>17</td>
<td>.206</td>
<td>1.031</td>
<td>97.759</td>
</tr>
<tr>
<td>18</td>
<td>.170</td>
<td>.851</td>
<td>98.610</td>
</tr>
<tr>
<td>19</td>
<td>.157</td>
<td>.786</td>
<td>99.396</td>
</tr>
<tr>
<td>20</td>
<td>.121</td>
<td>.604</td>
<td>100.000</td>
</tr>
</tbody>
</table>

Table 6.21 Initial Total Variance Explained: Amazon

Unlike the ASOS dataset which extracted 4 factors, Table 6.21 shows a five-factor solution. 5 factors with eigenvalues of 1 or more were extracted from the Amazon dataset with a cumulative extraction value of 60.979%. Individually, the five factors extracted variances of 35.386%, 7.851%, 6.107%, 7.790% and 3.845%. Factor 1 extracted a significant amount of the variance with 35.386%. This is less than the 40% guideline as stated by Blunch (2012), which implies that the scale used is not one-dimensional. Since there are five different latent factors, a five-factor solution was expected. A scree plot is shown in Figure 6.7.
Although the Total Variance Explained table (Table 6.21) extracted five factors, this is not obvious according to the scree plot. There is a break in the Eigenvalue at Factor 4. This suggests that with a four-factor solution ASOS and Amazon have a similar underlying factor structure.

**6.7.1.3 Factor Rotation**

For the same reasons as the ASOS dataset, maximum likelihood was applied with direct oblimin as the oblique rotation technique. It is important to note that applying oblique rotation in SPSS produces two different types of matrices with factor loadings, which includes the pattern matrix and the structure matrix (Pallant, 2013). Of the two, analysing the pattern matrix output is recommended (Hair et al. 2014).

**6.7.1.4 Factor Loadings**

Each of the factors in Table 6.22 display one significant loading, which is higher than the other loadings. There are notable marker variables for factor 1 and factor 2, which are PI3 and PF3 respectively. Since there are more than 250 respondents in the Amazon sample, a minimum factor loading of 0.35 and above are significant according to Hair et al. (2014). Most of the factor loadings are above 0.35 except for AE2, which has a low loading of 0.303, demonstrating that this variable has a small influence on factor 2. However, Hair et al. (2014) stipulate that accepting the minimum factor loading depends on the number of variables. In other words, a high number of variables is required to have a low cut-off.
Since there were 20 variables with a sample size of more than 250, 0.35 is considered an appropriate factor loading cut-off point.

### Table 6.22 Initial Pattern Matrix: Amazon

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Factor 4</th>
<th>Factor 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>P3</td>
<td>.974</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P4</td>
<td>.990</td>
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<td></td>
</tr>
<tr>
<td>P2</td>
<td>.733</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P1</td>
<td>.732</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PF2</td>
<td></td>
<td>.959</td>
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<td>PF1</td>
<td></td>
<td>.772</td>
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<tr>
<td>AE1</td>
<td></td>
<td>.361</td>
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<td>.614</td>
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<td>GE1</td>
<td></td>
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<td></td>
<td>.585</td>
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<tr>
<td>PF3</td>
<td></td>
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<td></td>
<td></td>
<td>.760</td>
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<tr>
<td>PF4</td>
<td></td>
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<td></td>
<td>.679</td>
<td></td>
</tr>
<tr>
<td>AE2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.303</td>
</tr>
</tbody>
</table>

Extraction Method: Maximum Likelihood.
Rotation Method: Obitlim with Kaiser Normalization.

- Rotation converged in 10 iterations.

In addition to the low loading of AE2, there were several issues with this pattern matrix. There are discriminant validity issues with perceptual fluency and aesthetic evaluation variables loading on both factor 2 and on factor 5. Variables PF1 and PF2 load on factor 2 but so do AE1 and AE3. This is also the case with factor 5 with PF4 and PF3 loading with AE2. It is important to note that aesthetic evaluation variables have loadings less than 0.5; AE4 does not produce a value since values less than 0.3 have been suppressed. Positive affect variables are negative, but this is not considered an issue according to Hair et al. (2014).

### 6.7.1.5 EFA Modifications

Modifications are required to this EFA. Firstly, the first factor extracted has a variance less than the guideline of 40%. Secondly, all the aesthetic evaluation variables have factor loadings less than 0.5. Although the cut-off is 0.35 based on the sample size, there is no high loading among any of the AE variables, which implies that the variables are not measuring the same thing. As all AE variables were removed from the ASOS EFA and CFA analysis, the results confirm this is also suitable for the Amazon dataset. On removal,
a KMO value of 0.871 was obtained. A total of 4 factors were subsequently extracted with 61.776% shared variance (Table 6.23).

### Table 6.23 Modified Pattern Matrix (1): Amazon

<table>
<thead>
<tr>
<th>Factor</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>PA2</td>
<td>.879</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA3</td>
<td>.652</td>
<td>.969</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA4</td>
<td>.810</td>
<td>.969</td>
<td>.737</td>
<td></td>
</tr>
<tr>
<td>PI3</td>
<td>.742</td>
<td>.732</td>
<td>.938</td>
<td></td>
</tr>
<tr>
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<td>.752</td>
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<td>.546</td>
</tr>
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<td></td>
<td>.654</td>
<td>.546</td>
</tr>
<tr>
<td>PF3</td>
<td></td>
<td></td>
<td>.632</td>
<td>.546</td>
</tr>
<tr>
<td>PF4</td>
<td></td>
<td></td>
<td></td>
<td>.546</td>
</tr>
<tr>
<td>CE2</td>
<td></td>
<td></td>
<td></td>
<td>.750</td>
</tr>
<tr>
<td>CE3</td>
<td></td>
<td></td>
<td></td>
<td>.597</td>
</tr>
<tr>
<td>CE1</td>
<td></td>
<td></td>
<td></td>
<td>.601</td>
</tr>
<tr>
<td>CE4</td>
<td></td>
<td></td>
<td></td>
<td>.593</td>
</tr>
</tbody>
</table>

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a Rotation converged in 9 iterations.

Results in Table 6.23 reveal a clean pattern matrix. As with the ASOS dataset, values for perceptual fluency were low for PF3 and PF4; they are less than 0.5. Since PF4 is below the minimum threshold of 0.35, this variable was also removed and the pattern matrix was re-estimated (Table 6.24).

### Table 6.24 Modified Pattern Matrix (2): Amazon

<table>
<thead>
<tr>
<th>Factor</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>PI3</td>
<td>.991</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PI4</td>
<td>.878</td>
<td>.1012</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PI1</td>
<td>.733</td>
<td>.732</td>
<td>.376</td>
<td></td>
</tr>
<tr>
<td>PI2</td>
<td></td>
<td>.1012</td>
<td>.701</td>
<td></td>
</tr>
<tr>
<td>PF2</td>
<td></td>
<td></td>
<td>.790</td>
<td>.546</td>
</tr>
<tr>
<td>PF1</td>
<td></td>
<td></td>
<td>.632</td>
<td>.546</td>
</tr>
<tr>
<td>PF3</td>
<td></td>
<td></td>
<td></td>
<td>.546</td>
</tr>
<tr>
<td>PA2</td>
<td></td>
<td></td>
<td>.881</td>
<td>.546</td>
</tr>
<tr>
<td>PA3</td>
<td></td>
<td></td>
<td>.938</td>
<td>.546</td>
</tr>
<tr>
<td>PA4</td>
<td></td>
<td></td>
<td>.790</td>
<td>.834</td>
</tr>
<tr>
<td>CE2</td>
<td></td>
<td></td>
<td></td>
<td>.750</td>
</tr>
<tr>
<td>CE3</td>
<td></td>
<td></td>
<td></td>
<td>.597</td>
</tr>
<tr>
<td>CE1</td>
<td></td>
<td></td>
<td></td>
<td>.601</td>
</tr>
<tr>
<td>CE4</td>
<td></td>
<td></td>
<td></td>
<td>.593</td>
</tr>
</tbody>
</table>

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a Rotation converged in 6 iterations.
Removing PF4 created an issue with PF1. The factor loading exceeded 1.0, thereby indicating the factor was not stable (Tabachnick and Fidell, 2013). Although the loading for the variables was low, Table 6.24 confirmed the importance of retaining PF4.

### 6.7.1.6 EFA Summary

As with the ASOS dataset, findings imply that perceptual fluency and aesthetic evaluation are similar for the Amazon dataset. Due to a high shared variance, EFA is not able to load these variables on separate factors. Overall, with the exception of AE variables, a clean pattern matrix was obtained. For this reason, aesthetic evaluation was also excluded from CFA.

### 6.7.2 Confirmatory Factor Analysis

CFA was applied to 16 variables adopted in the online questionnaire to test the measurement model with the Amazon dataset. Unlike EFA, the researcher specifies which variables go together in respect to the latent variable or factor (Byrne, 2010). The overall main goal of CFA is to validate a measurement model (Tabachnick and Fidell, 2013). The following sections outline the steps taken in CFA in determining the final measurement model before conducting SEM to establish the structural model.

### 6.7.2.1 Conceptual Model Development in CFA

Since constructs have already been defined prior to EFA using established scales from literature, the first step in CFA is to develop the measurement model. Along with error terms, the measurement model was drawn manually on AMOS. It is important to specify the measurement model to assess if the sample data fits with the hypothesised model (Byrne, 2010).
6.7.2.2 Model Specification

During this step, the researcher specifies which variables load onto which factor and the covariances between factors (Hair et al. 2014). As there were four observed variables per factor, the measurement model meets the three-indicator rule of a minimum of 3 variables per factor (Hair et al., 2014). There was 98 degrees of freedom. Therefore, the order condition to ensure positive degrees of freedom is satisfied.

Based on the scales and hypotheses, the measurement model is a first-order CFA model. It is a four-factor structure. Each of the four factors have been abbreviated and have four observed variables each. A chi-square statistical test and a reasonable model fit is required to confirm or reject the conceptual model (Schumacker and Lomax, 2016).

6.7.2.3 Model Identification

A minimum was achieved on AMOS with a chi-square value of 314.722 with 98 degrees of freedom. As well as the 16 parameter estimates, there are also 16 error variances and 6 covariances in Figure 6.9. Since there are more unique variances and covariance terms (136) than parameter estimates (38), the measurement model is overidentified. This type of identification is preferred as it permits fit values to be calculated (Hair et al., 2014).

6.7.2.4 Model Estimation

This stage requires evaluation of the parameter estimates i.e. factor loadings, standard errors and whether the parameter estimates in the model are statistically significant (Byrne, 2010). Figure 6.8 shows the estimated measurement model with standardised regression weights and correlations.
Most of the parameter estimate loadings exceed the threshold of 0.5 except for CE1, which has a low value of 0.47. Large loadings of 0.7 and above demonstrate indicators are well associated with their respective construct, which implies there is construct validity (Hair et al., 2014). PF4 is just above the minimum cut-off at 0.52. The low values for PF4 and CE1 were predicted given that these variables were also problematic variables for the ASOS dataset.

6.7.2.5 Model Fit Assessment

The last step of CFA is to assess the model validity. This is important to assess how well the observed data fits with the theory. One way to do this is to assess the overall model fit (Byrne, 2010) (Table 6.25).
Table 6.25 Model Fit of the Initial Measurement Model: Amazon

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Initial Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>314.722 $p = 0.000$</td>
<td>Small $\chi^2$ and $p &gt; 0.05$ (Hair et al., 2014)</td>
</tr>
<tr>
<td>Normed Chi-Square ($\chi^2$/df)</td>
<td>3.211</td>
<td>$&lt; 2$ (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>GFI</td>
<td>0.858</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013) $&gt; 0.95$ (Hoelter, 1983)</td>
</tr>
<tr>
<td>NFI</td>
<td>0.861</td>
<td>Value close to 1 (Hair et al., 2014) $&gt; 0.95$ (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.907</td>
<td>$&gt; 0.95$ (Hu and Bentler, 1999) $\leq 0.06$ (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.095</td>
<td>$&lt; 0.10$ (Browne and Cudeck, 1993)</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>0.000</td>
<td>Value close to 1 (Jöreskog and Sörbom, 1996a)</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.807</td>
<td>Value close to 1 (Jöreskog and Sörbom, 1993)</td>
</tr>
<tr>
<td>PGFI</td>
<td>0.619</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.095</td>
<td>$&lt; 0.10$ (Hair et al., 2014) $&lt; 0.05$ (Schumacker and Lomax, 2016)</td>
</tr>
</tbody>
</table>

With a high normed chi-square above 2 at 3.211 and a CFI value below 0.95, the model fit reveals an inadequate model fit. However, RMSEA and SRMR were within their thresholds. Hence, there was a need to obtain model diagnostic information. There was a high modification index between the error terms e3 and e4 i.e. for variables PF3 and PF4 respectively.

6.7.2.6 Summary of Initial Measurement Model

According to the path estimates, CE1 appeared to be a problem variable. PF4 also posed a problem. These are the same issues that were found with the ASOS dataset. Subsequently, further modifications were required to improve model fit and construct validity.

6.7.3 CFA Model Modifications

After correlating the error terms e3 and e4 for the variables PF3 and PF4, the measurement model was evaluated again. Due to issues with path estimates, i.e., PF4 declined from 0.52 to 0.39 revealing further miss-specification (Appendix 6), and inadequate model fit (Appendix 7), diagnostic model information was analysed. The modification indices output revealed a maximum MI of 43.608 between error terms CE1 and CE2. As a result, error terms e9 and e10 were correlated with a double headed arrow drawn manually on AMOS (Appendix 8). Although this produced a better model fit with CFI above 0.95 and normed chi-square, RMSEA and SRMR within their respective thresholds (Appendix 9), variables PF4 and CE1 remained an issue after model estimation with both loadings less than 0.5.
Despite a good model fit, the low factor loadings for PF4 and CE1 highlighted there was miss-specification in the measurement model. The MI output revealed 1 MI with a value of 5.450 between error terms e18 and e19 was permissible. Thus, the error terms for variables PI2 and PI3 were correlated using a double-headed arrow on AMOS. Figure 6.9 displays the modified measurement model for Amazon with the standardised parameter estimate values.

Figure 6.9 Modified Measurement Model (3): Amazon

There has been no change for the problem variables PF4 and CE1. In fact, most of the measurement model remains the same as the previous measurement model implying that correlating the error terms for e18 and e19 was irrelevant. However, the goodness of fit statistics reveals a good model fit (Table 6.26).
Table 6.26 Model Fit of the Modified Measurement Model (3): Amazon

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>180.596 (p = 0.000)</td>
<td>Small $\chi^2$ and p &gt; 0.05 (Hair et al., 2014)</td>
</tr>
<tr>
<td>Normed Chi-Square ($\chi^2$/df)</td>
<td>1.901</td>
<td>&lt; 2 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>GFI</td>
<td>0.916</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013); &gt; 0.95 (Hoelter, 1983)</td>
</tr>
<tr>
<td>NFI</td>
<td>0.926</td>
<td>Value close to 1 (Hair et al., 2014); &gt; 0.95 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.963</td>
<td>&gt; 0.95 (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.061</td>
<td>≤ 0.06 (Hu and Bentler, 1999); &lt; 0.10 (Browne and Cudeck, 1993)</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>0.092</td>
<td>&gt; 0.05 (Jöreskog and Sörbom, 1996a)</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.880</td>
<td>Value close to 1 (Jöreskog and Sörbom, 1993)</td>
</tr>
<tr>
<td>PGFI</td>
<td>0.640</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.0758</td>
<td>&lt; 0.05 (Schumacker and Lomax, 2016)</td>
</tr>
</tbody>
</table>

Both the chi-square value and the normed chi-square decreased further. There were also slight increases to the measures GFI, NFI and CFI. RMSEA decreased slightly with a further increase to PCLOSE from 0.053 to 0.092. SRMR also decreased slightly, but it remained above 0.05 indicating a mediocre value. Overall, there was an improvement in model fit.

6.7.4 Construct Validity and Reliability

At this point, no further modifications could be made unless problem variables were removed. Hence, construct validity and reliability were checked to assess whether these variables were still a concern (Table 6.27).

Table 6.27 Construct Validity and Reliability of the Measurement Model (3): Amazon

<table>
<thead>
<tr>
<th>Factor</th>
<th>CR</th>
<th>AVE</th>
<th>MSV</th>
<th>MaxR(H)</th>
<th>PosAffect</th>
<th>PerFluency</th>
<th>CogEffort</th>
<th>PurIntent</th>
</tr>
</thead>
<tbody>
<tr>
<td>PosAffect</td>
<td>0.918</td>
<td>0.738</td>
<td>0.379</td>
<td>0.930</td>
<td>0.859</td>
<td>0.660</td>
<td>0.639</td>
<td>0.862</td>
</tr>
<tr>
<td>PerFluency</td>
<td>0.739</td>
<td>0.436</td>
<td>0.198</td>
<td>0.948</td>
<td>-0.342</td>
<td>-0.292</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CogEffort</td>
<td>0.715</td>
<td>0.409</td>
<td>0.117</td>
<td>0.957</td>
<td>-0.342</td>
<td>-0.292</td>
<td></td>
<td>0.639</td>
</tr>
<tr>
<td>PurIntent</td>
<td>0.920</td>
<td>0.744</td>
<td>0.379</td>
<td>0.973</td>
<td>0.616</td>
<td>0.414</td>
<td>0.126</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.27 highlights the same issues as the ASOS dataset with construct validity. Namely, there were two convergent validity issues; the AVE values for perceptual fluency and cognitive effort were below 0.5. The convergent validity highlights variables for these two constructs are not measuring the same thing. AMOS outputs were referred to and the largest error variance was found for the error term e9 associated with problem variable...
CE1. CR values above 0.7 is indicative of adequate reliability (Hair et al., 2014). There were no issues with construct reliability with all CR values above 0.7.

6.7.5 Further CFA Model Modifications

This section outlines the steps taken to ensure there is construct validity among the variables and their respective latent variable. Due to the low parameter estimates and the low AVE values for perceptual fluency and cognitive effort, this highlights that these problem variables do not have enough shared variance. To decide which of the problem variables should be removed first, the error variance for these variables were examined. Because of the large error variance for CE1, this variable was removed, and the measurement model was estimated on AMOS (Figure 6.10). The regression weight was applied to CE2 after the removal of CE1.

Figure 6.10 Modified Measurement Model (4): Amazon

In the modified measurement model, all the standardised path estimates were above the minimum threshold of 0.5 except for the problem variable PF4, which remained low at 0.39. Apart from PF3 and CE2, all other variables displayed significant parameter estimates. The correlation between e9 and e10 was removed due to the removal of CE1. Model fit was re-calculated (Table 6.28).
Table 6.28 Model Fit of the Modified Measurement Model (4): Amazon

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>160.838 $p = 0.000$</td>
<td>Small $\chi^2$ and $p &gt; 0.05$ (Hair et al. 2014)</td>
</tr>
<tr>
<td>Normed Chi-Square ($\chi^2/df$)</td>
<td>1.961</td>
<td>$&lt; 2$ (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>GFI</td>
<td>0.920</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013) &gt; 0.95 (Hoelter, 1983)</td>
</tr>
<tr>
<td>NFI</td>
<td>0.931</td>
<td>Value close to 1 (Hair et al. 2014) &gt; 0.95 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.965</td>
<td>&gt; 0.95 (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.063</td>
<td>$\leq 0.06$ (Hu and Bentler, 1999) &gt; 0.10 (Browne and Cudeck, 1993)</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>0.07</td>
<td>$&gt; 0.05$ (Jöreskog and Sörbom, 1996a)</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.883</td>
<td>Value close to 1 (Jöreskog and Sörbom, 1993).</td>
</tr>
<tr>
<td>PGFI</td>
<td>0.629</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.075</td>
<td>$&lt; 0.10$ (Hair et al. 2014)</td>
</tr>
</tbody>
</table>

In comparison to the previous measurement model, most of the model fit measures in Table 6.28 had worsened slightly. However, there was adequate model fit with a CFI value above 0.95 at 0.965. The normed chi-square was less than the required threshold of 2. While GFI and NFI were not above 0.95, their values remained above 0.9, which are considered mediocre. Both RMSEA and SRMR are also mediocre. This indicates there is a construct validity issue with PF4. An evaluation of convergent validity, reliability and discriminant validity would confirm this (Hair et al., 2014). As a result, the measurement model in Figure 6.10 was tested for validity (Table 6.29).

Table 6.29 Construct Validity and Reliability of the Measurement Model (4): Amazon

<table>
<thead>
<tr>
<th></th>
<th>CR</th>
<th>AVE</th>
<th>MSV</th>
<th>MaxR(H)</th>
<th>PosAffect</th>
<th>PerFluency</th>
<th>CogEffort</th>
<th>PurIntent</th>
</tr>
</thead>
<tbody>
<tr>
<td>PosAffect</td>
<td>0.918</td>
<td>0.738</td>
<td>0.379</td>
<td>0.930</td>
<td>0.859</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PerFluency</td>
<td>0.739</td>
<td>0.436</td>
<td>0.198</td>
<td>0.948</td>
<td>0.445</td>
<td>0.660</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CogEffort</td>
<td>0.755</td>
<td>0.513</td>
<td>0.116</td>
<td>0.956</td>
<td>-0.341</td>
<td>-0.292</td>
<td>0.716</td>
<td></td>
</tr>
<tr>
<td>PurIntent</td>
<td>0.920</td>
<td>0.744</td>
<td>0.379</td>
<td>0.973</td>
<td>0.616</td>
<td>0.414</td>
<td>-0.126</td>
<td>0.862</td>
</tr>
</tbody>
</table>

Results reveal the convergent validity issue for cognitive effort was no longer an issue as the AVE value for cognitive effort exceeded 0.5 at 0.513. However, a convergent validity issue remained for perceptual fluency. There were no issues with reliability as all CR values for all the latent variables were greater than 0.7. There is also discriminant validity as the diagonal values for the latent variables are greater than the correlation values with other latent variables. Since removing the problem variable for cognitive effort resolved the issue, this indicated removing PF4 would also resolve the convergent validity issue for perceptual fluency. As a result of its removal, the correlation between the error terms PF3 and PF4 was removed automatically on AMOS. The measurement model was re-estimated (Figure 6.11).
The measurement model in 6.11 illustrates all parameter estimates were above 0.5. Variable PF3 had a borderline value at 0.51 and CE2 had a low value of 0.57. While these values were not significant, they were considered acceptable path estimate values. The model now demonstrates construct validity in terms of these values. To confirm that the estimated model correlates to the hypothesised model, an evaluation of the model fit is provided (Table 6.30).

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>140.652, p = 0.000</td>
<td>Small $\chi^2$ and p &gt; 0.05 (Hair et al. 2014)</td>
</tr>
<tr>
<td>Normed Chi-Square ($\chi^2/df$)</td>
<td>2.009</td>
<td>&lt; 2 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>GFI</td>
<td>0.920</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>NFI</td>
<td>0.936</td>
<td>Value close to 1 (Hair et al. 2014)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.966</td>
<td>&gt; 0.95 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.064</td>
<td>≤ 0.06 (Hair and Bentler, 1999)</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>0.062</td>
<td>&gt; 0.05 (Jöreskog and Sörbom, 1996a)</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.887</td>
<td>Value close to 1 (Jöreskog and Sörbom, 1993).</td>
</tr>
<tr>
<td>PGFI</td>
<td>0.617</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.064</td>
<td>&lt; 0.10 (Hair et al. 2014)</td>
</tr>
</tbody>
</table>

CFI is above 0.95 at 0.966. SRMR and RMSEA value were within their thresholds. While both GFI and NFI values were below 0.95, they were above 0.9 and therefore closer to the value of 1. Both the normed chi-square and PCLOSE were slightly above their respective boundary. With an adequate model fit and good factor loadings, there was no miss-
specification in the measurement model. Finally, construct validity and reliability was re-assessed in Table 6.31.

Table 6.31 Construct Validity and Reliability of the Measurement Model (5): Amazon

<table>
<thead>
<tr>
<th>Construct</th>
<th>CR</th>
<th>AVE</th>
<th>MSV</th>
<th>MaxR(H)</th>
<th>PosAffect</th>
<th>PerFluency</th>
<th>CogEffort</th>
<th>PurIntent</th>
</tr>
</thead>
<tbody>
<tr>
<td>PosAffect</td>
<td>0.918</td>
<td>0.738</td>
<td>0.379</td>
<td>0.930</td>
<td>0.859</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PerFluency</td>
<td>0.765</td>
<td>0.531</td>
<td>0.194</td>
<td>0.948</td>
<td>0.441</td>
<td></td>
<td>0.729</td>
<td></td>
</tr>
<tr>
<td>CogEffort</td>
<td>0.755</td>
<td>0.513</td>
<td>0.116</td>
<td>0.956</td>
<td>-0.341</td>
<td>-0.0295</td>
<td>0.716</td>
<td></td>
</tr>
<tr>
<td>PurIntent</td>
<td>0.920</td>
<td>0.744</td>
<td>0.379</td>
<td>0.973</td>
<td>0.616</td>
<td>0.411</td>
<td>-0.126</td>
<td>0.862</td>
</tr>
</tbody>
</table>

As Table 6.31 illustrates, there were no issues with construct validity or reliability. In terms of convergent validity, all AVE values exceeded the minimum cut-off of 0.5. Construct reliability values were acceptable as all values are higher than 0.7. There were also no issues with discriminant validity as the diagonal values for the latent variables are greater than the correlation values with other latent variables.

6.7.6 CFA Summary for Amazon

As with the coefficient alpha explored at the beginning of the chapter, the constructs positive affect and purchase intentions appear stronger than perceptual fluency and cognitive effort. There had been some improvements to the final CFA model fit with the common latent factor, but there had also been some regressions. The modifications made to the Amazon dataset in CFA were the same as the ASOS dataset. Efforts were made to retain the problem variables PF4 and CE1. However, miss-specification remained, and modification indices were added. Although this helped to improve the model fit, there were issues with convergent validity with constructs perceptual fluency and cognitive effort, which highlighted the issue of the problem variables in the measurement model. Therefore, the only way to address the convergent validity issue was to remove these problem variables.
6.7.7 Structural Equation Modelling (SEM)

This section outlines the steps taken to analyse the Amazon dataset during the SEM stage. As with CFA, an adequate sample size and ensuring model identification that is met is important in SEM (Hair et al., 2014). Like the ASOS structural model, the Amazon structural model was drawn according to theory, whereby perceptual fluency was considered the exogenous latent variable, while the other variables were all endogenous constructs that require an error term (Byrne, 2010). To assess the SEM model measurement, estimates were calculated (Figure 6.12).

**Figure 6.12 Path Diagram of the Structural Model: Amazon**

The values above the latent variable in Figure 6.12 is known as the squared multiple correlation coefficient. According to Schumacker and Lomax (2016, p.54), these values demonstrate ‘the amount of variance explained, predicted, or accounted for in the dependent variable by the set of independent predictor variables’. For the structural model, perceptual fluency explained 14%, 20% and 38% of shared variance of cognitive effort, positive affect and purchase intentions respectively. Though statistically significant, the $R^2$ for cognitive effort (i.e. 0.14) was a small effect, which suggests only 14% of variance in cognitive effort is explained by perceptual fluency and positive affect. A similar finding has been found by Mosteller et al. (2014) who report the same two predictor variables account for 24% variance in cognitive effort. Evaluation of the structural model validity
was the last stage in the SEM process with comparisons drawn between the model fit of the structural model (Table 6.32) with the model fit of the final CFA measurement model (Table 6.30).

### Table 6.32 Model Fit of Structural Model: Amazon

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>150.336, $p = 0.000$</td>
<td>Small $\chi^2$ and $p &gt; 0.05$ (Hair et al., 2014)</td>
</tr>
<tr>
<td>Normed Chi-Square ($\chi^2/df$)</td>
<td>2.088</td>
<td>$&lt; 2$ (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$&gt; 5$ (Kelloway, 1998)</td>
</tr>
<tr>
<td>GFI</td>
<td>0.921</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$&gt; 0.95$ (Hoelter, 1983)</td>
</tr>
<tr>
<td>NFI</td>
<td>0.931</td>
<td>Value close to 1 (Hair et al., 2014)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$&gt; 0.95$ (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.963</td>
<td>$&gt; 0.95$ (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.067</td>
<td>$\leq 0.06$ (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$&lt; 0.10$ (Browne and Cudeck, 1993)</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>0.034</td>
<td>$&gt; 0.05$ (Jöreskog and Sörbom, 1996a)</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.885</td>
<td>Value close to 1 (Jöreskog and Sörbom, 1993).</td>
</tr>
<tr>
<td>PGFI</td>
<td>0.632</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.0742</td>
<td>$\leq 0.08$ (Tabachnick and Fidell, 2013)</td>
</tr>
</tbody>
</table>

Whilst the model fit of the final measurement model is better, they are not too dissimilar. There is a good CFI value at 0.963. Both RMSEA and SRMR were considered mediocre as they do fall within the cut-off values, but they were not considered inadequate either. However, PCLOSE remained below the minimum cut-off value of 0.05. However, no further MI could be added between the error terms of the latent variables. Overall, the model fit of the structural model appeared to be adequate. All the path estimates were above 0.5 and the squared multiple correlations on the endogenous constructs i.e. positive affect, purchase intentions and cognitive effort had sufficient loadings.

#### 6.7.7.1 Hypotheses Testing

Table of direct effects is shown in Table 6.33. Findings show that all path estimates between the constructs were significant i.e. $p$-value should be less than 0.5 (Hair et al., 2014). This confirms the relationships between all the constructs are supported. As predicted, the estimates between perceptual fluency and cognitive effort were negative. The same was also true for positive affect and cognitive effort.
Unlike the paths in the ASOS structural model, the table above shows that all the paths in the structural model are significant at the 95% confidence level i.e. $p$-values are less than 0.05. The results confirm increasing perceptual fluency increases positive affect. Increasing perceptual fluency has a direct negative effect on cognitive effort. A positive significant relationship is also found for positive affect and purchase intentions as well as negative significant relationship between positive affect and cognitive effort. The results also confirm perceptual fluency directly influences purchase intentions indirectly via positive affect. The standardised regression weights are also summarised in Table 6.34.
Table 6.34 Standardised Regression Weights: Amazon

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>PosAffect</td>
<td>0.453</td>
</tr>
<tr>
<td>CogEffort</td>
<td>-0.184</td>
</tr>
<tr>
<td>PurIntent</td>
<td>0.618</td>
</tr>
<tr>
<td>CogEffort</td>
<td>-0.256</td>
</tr>
<tr>
<td>PF1</td>
<td>0.772</td>
</tr>
<tr>
<td>PF2</td>
<td>0.858</td>
</tr>
<tr>
<td>PF3</td>
<td>0.508</td>
</tr>
<tr>
<td>CE2</td>
<td>0.568</td>
</tr>
<tr>
<td>CE3</td>
<td>0.724</td>
</tr>
<tr>
<td>CE4</td>
<td>0.831</td>
</tr>
<tr>
<td>PA1</td>
<td>0.857</td>
</tr>
<tr>
<td>PA2</td>
<td>0.921</td>
</tr>
<tr>
<td>PA3</td>
<td>0.881</td>
</tr>
<tr>
<td>PA4</td>
<td>0.768</td>
</tr>
<tr>
<td>PI1</td>
<td>0.858</td>
</tr>
<tr>
<td>PI2</td>
<td>0.751</td>
</tr>
<tr>
<td>PI3</td>
<td>0.918</td>
</tr>
<tr>
<td>PI4</td>
<td>0.913</td>
</tr>
</tbody>
</table>

Although the regression weights of the structural relationships are of importance, it is still important to analyse the regression weights of the structural covariance matrix. All the regression weights between the variables and the factors exceed the 0.5 minimum required for valid relationships. Table 6.34 provides further clarification of the standardised regression weights that can also be observed in the structural model. These values also indicate whether a relationship in the structural model is positive or negative (Hair et al., 2005). The latter includes the relationships between perceptual fluency and cognitive effort as well as positive affect and cognitive effort.

6.7.8 SEM Summary for Amazon

The findings reveal that all the paths in the structural model for Amazon were supported due to significant p-values. While data suggests there is a negative relationship between perceptual fluency and positive affect with cognitive effort, these relationships were significant. However, several steps were required to attain construct validity and reliability as well as good model fit in the measurement model. This led to the removal of problem variables CE1 and PF4.
6.8 Chapter Summary

This chapter presents the SEM results obtained for the two datasets (i.e. ASOS and Amazon). The CFA was a useful, exploratory step in assessing whether variables are representative of their respective construct. For both datasets, there were issues concerning the covariance between perceptual fluency and aesthetic evaluation loadings during the EFA stage, which was also found to be problematic for the ASOS and Amazon datasets during CFA. While aesthetic evaluation variables had to be removed completely from both datasets, other variables also had to be removed to ensure there was adequate model fit as well as construct validity and reliability in the measurement models before proceeding to the path diagram of the structural models.
Chapter Seven: Eye Tracking Data Analysis and Results

7.1 Introduction

Following the online survey as the first research phase, this chapter presents data analysis and results of the second research phase with the eye tracking experimental design. Using mixed-methods, data includes fixation metric data from the eye tracking experiment, post survey data as well as verbal data from interviews conducted after with each experiment. Demographic analysis was also conducted to assess the suitability of the sample. A summary and review of the themes and sub-themes from the verbal data is also presented.

7.2 Data Screening

A total of 25 participants took part in the study. Data from one participant was excluded due to calibration issues with the eye tracking technology. This left a total of 24 participants with valid data. Although it was possible to compute average noise levels and to remove participants outside the standard deviation, as conducted by Otterbing et al. (2016), Holmqvist et al. (2011) assert caution must be exercised when removing outliers as this may create bias in the dataset. For this reason, no further data was removed.

7.3 Sample Descriptive Analysis

Analysis of the frequency of shopping data reveals the sample to be an appropriate sample for the eye tracking experiment and interview. Table 7.1 reveals the sample to be frequent fashion apparel shoppers. More than half of the sample shop for fashion clothing at least several times a day with 16.7% shopping at least once a day. All 24 participants shopped for fashion clothing in the last 6 months. Of the 24 participants, 20 participants had shopped on ASOS previously. This further illustrates the appropriateness of the sample given that ASOS is a popular online fashion retailer for female consumers aged between 18-24 (Mintel, 2018).
### Table 7.1 Summary of Frequency of Shopping for Fashion Clothing

<table>
<thead>
<tr>
<th>Frequency of Shopping</th>
<th>Frequency</th>
<th>%</th>
<th>Cumulative %</th>
</tr>
</thead>
<tbody>
<tr>
<td>At least once a day</td>
<td>4</td>
<td>16.7</td>
<td>16.7</td>
</tr>
<tr>
<td>Several times a week</td>
<td>11</td>
<td>45.8</td>
<td>62.5</td>
</tr>
<tr>
<td>Several times a month</td>
<td>6</td>
<td>25.0</td>
<td>87.5</td>
</tr>
<tr>
<td>Several times a year</td>
<td>3</td>
<td>12.5</td>
<td>100.0</td>
</tr>
<tr>
<td>Rarely</td>
<td>0</td>
<td>0.0</td>
<td>100.0</td>
</tr>
<tr>
<td>Total</td>
<td>24</td>
<td>100.0</td>
<td>100.0</td>
</tr>
</tbody>
</table>

#### 7.4 Analyzer Software

As instructed by the Tobii Manual, glasses recordings were imported into the Tobii Pro Glasses Analyzer software as a new project. There are a number of different gaze settings. This includes fixation pre-sets to choose from, which have defined parameters, as well as the raw data filter, which is the default setting on Analyzer (Tobii Technology, 2016b). For this study, the fixation Velocity-Threshold Identification (I-VT) filter was selected to sift out fixations from the raw data. This filter ‘processes and classifies the recorded gaze data samples into fixations and other eye movements’ (Tobii Technology, 2016b, p.11) and is commonly used in human behaviour research (Olsen, 2012).

With the Analyzer software, there were two ways to map eye movement data from the video onto the snapshots; this can be done manually or by utilising the Real-World Mapping function. Although it was tried, the latter was not suitable as browsing on a mobile webpage was not a stationary event. Additionally, there were moving images when catwalk videos and product rotation tools were used. To insert snapshots, screenshots were taken of the mobile website using the same iPad that participants used to browse from in the experiment.
Table 7.2 Overview of Snapshots

<table>
<thead>
<tr>
<th>Website</th>
<th>Type</th>
<th>Tops</th>
<th>Handbags</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASOS</td>
<td>Images</td>
<td>Front view</td>
<td>Front view</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Back view</td>
<td>Back view</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Close up view</td>
<td>Close up view</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Full length view</td>
<td>Model view</td>
</tr>
<tr>
<td></td>
<td>Visualisation tools</td>
<td>Zoom function</td>
<td>Zoom function,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Catwalk video</td>
<td>Product rotation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gestural zoom</td>
<td>Gestural zoom</td>
</tr>
<tr>
<td>Pretty Gal</td>
<td>Images</td>
<td>Front view</td>
<td>Front view</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Back view</td>
<td>Back view</td>
</tr>
<tr>
<td></td>
<td>Visualisation tools</td>
<td>Zoom function</td>
<td>Zoom function</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gestural zoom</td>
<td>Gestural zoom</td>
</tr>
</tbody>
</table>

A total of 14 snapshots were required to map ASOS data, while a total of 8 snapshots were required to map Pretty Gal (Table 7.2). Since participants browsed a selection of different tops and handbags, which would have resulted in too many snapshots, data from either website was mapped onto one particular product from the selection (i.e. one top and one handbag). The same top and handbag used to map ASOS data was also used map Pretty Gal data except with different snapshots as shown above.

7.5 Areas of Interest (AOI)

It is important to define AOIs on the snapshot images before mapping fixation data. Put simply, Holmqvist et al. (2011, p.187) define AOIs as ‘regions in the stimulus that the researcher is interested in gathering data about’. In other words, they are based on the hypotheses. AOIs were drawn manually on the Analyzer software using the AOI Editor (Figure 7.1). When drawn on a particular m-commerce website (i.e. ASOS or Pretty Gal), the AOIs were copied and pasted to other screenshots of the same website for accuracy. For this study, there were three product presentation AOIs: the product image, alternative photos, and the product description. An AOI was drawn over the product description area to detect whether changes in the visual product presentation led to lower or high fixations towards the product description, which were the same across both websites. Since the thumbnail images of alternative photos were a separate part on the website, they were drawn with a separate AOI, but grouped together with product images during statistical testing.
Since the AOIs were the same size throughout the study, this should not influence total fixation time. This was found to be the case by Ozcelik et al. (2010). With bigger AOIs, there is less chance of the eye tracker to miss eye movements. With snapshots of both ASOS and Pretty Gal, this was not an issue as the image size was relatively large and stayed constant when clicking on different product views. Once drawn, each fixation point was manually mapped from the glasses recording per frame onto the relevant snapshot. This often meant switching between various snapshots featuring different product views or different websites (i.e. ASOS or Pretty Gal). It was important to do this step carefully; to check the recorded data and manually map the fixation to the corresponding area of the snapshot for reliability (Holmqvist et al., 2011; Otterbring et al., 2016). Heat maps and gaze plots can be generated on the Visualization tab. An example of data mapped from one participant is displayed in Figure 7.2.
Figure 7.2 Heat Map Visualisation (Participant Browsing on ASOS Mobile Website)

For the purposes of this study, heat maps were not used for data analysis since participants viewed more than one product item and there are four product views for each product on ASOS as well as product views involving visualisation tools. This would have generated too many visualisations and data aggregation would have been challenging. Additionally, when mapping data from dynamic stimuli, such as catwalk videos, data was mapped to a screenshot with a static shot of the catwalk video. Therefore, using heat maps would not have been suitable as accurate mapping would not have been captured. Instead, the aim of drawing AOIs and mapping data was to analyse metric data exported as an Excel file to enable further statistical testing using software such as SPSS (Tobii Technology, 2016b; Holmqvist et al., 2011; Duchowski, 2007).

7.6 Quantitative Data Analysis

Comparisons were drawn between ASOS and Pretty Gal in terms of visual attention towards these two websites. For group coding on SPSS, ASOS was denoted as 1 while Pretty Gal was denoted as 2. Level of image interactivity was considered a categorical, independent between-subject variable. As there were three fixation metrics, there were three analyses of independent samples \( t \)-tests; one for each dependent variable towards each AOI. A separate analysis was also conducted to compare perceptual fluency and purchase intentions towards the use of different image interactivity tools on ASOS.
7.6.1 Total Fixation Duration (TFD)

Independent samples *t*-tests were conducted to compare TFD towards fashion product images, visualisation tools and the product description of Women’s Tops and Handbags for ASOS and Pretty Gal. Groups statistics were examined. Table 7.3 provides the mean and standard deviation for each AOI and for each participant group (ASOS/Pretty Gal).

Table 7.3 Summary of Group Statistics for TFD

<table>
<thead>
<tr>
<th></th>
<th>Mobile Website</th>
<th>N</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Std. Error Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tops</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Images</td>
<td>ASOS</td>
<td>12</td>
<td>12.82</td>
<td>5.75</td>
<td>1.66</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>8.20</td>
<td>3.93</td>
<td>1.13</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>ASOS</td>
<td>12</td>
<td>1.42</td>
<td>3.31</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>2.03</td>
<td>4.00</td>
<td>1.15</td>
</tr>
<tr>
<td>Product Description</td>
<td>ASOS</td>
<td>12</td>
<td>1.45</td>
<td>2.13</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>5.48</td>
<td>4.91</td>
<td>1.42</td>
</tr>
<tr>
<td><strong>Handbags</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Images</td>
<td>ASOS</td>
<td>12</td>
<td>11.11</td>
<td>3.95</td>
<td>1.14</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>7.43</td>
<td>2.70</td>
<td>0.78</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>ASOS</td>
<td>12</td>
<td>0.83</td>
<td>1.99</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>2.43</td>
<td>3.05</td>
<td>0.88</td>
</tr>
<tr>
<td>Product Description</td>
<td>ASOS</td>
<td>12</td>
<td>4.55</td>
<td>6.78</td>
<td>1.96</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>4.56</td>
<td>5.10</td>
<td>1.47</td>
</tr>
</tbody>
</table>

For product images, the results show the means for ASOS are higher than Pretty Gal. On average, there was a higher TFD towards product images on ASOS than on Pretty Gal. The opposite is true for the mean of visualisation tools and product description. The mean is higher for Pretty Gal than for ASOS across both tops and handbags for these two AOIs. Nevertheless, there is little difference in the product description means for handbags; ASOS (M=4.55), Pretty Gal (M=4.56).

Assumptions were also examined. Levene’s Test for equality of variances ‘*tests whether the variance (variation) of scores for the two groups is the same*’ (Pallant, 2013, p.249). Two sets of variances were presented in the SPSS output (Equal variances assumed/Equal variances not assumed). The correct *t*-value to use is based on whether these variances are equal or not equal. If the significance value of Levene’s test is greater than 0.05, then the values for Equal variances assumed are used (Pallant, 2013). For example, for Images (Tops) the *p*-value for Levene’s Test was 0.022. Therefore, the *t*-values were obtained from the row: Equal variances not assumed. Effect sizes of significant differences was calculated using eta squared formula. This is useful in determining the ‘*magnitude of the differences between the groups*’ (Pallant, 2013, p.250).
An independent sample t-test was performed and revealed that only three differences were significant (Figure 7.4). For product images, there was a significant difference in the TFD between ASOS \((M = 12.82_{\text{tops}}, \ SD = 5.75)\) and Pretty Gal \((M = 8.20_{\text{tops}}, \ SD = 3.93; \ t(19.43) = 2.30, \ p = 0.033, \ \text{two tailed})\) when browsing for tops. According to the guidelines by Cohen (1998), the effect size of the difference in the mean was a very large effect (\(\text{eta squared} = 0.194\)).

**Table 7.4 T-Test Results for TFD**

<table>
<thead>
<tr>
<th></th>
<th>T-Test for Equality of Means</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(t)</td>
<td>df</td>
<td>Sig (2-tailed)</td>
<td>Mean Difference</td>
</tr>
<tr>
<td><strong>Tops</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Images</td>
<td>2.299</td>
<td>19.426</td>
<td>0.033*</td>
<td>4.622</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>-0.413</td>
<td>22</td>
<td>0.683</td>
<td>-0.617</td>
</tr>
<tr>
<td>Product Description</td>
<td>-2.611</td>
<td>14.983</td>
<td>0.020*</td>
<td>-4.033</td>
</tr>
<tr>
<td><strong>Handbags</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Images</td>
<td>2.672</td>
<td>22</td>
<td>0.014*</td>
<td>3.687</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>-1.522</td>
<td>22</td>
<td>0.142</td>
<td>-1.599</td>
</tr>
<tr>
<td>Product Description</td>
<td>-0.005</td>
<td>22</td>
<td>0.966</td>
<td>-0.013</td>
</tr>
</tbody>
</table>

* indicates significant difference, \(p \leq 0.05\)

There was also a significant difference for product images viewed when browsing for handbags between ASOS \((M = 11.11_{\text{handbags}}, \ SD = 3.95)\) and Pretty Gal \((M = 7.43_{\text{handbags}}, \ SD = 2.70; \ t(22) = 2.67, \ p = 0.014, \ \text{two tailed})\). This effect size is also very large (\(\text{eta squared} = 0.245\)).

Although the mean for visualisation tools AOI is higher for Pretty Gal \((M=2.03_{\text{tops}})\) than for ASOS for tops \((M=1.42_{\text{tops}})\), the difference was not significant. This was also found with handbags; the mean TFD was greater for Pretty Gal \((M=2.43_{\text{handbags}})\) than for ASOS \((M=0.83_{\text{handbags}})\). For the AOI product description, a significant difference was found between ASOS \((M = 1.45_{\text{tops}}, \ SD = 2.13)\) and Pretty Gal \((M = 5.48_{\text{tops}}, \ SD = 4.91; \ t(14.98) = -2.61, \ p = 0.02, \ \text{two tailed})\) when browsing for tops. In terms of the differences in the means, this effect size is a very large effect (\(\text{eta squared} = 0.236\)). For handbags, no significant difference was found between the two websites for product description.
7.6.2 Average Fixation Duration (AFD)

A summary of the means and standard deviations of the group statistics for AFD is displayed in Table 7.5. The group statistics for average fixation duration are similar to TFD. The ASOS means were higher than Pretty Gal means for the AOI images for both conditions (tops & handbags). In contrast, the means for the AOIs visualisation tools and product description were higher for Pretty Gal than for ASOS when browsing both conditions (tops & handbags).

<table>
<thead>
<tr>
<th>Table 7.5 Summary of Group Statistics for AFD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile Website</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td><strong>Tops</strong></td>
</tr>
<tr>
<td>Images</td>
</tr>
<tr>
<td>ASOS</td>
</tr>
<tr>
<td>Pretty Gal</td>
</tr>
<tr>
<td>Visualisation tools</td>
</tr>
<tr>
<td>ASOS</td>
</tr>
<tr>
<td>Pretty Gal</td>
</tr>
<tr>
<td>Product Description</td>
</tr>
<tr>
<td>ASOS</td>
</tr>
<tr>
<td>Pretty Gal</td>
</tr>
<tr>
<td><strong>Handbags</strong></td>
</tr>
<tr>
<td>Images</td>
</tr>
<tr>
<td>ASOS</td>
</tr>
<tr>
<td>Pretty Gal</td>
</tr>
<tr>
<td>Visualisation tools</td>
</tr>
<tr>
<td>ASOS</td>
</tr>
<tr>
<td>Pretty Gal</td>
</tr>
<tr>
<td>Product Description</td>
</tr>
<tr>
<td>ASOS</td>
</tr>
<tr>
<td>Pretty Gal</td>
</tr>
</tbody>
</table>

A summary of the t-test results for AFD are provided in Table 7.6. Only two significant differences were found. Like TFD, there was a significant difference in AFD towards product images for tops between ASOS ($M = 1.06_{\text{tops}}, SD = 0.43$) and Pretty Gal ($M = 0.61_{\text{tops}}, SD = 0.15$; $t (13.527) = 3.411, p = 0.004, \text{two tailed}$). The magnitude of the differences in means was considerably very large ($\text{eta squared} = 0.346$). A similar result was found for product images for handbags; a significant difference was found between ASOS ($M = 0.90_{\text{handbags}}, SD = 0.19$) and Pretty Gal ($M = 0.57_{\text{handbags}}, SD = 0.13$; $t (22) = 5.028, p = 0.000, \text{two tailed}$). This effect size is also very large ($\text{eta squared} = 0.535$).
### Table 7.6 T-Test Results for AFD

<table>
<thead>
<tr>
<th></th>
<th>t</th>
<th>df</th>
<th>Sig (2-tailed)</th>
<th>Mean Difference</th>
<th>Std. Error Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tops Images</td>
<td>3.411</td>
<td>13.527</td>
<td>0.004*</td>
<td>0.449</td>
<td>0.132</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>-1.329</td>
<td>22</td>
<td>0.197</td>
<td>-0.080</td>
<td>0.060</td>
</tr>
<tr>
<td>Product Description</td>
<td>-1.946</td>
<td>22</td>
<td>0.064</td>
<td>-0.207</td>
<td>0.106</td>
</tr>
<tr>
<td><strong>Handbags</strong> Images</td>
<td>5.028</td>
<td>22</td>
<td>0.000*</td>
<td>0.334</td>
<td>0.066</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>-1.328</td>
<td>22</td>
<td>0.198</td>
<td>-0.129</td>
<td>0.097</td>
</tr>
<tr>
<td>Product Description</td>
<td>-0.215</td>
<td>22</td>
<td>0.832</td>
<td>-0.018</td>
<td>0.082</td>
</tr>
</tbody>
</table>

* indicates significant difference, \( p \leq 0.05 \)

#### 7.6.3 Number of Fixations (NOF)

A summary of the group means, and standard deviations for the NOF are presented in Table 7.7. The results are similar to TFD and AFD.

### Table 7.7 Summary of Group Statistics for NOF

<table>
<thead>
<tr>
<th></th>
<th>Mobile Website</th>
<th>N</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Std. Error Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tops</strong> Images</td>
<td>ASOS</td>
<td>12</td>
<td>44.24</td>
<td>22.12</td>
<td>6.39</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>24.00</td>
<td>11.22</td>
<td>3.24</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>ASOS</td>
<td>12</td>
<td>3.08</td>
<td>7.20</td>
<td>2.08</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>6.08</td>
<td>10.68</td>
<td>3.08</td>
</tr>
<tr>
<td>Product Description</td>
<td>ASOS</td>
<td>12</td>
<td>4.92</td>
<td>6.33</td>
<td>1.83</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>14.00</td>
<td>10.79</td>
<td>3.11</td>
</tr>
<tr>
<td><strong>Handbags</strong> Images</td>
<td>ASOS</td>
<td>12</td>
<td>44.00</td>
<td>15.44</td>
<td>4.46</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>26.92</td>
<td>7.48</td>
<td>2.16</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>ASOS</td>
<td>12</td>
<td>1.42</td>
<td>4.06</td>
<td>1.17</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>7.92</td>
<td>10.17</td>
<td>2.94</td>
</tr>
<tr>
<td>Product Description</td>
<td>ASOS</td>
<td>12</td>
<td>15.67</td>
<td>22.38</td>
<td>6.46</td>
</tr>
<tr>
<td></td>
<td>Pretty Gal</td>
<td>12</td>
<td>17.58</td>
<td>18.11</td>
<td>5.23</td>
</tr>
</tbody>
</table>

For both conditions (tops/handbags), the NOF for ASOS were higher than the number of fixations for Pretty Gal towards the AOI product images. For the other two AOIs (visualisation tools and product description), the NOF were higher for Pretty Gal than for ASOS. This was found across both conditions of tops and handbags. The \( t \)-test results for NOF are provided in Table 7.8.
Table 7.8 T-Test Results for NOF

<table>
<thead>
<tr>
<th></th>
<th>t</th>
<th>df</th>
<th>Sig (2-tailed)</th>
<th>Mean Difference</th>
<th>Std. Error Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tops</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Images</td>
<td>2.852</td>
<td>16.306</td>
<td>0.011*</td>
<td>20.417</td>
<td>7.160</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>-0.807</td>
<td>22</td>
<td>0.429</td>
<td>-3.000</td>
<td>3.719</td>
</tr>
<tr>
<td>Product Description</td>
<td>-2.516</td>
<td>17.774</td>
<td>0.022*</td>
<td>-9.083</td>
<td>3.611</td>
</tr>
<tr>
<td><strong>Handbags</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Images</td>
<td>3.450</td>
<td>15.891</td>
<td>0.003*</td>
<td>17.083</td>
<td>4.952</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>-2.057</td>
<td>14.414</td>
<td>0.058</td>
<td>-6.500</td>
<td>3.160</td>
</tr>
<tr>
<td>Product Description</td>
<td>-0.231</td>
<td>22</td>
<td>0.820</td>
<td>-1.917</td>
<td>8.311</td>
</tr>
</tbody>
</table>

* indicates significant difference, p ≤ 0.05

Findings from the results were the same as the findings found with TFD. There is a significant difference in the NOF towards product images for tops between ASOS (M = 44.24_{tops}, SD = 21.22) and Pretty Gal (M = 24.00_{tops}, SD = 11.22; t(16.306) = 2.852, p = 0.011, two tailed). As the effect size (eta squared = 0.270) is above 0.14, it is considered a very large effect size. No significant difference was found for visualisation tools across either condition. Unlike the handbag condition, a significant difference in the NOF was found towards product description for tops between ASOS (M = 4.92_{tops}, SD = 6.33) and Pretty Gal (M = 14.00_{tops}, SD = 10.79; t(17.774) = -2.516, p = 0.022, two tailed). The magnitude in the difference in the means is very large (eta squared = 0.223). Similarly, a significant difference towards product image for handbags was found between ASOS (M = 44.00_{handbags}, SD = 15.44) and Pretty Gal (M = 26.92_{handbags}, SD = 7.48; t(15.891) = 3.450, p = 0.003, two tailed). This effect size is also very large (eta squared = 0.351).

### 7.6.4 Perceptual Fluency and Purchase Intentions

Independent samples t-tests were also conducted to compare differences between perceived perceptual fluency and purchase intentions towards the fashion mobile website between the two treatment conditions (ASOS vs Pretty Gal) (Table 7.11). Items were selected based on relevant eye tracking literature (Table 7.9). Responses were coded numerically in Excel.
Table 7.9 Post Survey Questions

<table>
<thead>
<tr>
<th>Question</th>
<th>Scales</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Perceptual fluency</strong></td>
<td>How easy is it to see product information from the image?</td>
<td>Semantic differential scale from 1-7 (1 = very easy, 7 = very difficult)</td>
</tr>
<tr>
<td><strong>Purchase intentions</strong></td>
<td>What is the likelihood that you would buy from this website?</td>
<td>Likert scale from 1-7 (1= very likely, 7 = very unlikely)</td>
</tr>
</tbody>
</table>

Both means for perceptual fluency and purchase intentions are higher for ASOS than for Pretty Gal indicating it was easier to extract product information and that purchase intentions were higher (Table 7.10). Since the \( p \)-value for Levene’s Test was 1.000 for perceptual fluency, the \( t \)-values were obtained from the row: Equal variances assumed. This was also the same for purchase intentions, whereby the \( p \)-value for Levene’s Test was 0.502.

Table 7.10 Summary of Group Statistics for Perceptual Fluency and Purchase Intentions

<table>
<thead>
<tr>
<th>Mobile Website</th>
<th>N</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Std. Error Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceptual fluency</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASOS</td>
<td>12</td>
<td>1.83</td>
<td>0.781</td>
<td>0.207</td>
</tr>
<tr>
<td>Pretty Gal</td>
<td>12</td>
<td>2.67</td>
<td>0.651</td>
<td>0.188</td>
</tr>
<tr>
<td>Purchase Intentions</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASOS</td>
<td>12</td>
<td>2.00</td>
<td>1.348</td>
<td>0.389</td>
</tr>
<tr>
<td>Pretty Gal</td>
<td>12</td>
<td>3.42</td>
<td>1.443</td>
<td>0.417</td>
</tr>
</tbody>
</table>

Results in Table 7.11 reveal there was a significant difference in perceptual fluency between ASOS (\( M = 1.83, SD = 0.78 \)) and Pretty Gal (\( M = 2.67, SD = 0.65 \)); \( t (22) = -2.978, p = 0.007, \) two tailed). There was also a significant difference in purchase intentions between ASOS (\( M = 2.00, SD = 1.35 \)) and Pretty Gal (\( M = 3.42, SD = 1.44 \)); \( t (22) = -2.845, p = 0.021, \) two tailed).

Table 7.11 T-Test Results for Perceptual Fluency and Purchase Intentions

<table>
<thead>
<tr>
<th>T-Test for Equality of Means</th>
<th>( t )</th>
<th>df</th>
<th>Sig (2-tailed)</th>
<th>Mean Difference</th>
<th>Std. Error Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceptual fluency</td>
<td>-2.978</td>
<td>22</td>
<td>0.007*</td>
<td>-0.833</td>
<td>0.280</td>
</tr>
<tr>
<td>Purchase intentions</td>
<td>-2.845</td>
<td>22</td>
<td>0.021*</td>
<td>-1.417</td>
<td>0.570</td>
</tr>
</tbody>
</table>

* indicates significant difference, \( p \leq 0.05 \)
7.6.5 Summary of Quantitative Results

There are similarities in the findings across the three metrics. For all three eye tracking metrics, there appears to be greater interest towards the ASOS product images than Pretty Gal product images (Table 7.12). For ASOS, there were more glances towards this AOI and participants spent more time looking at the product images. This finding was consistent for both product categories. Although no significant differences were found in the metric data towards the visualisation tool AOI, all three metrics (TFD, AFD and NOF) towards visualisation tools were greater on the Pretty Gal website. Findings also reveal participants spent more time looking at detailed product description when browsing for tops on the Pretty Gal website. There were also more fixations directed towards this AOI when browsing for tops indicating attraction towards this AOI on this mobile website. As there were fewer product images of tops on Pretty Gal, this suggests participants looked at the product description to compensate for the lack of product information obtained from the product images. However, this was not significant for the handbag condition.

<table>
<thead>
<tr>
<th>Area of Interest</th>
<th>Website with higher TFD</th>
<th>Is the result significant?</th>
<th>Website with higher AFD</th>
<th>Is the result significant?</th>
<th>Websites with higher NOF</th>
<th>Is the result significant?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tops</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product Images</td>
<td>ASOS</td>
<td>Yes</td>
<td>ASOS</td>
<td>Yes</td>
<td>ASOS</td>
<td>Yes</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>Pretty Gal</td>
<td>No</td>
<td>Pretty Gal</td>
<td>No</td>
<td>Pretty Gal</td>
<td>No</td>
</tr>
<tr>
<td>Product Description</td>
<td>Pretty Gal</td>
<td>Yes</td>
<td>Pretty Gal</td>
<td>No</td>
<td>Pretty Gal</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Handbags</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product Images</td>
<td>ASOS</td>
<td>Yes</td>
<td>ASOS</td>
<td>Yes</td>
<td>ASOS</td>
<td>Yes</td>
</tr>
<tr>
<td>Visualisation tools</td>
<td>Pretty Gal</td>
<td>No</td>
<td>Pretty Gal</td>
<td>No</td>
<td>Pretty Gal</td>
<td>No</td>
</tr>
<tr>
<td>Product Description</td>
<td>Pretty Gal</td>
<td>No</td>
<td>Pretty Gal</td>
<td>No</td>
<td>Pretty Gal</td>
<td>No</td>
</tr>
</tbody>
</table>

Data from the survey questions reveal significant differences in perceptual fluency and purchase intentions between ASOS and Pretty Gal. Results were more positive for ASOS indicating higher perceptual fluency and purchase intentions. To explain these results further, qualitative data was also examined.
7.7 Qualitative Data Analysis

This section presents findings from the interviews. Each interview was conducted straight after the eye tracking experiment. Participants were also asked to explain why they did or did not use the visualisation tools when shopping on either ASOS or Pretty Gal, as well as their general thoughts towards these tools and their overall perceptions of shopping on a tablet device. Results revealed two main themes with several sub-themes with at least two codes. The results are presented in the sub-sections below. When asked why they use these tools in general, fit, quality, and the texture of the product were provided as a reason. The main themes that emerged from the interview data were fashion images as a visual stimulus and the mobile shopping user experience.

7.7.1 Fashion Images as a Visual Stimulus

Sub-themes of visual stimuli included visualisation tools, shopping behaviours, product views, and imagery. Several codes within visualisation tools were identified and discussed below. On the whole, attitudes towards image product presentation were positive; participants considered them to be useful tools.

Detailed view
On ASOS, the zoom-in function, catwalk video and rotation tools provide a detailed view that offers greater information about the product. Since participants were unable to interact with the product in real life, these tools played a key role in extracting product information. This is important as online returns are likely if the product does not exceed expectations. In contrast, there was difficulty when trying to zoom in on the product on Pretty Gal due to the poor-quality images and image enlargement tool. A detailed view may be a particular feature of the product or to do with the material, for example:

I perhaps look at the stitching or something, or how stable the garment sort of looks definitely or to see it on the bags, for example to see perhaps the level of what fake leather quality is like. Does it look a bit too fake or does it look realistic? I often zoom in to see the prints on something [5 – Pretty Gal].
I always find it useful when companies give like… like ASOS gives a video […] Like you can actually see what it looks like, which is good […] rather than just a photo, a still image, so that’s really useful [16 – Pretty Gal].

[…] there are so many people who order stuff online - they come and it’s quite disappointing. So, I definitely think it’s very important [5 – Pretty Gal].

I think that [360° product rotation] are more useful than the catwalk video even though that’s more the person seeing how it’s worn, [8 – ASOS].

They were good, they showed you what you needed to see, like in detail […] I think yeah it gave you a better idea of the products from the first picture. Because one of them was like, I like the product but when I looked at it on I was a bit like hmm… I didn’t really like it so much [8 – ASOS].

I think I never use the catwalk video because on some websites they’re a bit blurry [8 – ASOS].

Comparisons with the model
The catwalk video was found to be useful in showing how the model wears and moves with the top. Participants were then able to draw comparisons with the model and assess the fit and length of the top. Catwalk videos were helpful in that participants were able to see how the material falls and moves with the model. Although the model was criticised of being a certain size, shape and height, it was still useful to have the model as a point of reference.

I normally do, like with swimsuits because when you walk you see how it moves with the body and with dresses I probably would as well because I’m a quite a tall person – I need to see where it comes to on a model’s body and see how it moves because it might be a bit short for me [3 – ASOS].

[…] having a video as well is really useful […], where you can see kind of other models wearing it on, how the garment interacts with their body [19 – ASOS].

Obviously, they would definitely benefit from the catwalk video, I always watch the catwalks on ASOS. You can work out how the clothes would fit better and what they’re actually going to look like when you move and things [12 – Pretty Gal].

I think they’re useful definitely, and the catwalks are sometimes good, but only if like you’re that dress size, shape and height [15 – ASOS].
The catwalk video shows the clothing on one body type, but it does give a better indication than no indication at all if it wasn’t there so... it does help [1 – ASOS].

Type of product
The type of product is also important. Findings show the zoom function and catwalk videos are not necessarily used for t-shirts, whereby product images were considered adequate. This suggests visualisation tools are less likely to be used for products where there is greater familiarity with the material or fit as comments reveal the usefulness of these tools for other types of clothing, such as trousers and dresses, where it is difficult to gauge the fit or for items they would not normally wear.

I think the catwalk view thing is er more appropriate for something like a dress or a pair of trousers or something. I think it’s probably a really good tool for something that’s quite outlandish – consumers are going to be put off by seeing a single image of, [...] if you see how it flows on the body you would be more likely to purchase it. But, I think in terms of day to day if I was buying a t-shirt from Missguided or Topshop I wouldn’t want... I doubt I would look at a catwalk show visualisation of it or a 360 of it if there were adequate pictures [11 – Pretty Gal].

I think I got everything I needed from just the pictures that were there. If it’s a kind of more daring thing, so if it’s like... I don’t know, a dress that I wouldn’t normally wear I would maybe look at the catwalk image to see how they styled it, but in terms of zoom in and out I never really use that stuff. [...] I get a clear enough picture without it [14 – ASOS].

I prefer the 360 thing [...] Umm, I dunno just being able to... you don’t feel like you need 3 photos. You can see all sides of [the bag] and how it would look [8 – ASOS].

Yeah, so with dresses I like to look at the videos to see how they wear, but with other things I’m not so fussed about the video [2 – ASOS].

Awareness
Comments reveal there was a lack of awareness of these tools. This was found with the 360⁰ product rotation tool on ASOS. Interestingly, while people state the usefulness of this tool, many were unaware the tool is available on ASOS for handbag accessories. This may due to the fact that tool is still new on ASOS. Videos are more commonplace than rotation tools, but some of the participants were aware of product rotation in general.
I just didn’t see them. I definitely would’ve used the 360 tool [4 – ASOS]

I don’t think it’s that noticeable you can use or that they are there to use. But I think the pictures are pretty clear, you saw what you’re getting, so it’s not always necessary I suppose [9 – ASOS].

I didn’t realise there was a 3D function actually… 3-dimensional view, so like I think if I did know about it I would’ve looked at that because it’s quite useful [18 – ASOS].

Availability and Experience
Catwalk video and product rotation are not available on all shopping websites. There may be differences in the tools available when using a particular platform to shop from i.e. a mobile device rather than a PC device. Some participants noted the lack of visualisation tools on Pretty Gal and also stated the limited zoom function on Pretty Gal could be improved, as this appeared to be blurry. Comparisons were even drawn against other websites they shop on, such as ASOS and Schuh.

[… I can’t really think of any retailers that I use that do currently use that apart from ASOS using it- the umm catwalk feature, I don’t tend to use that much. […] Yeah, I think partly because it’s not that available, and partly because sometimes a lot of the time when I’m shopping online, I just want to like... keep like... keep moving, keep looking at different stuff [6 – Pretty Gal].

I do quite like what ASOS does actually. They do all the catwalk kind of stuff and I know not many retailers have caught onto that yet, so I think that a little bit more widespread would be handy. But I do understand that there’s logistics behind that and things and not every retailer would be able to do that [5 – Pretty Gal].

[…] catwalk feature, I don’t tend to use that much. […] Yeah, I think partly because it’s not that available [6 – Pretty Gal].

Obviously, they would definitely benefit from the catwalk video, I always watch the catwalks on ASOS [12 – Pretty Gal].

Visualisation tools may or may not be used due to previous experience and the know-how in using these tools.
I tried to, but I don’t know how to do it. I tried to click the zoom thing, but don’t know whether it worked [16 – Pretty Gal].

I use like the 360 thing. I think Schuh do it I’ve definitely looked at it on there. [...] you don’t feel like you need 3 photos. You can see all sides of it and how it would look. They are nice and clear [8 – ASOS].

Maybe it’s the bad experience before, so like I’ve never bothered with [catwalk videos] again [8 – ASOS].

Delay in Viewing

While there is a tendency to click onto a product page if there is enough interest in the product, using the tools may be inconvenient; it may slow down the browsing process. For example, tools such as catwalk video take a while to load and watch.

[…] I can’t be bothered to wait for it to load and stuff. I dunno, I think it’s easier to look at the photos [...]. It took a while to load and I was like it’s a bit of a faff [8 – ASOS].

[…] sometimes a lot of the time when I’m shopping online I just want to like... keep like... keep moving, keep looking at different stuff [6 – Pretty Gal].

Shopping Motivation

Another sub-theme that was found was shopping motivation. Depending on how individuals shop they may or may not use the visualisation tools. There was a greater tendency to not use the tools if participants were casually browsing. Fashion retailers such as ASOS have typically more than 1,000 clothing products per product category; viewing products on the product page may slow down the shopping process. Conversely, comments suggest visualisation tools are more likely to be used if shopping for a specific type of product. This suggests these tools are more likely to be utilised if shopping for utilitarian purposes.

I think they are good, maybe not for general shopping but if you’re looking for something in particular, it’s nice to see what items for it to go with or something like that. [...] to see finer details, but if you’re just having a general browse I don’t feel like it’s necessary, only if you’re looking into detail or if you’re looking at
something in particular. I think it’s quicker to go normally and just scroll [9 – ASOS].

**Interest in product**
Alongside browsing tendency is interest in product. If there is enough interest towards the clothing or accessory product generated on the product page, this increases the likelihood of using visualisation tools.

*I must admit I would only use it if I was 100% into the product. As much as I liked some of the products and I think with some of them I could kind of tell what they would look like all around if that makes sense. I didn’t feel like it was necessary [3 – ASOS].* 

*I don’t really use the zoom in function unless I’m really interested in what the item is and I really want to check like the details or stuff like that [18 – ASOS].*

**Purchase decisions**
Usage of these tools increases when participants are likely to purchase the garment or accessory. This is because these tools help to assess the overall product quality and to make an informed decision. This suggests visualisation tools are particularly useful once consumers have invested the time in looking at the product in detail and would like the buy the item. Majority of participants stated this would be the reason for using these tools in the first place.

*It definitely makes you more likely to buy something, the more you can see something, the higher the visibility, the more likely I am to buy something. I guess it creates a sense of trust and like an expectation of what it would like when it comes [...] I guess, the key challenge to shopping online for me is just... I want to see the product in quite a lot of detail, and obviously you can’t do that like you can when you go into a shop. I guess the more detail in terms of like the visuals and the.. erm information the better. Makes me more likely to buy something promptly [10 – Pretty Gal].*

*Zooming in is really important I think to have. I think most people try to zoom in when they’re looking at photos and stuff they’re gonna buy [7 – Pretty Gal].*
In addition to visualisation tools and shopping behaviours, product views and imagery were found to be sub-themes. In terms of design, participants considered both websites (ASOS and Pretty Gal) website to be clean and well laid out. However, opinions differed on the views of the product and the overall use of imagery on the mobile websites.

**Number of images**

In terms of the product views on the ASOS website, participants found them to be adequate as there was more than one photo to see different angles of a product. Some comments suggest the different views on ASOS were sufficient that they did not need to use a visualisation tool to obtain further information. However, majority of participants would have liked to see more images of the product on the Pretty Gal website since the website only featured a front view and back view. Interestingly, participants who shopped on Pretty Gal stated there were a lack of images, lack of visualisation tools and product description when asked about their thoughts on the product pages.

*Yeah, I thought they were good actually, er, I think maybe with the tops there could’ve been a few more. It was just the front and back I noticed. I quite like... I tend to look through all the photos to see how the top fits essentially [5 – Pretty Gal].

I like the layout. [...] it’s quite similar to how most, kind of online retailers’ kind of lay their things out. [...] I like that they had the product description and stuff like that. Umm, yeah it could’ve done with having potentially more product photos [6 – Pretty Gal].

I don’t think there was a lot of information about the product. Obviously, it was really useful to have the zoom in, but it was only like... it was quite limited to two pictures. There wasn’t like a video or anything on there. Umm, I found er that a lot of the writing was quite limited as well. It didn’t explain erm what type of... how tall the model was and things like that, which I find really difficult when shopping online [19 – Pretty Gal].

They normally give you at least 4 angles, or you can see the inside, especially the handbag so you can see the lining. And then tops, it’s important to see the back, so you can see the full fit [15 – ASOS].

It’s got... er I like that they had the product description and stuff like that. [...] yeah it could’ve done with having potentially more product photos [6 – PG].
I think maybe with the tops there could’ve been a few more. [...] I tend to look through all the photos to see how the top fits essentially [5 – PG].

Close-up view
Participants also emphasised the importance of an image with a close-up view. Majority of participants who shopped on Pretty Gal stated the usefulness of having close-up images of the product. A close-up view allows particular detail to be seen without using a zoom-in function. Comments differed between tops and handbags. Close-up images of the product are useful when shopping for tops, whereas different angles of an accessory product as well as an inside view of the bag itself are preferred when shopping for handbags.

I like the fact that I could see the different clothes from the different angles, and it was fairly detailed in terms of washing instructions and stuff and purchasing. But, maybe, I guess quite often retailers have like videos that you can see how the garment fits and hangs and moves and stuff. That’s usually quite useful. Also, maybe, like close-up images of the fabric and stuff, which is something I’d enjoy. [...] I found the sort of different angles and I found the details useful. But it could’ve done with other things that I just mentioned [10 – Pretty Gal].

They’re all really clear and there were obviously different angles, which is good to see. There was one on the top, it had like writing on the top that wasn’t that clear I don’t think. But the rest of them you could see everything. You could see the inside of the bags as well [9 – ASOS].

They always have zoomed in pictures anyway. [...] as long as I’ve got a clear enough view without it, I don’t use them [14 – ASOS].

The only thing I would probably say in terms of things to change if they were going to be changed would be more in-depth photographs of things like the fastenings [11 – PG].

Model view
Like the catwalk video, comparisons were drawn with the model posing in the still images. A model view with a handbag would be useful on Pretty Gal as this view was not provided. Offering an image of a model wearing the handbag is useful and easier in assessing the size and dimensions of the bag rather than reading the measurements
provided in the product description. For clothing, the tops worn on models with a certain body type was an issue. However, this still provided information which was better than no information at all.

Yeah, I think even though some people may have an issue because it shows the clothing on one body type, but it does give a better indication than no indication at all if it wasn’t there so… it does help [1 – ASOS].

Umm, like all the images are kind of shot from the same angle and like the same pose, er and none of the accessories are styled up, so you just kind of… don’t get an idea of how they look on the body, er and the size and things like that – you don’t really know how big the bags are unless you read the dimensions, which you don’t really do [12 – Pretty Gal].

**Quality of images**

In comparison to the images on Pretty Gal, images on ASOS were considered better quality. The images are clear enough to see detail. Participants who browsed on Pretty Gal noted the poor quality of the images when trying to look at the products in detail. Overall with ASOS, participants were satisfied with the amount of information available from the images alone.

I feel like the pictures of the tops were quite blurry when you zoom in. [...] you could still zoom in, but they weren’t great; they weren’t that high quality. [...] it didn’t really stand out to me. The price was quite small, and the pictures weren’t the best [7 – Pretty Gal].

I feel like the pictures are always good quality. The bags and all the products [3 – ASOS].

I think from shopping on there quite a lot I think the photography is something they pride themselves on a lot [...] even though is obviously like a still photo I think they do well to show movement on clothing just from a photograph [1 – ASOS].

**Fashion photography**

Comments about the photography on ASOS suggest images are shot in an artistic and fashionable way. Styling a model for a photograph with a high fashion look seems to be
based on preference. While some participants favoured this, others did not like this. The way the model was posed and the way the photo was shot was an issue when this obscured visual information. Participants found acquiring product information such as movements of the product difficult when the model was posed in an artful way. Interestingly, photography on Pretty Gal was described as static despite having the same images as ASOS. This suggests it may be difficult to display fashionable images with just a front view and back view while trying to display as much as visual information about the product at the same time.

[…]
in some of the images I see the positions of the girls swaying like something. I guess it’s good to show the movement, but then on one of them it’s cut out half of her body and you just see the flow of the top, so I guess trying to make it less edge and arty would make it simply for the products cause you kind of know how you’re gonna style it. You’re not gonna stand there and pose in those weird positions [15 – ASOS].

Some of the items look different to real life and sometimes the model makes the item look a lot better by like posing in a certain way like leaning back […] I would say that I don’t really like when the item is like half on the page and half off the page because I can’t really see it. Or when the model is kind of modelled sideways because I don’t get a full-on view of what it looks like without the model posing [18 – ASOS].

[…]

obviously the tops have models, but it was just like very static poses and the bags were just kind of sitting there […] Umm, like all the images are kind of shot from the same angle and like the same pose, er and none of the accessories are styled up [12 – Pretty Gal].

 […] in some of the images I see the positions of the girls swaying like something. […] I guess trying to make it less edge and arty [...] You’re not gonna stand there and pose in those weird positions [15 – ASOS]

**Styling the product**

It was also interesting to note that while product images on the Pretty Gal websites were the same ones as the ASOS website, participants still considered the images to have a lack of styling and appear to be cheap and plain. Styling includes accessorising the product with other items to display the product as part of an outfit.
Umm, even though is obviously like a still photo I think they do well to show movement on clothing just from a photograph. And obviously there is an option to view a video as well. It is something I always look at because obviously with clothing I think I look a lot different in motion than a still photo. But yeah, I think they do capture the item of clothing well and put outfits together well [1 – ASOS].

They looked quite cheap because it was just plain white, so like ASOS they use colours, or they use models. [...] none of the accessories are styled up [12 – Pretty Gal].

**Amount of information**

Comments reveal if there is too much information available online, this can be overwhelming. Equally, if there is less information than what is expected then this may have an effect on confidence to buy from the website.

*I think it was probably wasn’t too overwhelming, those were good pictures to have on the page [...] Yeah, I didn’t think this was too much, or I can’t see what I’m looking at [21 – ASOS].*

*It definitely makes you more likely to buy something, the more you can see something, the higher the visibility, the more likely I am to buy something. I guess it creates a sense of trust and like an expectation of what it would like when it comes [10 – Pretty Gal].*
7.7.2 Mobile Shopping User Experience

Within this theme, two sub-themes were identified: interaction and usage. The former relates to how participants interacted on the device when shopping on ASOS or Pretty Gal, whilst the latter relates to thoughts and attitudes towards using a mobile device to shop from. Overall, there was a greater preference of shopping on the tablet compared to laptop or desktop devices. Findings were similar across ASOS and Pretty Gal participants. Participants also likened tablet devices to smartphones.

Gestural interactivity

Findings indicate that the interaction on a mobile device is gestural; interactions such as swiping make it easier to shop on smartphones and tablets with the ability to touch the screen using fingers. Comments also suggest that this type of interaction is easier than interacting with a PC or laptop device that typically requires a mouse or a touchpad.

*It feels... I think it feels more interactive because you’re physically touching the screen [6 – Pretty Gal].*

*I find it easier shopping on a tablet, just because you can click all over the place, and it’s just quite straightforward. It’s mostly similar to shopping on my phone, which I do quite a lot as well [14 – ASOS].*

*[...] more likely to click on them on a tablet I think because you’re like touching the screen [...] you can click it and click back, whereas there’s more movement involved in a laptop like the trackpad and using the mouse [12 – Pretty Gal].*

*Because you’re just using your finger swiping it and stuff it’s a bit easier than a computer [17 – PG].*

*It can sometimes be easier because you’re literally just one hand, probably one finger [15 – ASOS].*

Closeness

With a tablet, it is possible to move the tablet a lot closer to see the screen. This also provides an advantage when using the zoom-in function on when using fingers to zoom-in
on the page itself; greater detail can be seen. As a result, this can provide a shopping experience that is closer to an individual. Some participants suggested that control of moving the tablet helps them to shop better on the tablet.

[…] it feels kind of closer to the shopping experience rather than the… kind of feeling a bit more distance on a computer [6 – Pretty Gal].

I think I prefer it on the tablet. It’s just easier to manoeuvre around it and stuff and the pictures – you can zoom in a lot more, it’s closer to you [13 – ASOS].

Ease of use

Majority of comments about shopping on mobile devices mentioned how easy it to use. In comparison to laptops and desktops, tablets are easy to transport and can be held by an individual. Interactions such as swiping are considered to be easier than using a mouse or touchpad to click, as the finger is directly engaging with the screen. With these devices, it’s also possible to shop using one hand with one finger.

Well, I normally use a tablet. I just find it a lot easier. Laptops are kind of bulky, aren’t they? […] obviously you can do it on the go, especially if you’ve got an iPad Mini, umm just past time and spend money that you’ve not got! […] I would say 95% of my shopping is done on a tablet or mobile as opposed to like a big computer. I just find it easier. [1 – ASOS].

I definitely prefer – it’s just the same as the phone. I prefer being able to swipe yourself. I feel like it is easier, just a bit easier to use [3 – ASOS].

I found it easier because you can hold it yourself. […] it’s more mobile, you can take it everywhere [9 – ASOS].

It can sometimes be easier because you’re literally just one hand, probably one finger [15 – ASOS].

I think I prefer it on the tablet. It’s just easier to manoeuvre around it and stuff and the pictures [13 – ASOS].
Experience
Comments suggest that participants who have a greater preference to shop on a mobile device find these devices easier to use. Subsequently, there were a few participants who preferred laptops and desktop devices. When probed further, it appears they have a lack of shopping experience on tablets, i.e. they do not have an iPad or do not use an iPad often. These participants also find it easier to open tabs of different products when shopping, thus finding it easier to find and save for later.

I tend to feel like I have more control when I’m on a laptop just because of the mouse, there are separate desktops I feel like they’re easier to handle, [...] I feel like it’s kind of more saved on a desktop. It’s much easier to get straight back to them. [...] I try to not shop on tablets [4 – ASOS].

[...] I think on a laptop device, I probably open things like a new tab rather than erm click on them and just go back, cause then you can have multiple things open and you can compare them, but I don’t know how to do that on the iPad! [16 – Pretty Gal].

I tend to mainly shop on the desktop, so it was different to use online [...] I don’t have an iPad! [2 – ASOS].

7.7.3 Summary of Qualitative Results
Overall, the results indicate the usefulness of product presentation. On the whole, responses towards product presentation on ASOS were more positive. Of the three tools available on ASOS, the zoom-function was found to be the most useful tool for both tops and handbags with opinions divided over catwalk videos and product rotation. Catwalk videos are useful when comparing the fit on the model’s body to assess how the product looks when worn. This tool is especially important to see “movement” of the item on the body, and usage of this tool may depend on the product category, i.e. products that may have greater fit issues. Product rotation is helpful in seeing all sides of a product rather than referring to additional product views. Responses towards Pretty Gal were positive in terms of design and layout but reinforced the need for better visualisation tools and for better product views.
Findings reveal visualisations tools are particularly important if an individual is highly interested and/or is considering purchasing the product. Shopping on a tablet device was positive for individuals who have experience and preference of shopping from these devices. Interview data also illustrates the potential of gestural interaction when shopping on mobile devices; it was found to be more interactive and facilitates a shopping experience that is considered easier to use. By being able to move these devices with ease, the shopping experience was described as “close”. Results also highlight the importance of good quality product views, if tools such as catwalk video are not present or if the zoom function does not perform as expected, which can have a negative effect. Overall, participants considered these tools to be helpful in judging the material, quality, fit and the fabric draping properties in helping to make purchase decisions. A summary is provided in Table 7.13.
Table 7.13 A Summary of Qualitative Findings

<table>
<thead>
<tr>
<th>Open Code</th>
<th>Axial Code</th>
<th>Selective Code</th>
<th>Summary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual Stimuli</td>
<td>Visualisation</td>
<td>Detailed view</td>
<td>While some participants state they use different tools for different reasons, on the whole these tools enable individuals to obtain detailed product information.</td>
</tr>
<tr>
<td></td>
<td>tools</td>
<td></td>
<td>Comparisons with the model Watching the catwalk video was useful to obtain size comparisons and for understanding how the product moves on a human body.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Type of product For certain products, visualisations tools are more useful. For clothing items that may be difficult to gauge in terms of fit or material, these tools are more likely to be used.</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Awareness Usage also depends on awareness and recognition that visualisation tools are available on the mobile website or app.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Availability and experience These tools are not available on all fashion websites. Usage also depends on previous experience and know-how in using them.</td>
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<td></td>
<td></td>
<td></td>
<td>Inconvenience Negative comments towards the catwalk video was the time it took to load and view the video when shopping.</td>
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<tr>
<td>Shopping behaviours</td>
<td></td>
<td></td>
<td>Shopping motivation Usage of these tools may depend on the shopping motivation with comments indicating they are more likely to be used when the shopping is goal-directed rather than hedonic reasons.</td>
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<td></td>
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<td></td>
<td>Interest in product Usage is higher if there is high interest in the product. At this point, an individual is invested in acquiring more product detail.</td>
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<td></td>
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<td></td>
<td>Purchase decisions Responses indicate these tools facilitate purchase decisions. By acquiring more detail, individuals are able to make an informed decision about purchasing the product.</td>
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<td></td>
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<td></td>
<td>Product views Number of images Comments reveal the importance of the number of product views i.e. more than a front view and back view. Having a variety of product views can help to see detail from different angles. Comments towards Pretty Gal revealed a lack of images and products views hindered further visualisation.</td>
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<tr>
<td></td>
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<td></td>
<td>Close-up view This view helped to access detail of particular product features, such as embellishment, that is difficult to view from just the front and back view.</td>
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<td></td>
<td></td>
<td></td>
<td>Model view A model view with a handbag was particularly useful and was preferred rather than reading product dimensions. There was criticism towards the use of a model who was a certain size and body type. However, it was still useful as a point of reference.</td>
</tr>
<tr>
<td>Imagery</td>
<td>Quality of images</td>
<td></td>
<td>Comments highlighted the importance of good quality images in obtaining an adequate level of product information. There was a difference in the perceived quality of images on Pretty Gal; images were considered small and blurry.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Fashion photography Comments revealed the use of fashion photography in displaying the products in an artful way to be a disadvantage; they lack realism and can obscure obtaining product information.</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Styling the product Despite using the same images, there were perceived differences in the styling. Products on Pretty Gal were considered plain.</td>
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<td></td>
<td></td>
<td></td>
<td>Amount of information It is important to use a balance of static and dynamic imagery to provide enough product information without overwhelming the individual.</td>
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<tr>
<td>Mobile shopping</td>
<td>Interaction</td>
<td></td>
<td>Gestural Findings indicate that the interaction on a mobile device is gestural and is found to be easier to use. As a result of this interaction, most participants preferred to shop on this platform.</td>
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<tr>
<td>user experience</td>
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<td>Closeness Compared to PCs, it is easier to move a mobile device closer to an individual’s line of vision. This generates a “closer” shopping experience.</td>
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<tr>
<td></td>
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<td></td>
<td>Usage Using a tablet device to shop from was found to be easier than using a PC or laptop.</td>
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<td></td>
<td></td>
<td></td>
<td>Experience Those with more experience of shopping on mobile devices indicated a preference for this channel. The opposite was also found with participants that mainly used laptops to shop from.</td>
</tr>
</tbody>
</table>
7.8 Comparison of Quantitative and Qualitative Data

Significant differences were found in visual attention towards product images of tops, which was higher for the high product presentation condition. Qualitative findings explain fashion apparel and accessories presented on ASOS are better quality and more informative than those presented on Pretty Gal. Although interview responses varied according to the product item, whether it was a top or handbag, the use of additional product views, visualisation tools and imagery were highlighted as key aspects. Qualitative findings further highlights usage of visualisation tools can vary depending on an individual’s behaviour with reasons including the shopping motivation, the level of interest in the product and whether a product was being considered for purchase. This reaffirms the importance of good quality static imagery when an individual is casually browsing on a mobile device.

Survey results confirm there was greater perceptual fluency towards ASOS than Pretty Gal. In other words, it was easier to see product information on ASOS, which was also corroborated by the interview data. Despite having the same product description, it appears participants focussed on the product description of tops due to a lack of visual information on Pretty Gal; there were more fixations and a longer fixation duration towards this AOI than the same AOI for ASOS. This was supported by interview data with participants stating there was a lack of product information from the product picture and zoom function on Pretty Gal. Data from all three methods indicate a high level of fixation data is generally associated with interest rather than cognitive effort towards the product presentation with the exception of textual product presentation that was referred to due to a lack of visual information on Pretty Gal.
7.9 Chapter Summary

Overall, quantitative and qualitative data reveal differences in product presentation has an influence of visual attention as well as thoughts and perceptions on product presentation in relation to mobile shopping. Fixation data and survey data confirm a high level of product presentation is attractive and can help an individual to acquire product information with greater perceptual fluency. Corroborated by interview data, fixation data also confirms the importance of textual information with greater attention directed at the product description AOI for tops displayed during the low product presentation condition. Despite screen size concerns, qualitative findings demonstrate preference on mobile devices due to quick and easy interactions on a touchscreen as well as the importance of both static and dynamic product imagery on the product page with usage depending on shopping motivations and interest in the product.
Chapter Eight: Discussion

8.1 Introduction

This chapter evaluates the findings from the two-phase mixed-methods approach that includes findings from the online survey study and the eye tracking study comprised of the eye tracking experiment, survey and interview data. This chapter discusses and converges findings from both studies to establish the overall influence of product presentation technology on fashion m-commerce. Theoretical contributions, managerial implications and future research are also discussed in the following sub-sections.

8.2 Discussion

The first data collection phase entailed an online survey. Since product presentation is an essential visual stimulus when shopping for fashion apparel online, it was important to understand behaviour from a cognitive processing perspective. Specifically, fluency theory was integrated into the framework to understand the effect of this processing on consumer behaviour towards product presentation. Unlike other stimuli examined in fluency studies, static and dynamic product imagery used to display fashion products online is unique in that increasing the level of this stimuli also increases the amount of product information that may prove counterintuitive in terms of fluent processing. Shopping on a device with a smaller screen size may enhance this effect (Kahn, 2017). Hence, greater clarification was required to establish whether a high level of product presentation accessed on a mobile device results in greater perceptual fluency than a low level of product presentation.

Overall, the survey results support the relationships in the fluency framework between the constructs perceptual fluency and positive affect as well as the relationship between positive affect and purchase intentions. Relationships with cognitive effort were supported for the low product presentation condition, while the relationship between perceptual fluency and aesthetic evaluation was not supported in either low or high product presentation conditions.
The second data collection phase involved a concurrent approach with data collected at the same time. Fixation metric data confirms participants spent more time and a greater number of times looking at the product views on ASOS than on Pretty Gal. By conducting interviews, it was possible to ask participants to elaborate on their perceptions and attitudes on product presentation on mobile devices after browsing either fashion m-commerce site. The survey conducted after the eye tracking experiment and interview also reveals whether processing the visual product information was done with ease or difficulty. Alongside survey data and fixation data, interview data helped to clarify whether high fixation data occurred as a result of attraction or cognitive effort in addition to understanding attitudes and perceptions towards product presentation on m-commerce.

Online survey research was conducted using actual fashion websites. It was difficult to find a website equivalent to ASOS with a lack of image interactivity and similar products that appeal to the same target consumers as ASOS as well as the exact range of brands. Hence, for the survey, Amazon was considered to be the only suitable alternative. For the eye tracking, which was under experimental conditions, other websites that are considered equivalent were not ideal for the low product presentation condition. Thus, a mock website (i.e. Pretty Gal) that looked similar to ASOS and featured the same set of products to shop from was created using an online fashion template on Wix.com.

This research addresses a number of existing gaps in literature. Firstly, fluency theory was employed as an underlying visual theory to assess whether different levels of product presentation resulted in a difference in how consumers process product information on a perceptual level. Acknowledging this difference furthers understanding on antecedents that shape consumers’ affective and behavioural outcomes towards product presentation. Specifically, this includes the underlying perceptual processing towards static and dynamic imagery. Recent application of this theory to the retail environment (Mosteller et al., 2014, Wu et al., 2016) including m-commerce (Sohn, 2017b) as well as the recent adoption of imagery fluency in product presentation literature (Flavián et al., 2017; Orús et al., 2017) confirmed the suitability of studying perceptual fluency towards product presentation.

Secondly, both research phases examine the influence of product presentation on mobile devices. Product presentation literature has mainly focussed on shopping online via a PC. Higher levels of shopping from a smartphone or tablet device (Faulds et al., 2018; Pantano
and Priporas, 2016; Mintel, 2017), illustrates m-commerce is no longer a new phenomenon for young female consumers who are accustomed to shopping for fashion on this platform. There are also a number of notable differences between online and mobile devices. This includes differences in size and the interface (Wang et al., 2015; Kahn, 2017). Specifically, mobile devices are touchscreen devices with gestural interaction (LaViola, 2013; Brasel and Gips, 2014), which indicates the importance of researching the capabilities of product presentation technology from a mobile perspective. Due to these differences, e-commerce product presentation literature may not be applicable.

Thirdly, this research provides a methodological contribution to product presentation literature by using a multi-phase mixed-method approach. With the exception of fMRI technology used in the study by Jai et al. (2014) and De et al. (2013) who analysed data from an online fashion retailer, there is widespread usage of subjective measures, such as surveys, in product presentation literature (Kim, 2018; Beuckels and Hudders, 2016; Cano et al., 2017; Li et al., 2016b; Roggeveen et al., 2015; Ashman and Vazquez, 2012). Using technology such as EEG, fMRI and eye tracking can help to overcome limitations associated with surveys, such as verbal recall and general clicking through (Stieger and Reips, 2010; Bryman and Bell, 2015). Such data can provide further support when used in conjunction with subjective data collection methods (Wedel and Pieters, 2008). Interview data enhances understanding of consumers’ attitudes and behaviours towards visualisation tools from a mobile shopping context. Hence, there is a need to use additional data sources rather than relying on surveys to obtain a holistic understanding towards product presentation technology, i.e. to appreciate the significance of these tools in relation to the online shopping experience on a mobile device. Adopting a holistic approach was appropriate in assessing the overall influence of this type of atmospheric cue and is advocated in consumer research (Kawaf and Tagg, 2017; Démangeot and Broderick, 2007).

Fourthly, this study addresses the research gap in understanding the influence of both static and dynamic imagery on current online fashion retailing. With continual developments and emphasis on the user experience, online fashion websites and apps are incorporating high quality product images, a number of product views as well as newer tools such as product rotation. While literature has previously focussed on tools such as image enlargement, product rotation and catwalk video, it is important to recognise these findings may not be
up to date given the changes in online retailing and consumer shopping behaviours, i.e. due to smartphones, online shopping has become habitual and consumers no longer follow a traditional decision-making process. This suggests consumer perceptions and usage towards product presentation technology may have also shifted.

Majority of product presentation literature are based on US studies (Kim, 2018; Roggeveen et al., 2015; Jai et al., 2014; Yoo and Kim, 2014; Jeong et al., 2009; Kim et al., 2007), and other countries (Algharabat et al., 2017; Beuckels and Hudders, 2016; Flavián et al. 2017; Orús et al., 2017; Verhagen et al., 2014), with only a few papers based on UK studies (Cano et al., 2017; Ashman and Vazquez, 2012; McCormick and Livett, 2012). Previous research has analysed product presentations functions such as the mix and match function (Lee et al., 2006; Fiore et al., 2005a; Fiore et al., 2005b; Fiore and Jin, 2003), which is currently available. Therefore, most findings lack relevance to current online fashion in the UK. Additionally, there has been some attention on virtual model technology offered as part of a VR or AR tool for online fashion apparel, but research has been either conceptual (Yaoyuneyong et al., 2014; Miell et al., 2018) or based on older literature (Yang and Wu, 2009; Kim and Forsythe, 2008; Kim et al., 2007; Kim and Forsythe, 2009). Whilst research suggests the importance of digital tools and new technologies in leveraging a customised experience through technologies such as virtual sizing and fit, with companies such as Metail trialling such technology, (Guercini et al., 2018; Miell et al., 2018), virtual model try-on has yet to become widespread in the e-commerce and m-commerce fashion apparel sector.

Some studies have evaluated product presentation in an experimental setting by either using a still picture, an experimental interface or a mock website that is not shoppable (Flavián et al. 2017; Orús et al., 2017; Cano et al., 2017; Jai et al., 2014; Yoo and Kim, 2014), while other studies have instructed participants to view particular products (Kim, 2018; Beuckels and Hudders, 2016). Due to developments in fashion e-commerce and m-commerce and the huge assortment of products that are typically available on fashion websites, such as Zara and ASOS, these studies lack external validity. Particularly, they lack realism and are not reflective of actual browsing behaviour when directly engaging with the fashion product online, whether it is static or dynamic product imagery. Hence, there is a need to update product presentation literature with relevant findings and applicability to current online fashion shopping behaviours.
8.2.1 Study 1: Online Survey

Empirical data confirms the relationship between the constructs perceptual fluency, positive affect and purchase intentions, which was based on a SOR framework with product presentation as the stimuli. By using the same survey for ASOS and Amazon, comparisons were drawn between the two online fashion websites that employed different levels of product presentation. Most of the propositions were supported by model estimation as well as being guided by theory. The original model is illustrated in Figure 8.1.

Figure 8.1 Theoretical Model (H1-H5)

Conducting an EFA was useful as the findings supported appropriate changes that were made during the SEM stage. Specifically, the removal of aesthetic evaluation from both ASOS and Amazon datasets. This construct had high discriminant validity with perceptual fluency. In other words, aesthetic evaluation and perceptual fluency constructs were too similar. Despite efforts to modify the measurement model during CFA, it was not possible to obtain a good model fit as well as construct validity and reliability with aesthetic evaluation retained in the hypothesised measurement model. As a last resort, aesthetic evaluation was removed, which led to changes in an improved model fit, construct validity and reliability for both datasets.
Both structural models confirm positive affect as a mediator. This is consistent with Im et al., 2010). Unlike ASOS, all the relationships proposed in the theoretical framework for Amazon were supported. This was unexpected as Amazon features less advanced product presentation with a basic zoom function only and a lack of product views (mostly front view and back view only). The final structural models for ASOS and Amazon are shown in Figure 8.2 and Figure 8.3. These models closely resemble the model posited by Mosteller et al. (2014), which confirms perceptual fluency as a suitable antecedent that can explain the influence of different levels of product presentation on affective and behavioural responses.

**Figure 8.2** Final SEM model: ASOS

**Figure 8.3** Final SEM model: Amazon
Relationship between Perceptual Fluency and Positive Affect

Processing product information via perceptual processing was positively associated with positive affect for both ASOS and Amazon. Despite having a higher level of product information in terms of static and dynamic product imagery, the relationship between these two constructs was stronger for the high product presentation condition (i.e. ASOS). Results support literature in that fluency is “hedonically marked” (Reber et al., 2004a; Mosteller et al., 2014), which indicates consumers are more likely to experience a feel-good factor if they are able to process product information with ease. In comparison to Amazon, ASOS employs bigger and clearer images with several product viewing options instead of just a front view and back view, and also offers more than one visualisation tool for fashion apparel (i.e. zoom function and catwalk video). While results by Mosteller et al. (2014) confirm verbal information on e-commerce websites impacts fluent processing, which also influences positive affect, this result confirms this is also true for visual product information.

Relationship between Perceptual Fluency and Cognitive Effort

For Amazon, the relationship between perceptual fluency and cognitive effort was supported; perceptual fluency negatively influenced cognitive effort. Although product presentation of fashion products on Amazon m-commerce sites may be considered basic, this result suggests some level of visual display of product information is still useful in decreasing time, effort and complexity experienced. Unlike Im and Ha (2011), the results suggest there is a direct relationship between perceptual fluency and cognitive effort, which is also supported and confirmed by Mosteller et al. (2014). For ASOS, this was not supported. Cognitive effort responses were found to be inconsistent for ASOS; neither agree nor disagree. This finding suggests there may be subjective differences in cognitive effort experienced towards the visual product information on the product page.

Relationship between Positive Affect and Cognitive Effort

Findings reveal that increasing positive affect had a negative impact of cognitive effort when processing information online. This was found with Amazon. Despite the lack of visualisation tools as well as visual information available, an enjoyable shopping experience on Amazon can help to offset cognitive difficulties when processing visual
information. Interestingly, this finding was not supported for ASOS, despite the high positive affect experienced when shopping on this website.

Previous research by Garbarino and Edell (1997, p.156) show that if a stimulus requires more cognitive effort but has a high evaluation, it was still chosen by respondents ‘despite the negative process-induced affect associated with it’. The process-induced affect has an impact on choice if there are alternatives that require less cognitive effort, but that this also depends on other factors such as the evaluation, time and skill (Garbarino and Edell, 1997). This suggests if an individual is lowly skilled in manipulating product presentation via a mobile device that requires gestural interactions, they are more likely to choose a lower level of product presentation stimulus. Generally, using a variety of product presentation tools can further lower mental intangibility that would help consumers to visualise fashion apparel products in their mind (Song and Kim, 2012).

**Relationship between Positive Affect and Purchase Intentions**

Both ASOS and Amazon confirm the relationship between positive affect and purchase intent. This is a direct and positive relationship. This reveals an enjoyable shopping experience on a mobile device is positively associated with behavioural intentions, which is consistent with m-commerce literature (Kim et al., 2009a; Pantano and Priporas, 2016) as well as e-commerce literature that has analysed perceptual fluency (Im et al., 2010). Hence, an indirect relationship between perceptual fluency and purchase intentions is confirmed. Interestingly, the relationship between positive affect and purchase intentions appears to be stronger for Amazon than for ASOS. This may be due to greater familiarity and/or higher usage levels with the Amazon mobile website and/or app.

This section posits there may be several reasons why all the relationships proposed in the framework were significant for Amazon. Firstly, Amazon is a well-established and popular online retailer that is typically associated with utilitarianism with its focus on low prices and convenient next day delivery with Prime membership. As a website, Amazon have simplified the ordering process with its 1-click® buying option (Cronin, 2014; Dholakia and Zhao, 2009). Initially, the retailer was not synonymous with fashion apparel, as fashion products are typically described as hedonic or experience products (Hirschman and Holbrook, 1982), which does not reflect Amazon’s utilitarianism. Literature confirms shopping for fashion products is hedonistic in nature compared to other products such as
electronics and books (Roggeveen et al., 2015), which are routinely sold on Amazon (Cronin, 2014).

From a fashion apparel perspective, product presentation is considered limited on Amazon when accounting for the image quality, size and the number of product views as well as visualisation tools. However, evidence reveals Amazon was the most popular pureplay retailer for fashion between 2016 and 2017 (Mintel, 2017). This may explain why there were stronger relationships with Amazon, particularly with purchase intentions, despite a lower level of product presentation. Literature states that with increasing repetition and exposure, the stimuli are said to be easier to process (Berger and Fitzsimons, 2008), which can lead to positive brand evaluation (Lee and Labroo, 2004). As an individual becomes accustomed to the stimuli it is perceived as less harmful (Zajonc, 1980, 1968).

Secondly, Amazon offers product reviews that can be found by scrolling down the webpage that may have affected evaluation towards the website when browsing on a mobile device. According to Yoo and Kim (2012), a greater amount of product information is found to elicit a positive effect on purchase intentions. This is in contrast with findings from the survey as ASOS has greater visual product information than Amazon. However, Amazon provides greater verbal information via customers’ product reviews, available below the product. Participants may be accustomed to scrolling down when shopping on Amazon, and therefore may not have assessed or evaluated visual product presentation as they would on a different website. Song and Kim (2012) find that if a consumer has to scroll down to look at product information, this may increase the amount of cognitive effort experienced. However, this can also depend on the level of information load (Li et al., 2016b).

Thirdly, perceptual fluency statements were adapted from several papers, which did not strictly relate to processing visual product information as the scale items were adapted from papers concerned with evaluating the overall online environment including background and contrast as well as the size and font of the text (Im and Ha, 2011; Im et al., 2010; Mosteller et al., 2014). It is important to note perceptual fluency as a construct is recognised as a formative construct (Mosteller et al., 2014; Wu et al., 2016). Unlike the other constructs in the theoretical model, which are classified as latent or reflective
constructs, formative constructs require greater specification (Diamantopoulos and Winklhofer, 2001).

Fourthly, a task in the online survey would be suitable to better understand the cognitive effort experienced towards the product presentation. The scale items for cognitive effort were adapted from Mosteller et al. (2014) who relate these scale items to a task when shopping online. Statements for cognitive effort include the following: Looking at an individual product required… time/effort/was complex/was frustrating. However, this may influence the responses as this browsing task was used to determine the effects of product presentation during general browsing rather than understanding this stimulus under task-based conditions.

Overall, findings demonstrate the importance of perceptual fluent processing as an underlying mechanism when shopping for fashion apparel on a smartphone device. Like the results from Im et al. (2010) and Im and Ha (2011), this study confirms there is an indirect relationship between perceptual fluency and purchase intentions. Results show that fashion apparel on product pages with a high level of product information, accessed using a smartphone device, does not negatively affect perceptual processing. Although fashion apparel should be presented in clear and simple manner to aid processing when shopping on a smaller screen, being able to acquire a sufficient level of visual product information without creating an increase in visual complexity is essential. This is consistent with market reports and e-commerce fashion literature, which demonstrate that if there are difficulties with visualisation towards fashion apparel products, this can affect decision making leading to reluctance and greater perceived risk when buying online (Forsythe and Shi, 2003; de Klerk et al., 2015, Mintel, 2015a). For mobile optimised fashion sites and apps with a low level of product presentation, an enjoyable experience can help lower cognitive effort, while increasing the ease of processing visual stimuli can augment this effect.
8.2.2 Study 2: Eye Tracking Study

To evaluate findings from the eye tracking study, eye tracking metric data was assessed alongside post survey and interview data. The theoretical model for this research phase is illustrated in Figure 8.4.

**Figure 8.4 Theoretical Model (H6-H10)**

Overall, results revealed there were significant differences in visual attention as well as significant differences in purchase intentions and perceptual fluency. Of the two websites, higher fixation metric data towards product presentation was found on ASOS. In comparison to Pretty Gal, perceptual fluency and purchase intentions were higher, which implies high product presentation is more attractive as stimuli and is perceptually more fluent than low product presentation. Results across the three methods for this research phase are summarised in Table 8.1.
### Table 8.1 Summary of Eye Tracking Study Results

<table>
<thead>
<tr>
<th>Hypotheses/Proposition</th>
<th>Finding</th>
<th>Eye tracking experiment</th>
<th>Post survey</th>
<th>Post Interview</th>
</tr>
</thead>
<tbody>
<tr>
<td>Higher fixation metric data for high product presentation towards visual information</td>
<td>Supported</td>
<td>Means were higher towards product presentation AOIs.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>There is a significant difference in the metric data towards visual information</td>
<td>Partially supported</td>
<td>For tops, product presentation AOIs were mostly supported.</td>
<td>There was a preference for high product presentation, i.e. with both static and dynamic elements.</td>
<td></td>
</tr>
<tr>
<td>There is a significant difference in the metric data towards verbal information</td>
<td>Partially supported</td>
<td>For tops, verbal AOIs were significant, (but only for NOF and TFD)</td>
<td>Results confirm verbal information was referred to on Pretty Gal due to difficulties in product visualisation.</td>
<td></td>
</tr>
<tr>
<td>There is a significant difference in purchase intentions between high and low product presentation</td>
<td>Supported</td>
<td>Purchase intentions ($t = -2.845, p &lt; 0.05$)</td>
<td>Participants stated visualisation tools are helpful during decision making, particularly when making a purchase.</td>
<td></td>
</tr>
<tr>
<td>There is a significant difference in perceptual fluency between high and low product presentation</td>
<td>Supported</td>
<td>Perceptual fluency ($t = -2.978, p &lt; 0.01$)</td>
<td>Participants found it easier to view product images on ASOS.</td>
<td></td>
</tr>
<tr>
<td>Behavioural differences towards product presentation using retrospective verbalisations</td>
<td>Differences found</td>
<td>Visual attention towards product description was higher for Pretty Gal.</td>
<td>Interview data confirmed it was difficult to obtain product information from product images and visualisation tools on Pretty Gal.</td>
<td></td>
</tr>
<tr>
<td>Perceptions and attitudes towards product presentation on mobile devices including the influence of gestural interactivity</td>
<td>Differences found</td>
<td>Codes such as number of images and quality of product presentation are important.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Visual attention was compared between two optimised mobile fashion websites (ASOS vs. Pretty Gal) that differed in the level of product presentation among three areas of interest: static imagery, dynamic imagery and verbal product information. As hypothesised, findings reveal that between the two fashion websites accessed on a tablet device more visual attention (i.e. more time and a higher number of fixations) was directed towards static imagery with a higher level of product presentation whereby imagery was large, clear and good quality with alternative product views across both product categories (tops and handbags).

By following the eye tracking experiment with an interview, it was possible to obtain a more detailed assessment. Findings confirm the importance of clear and good quality static
imagery in extracting product information. Unlike product presentation literature that place significance on dynamic imagery, static product imagery was found to be particularly useful and necessary under general browsing conditions. Comments suggest today’s fashion consumers do not have sufficient time or effort to evaluate each product using visualisation tools. This is not surprising given that there are typically 1000s of products per product category on fashion websites and apps, such as ASOS. In fact, there was preference towards viewing alternative product images, i.e. the “model view” and “close up view” as an easier and quicker way of procuring further detail. This is consistent with findings from Dörnyei et al. (2017); by increasing the assortment size on online shopping websites, there is less focus on product attributes when consumers search for information. However, unlike the findings of this research, Dörnyei et al. (2017) state additional product attributes does not lead to less or more acquisition of product information. This may be due to findings based on information search behaviour and FMCG products, which may not be applicable to online fashion retailing.

Findings also support the relationship between a lack of visual product information and greater attention towards verbal information. Although both fashion websites featured the same textual product information and the same set of products, there were longer fixations and a greater number of fixations towards the verbal area of interest for the low product presentation condition. Nevertheless, this differed according to the product category with significance for fashion tops. Interview findings explained this was due to difficulty in accessing product attributes and fit information from the static images and the zoom function as well as the gestural zoom on the tablet device. Data from the post survey corroborates this finding; ease of obtaining product information was less perceptually fluent on the low product presentation condition. Compared to the verbal information, majority of visual attention was directed at the visual product information indicative of the “visual superiority effect” confirmed in literature (Pieters and Wedel, 2004; Hong et al., 2004).

Irrespective of the insignificance of visual attention towards the visualisation tools AOI, interview data confirmed the overall usefulness of particular visualisation tools. It was interesting to note that despite the newness and potential of other tools reported in literature, such as catwalk videos and product rotation, image enlargement (i.e. zoom function) that is considered low image interactivity (Beuckels and Hudders, 2016; Lee et
(Algharabat et al., 2010) was found to be the most useful in consumers’ product evaluation when shopping on a mobile device. This may be due to the fact that the product image can be easily manipulated gesturally by using zooming and pinching motions to provide close-up detail. Collectively, visualisation tools available on the high product presentation condition offer greater product information on fit, quality and material. Literature confirms the use of visualisation tools, such as 3D rotation, increase product knowledge (Algharabat et al., 2017; Jiang and Benbasat, 2007).

Findings from the post survey also confirm significant differences in perceptual fluency and purchase intentions between low and high product presentation; responses were more favourable towards the high product presentation condition. Qualitative data validate these findings with comments affirming the use of effective static and dynamic imagery increase visual salience that plays a role in processing product information with ease as well as contributing towards informed purchase decisions. Previous marketing literature has analysed the influence of simple and complex stimuli on perceptual fluency. Whilst there have been studies on webpage design with stimuli such as text and images (Mosteller et al., 2014; Im et al., 2010), this study goes further by comparing product presentation with varying levels of static and dynamic product imagery to assess whether product imagery that is comprised of higher levels of information intensity leads to ease or difficulty in processing product information. Despite higher levels of information intensity, findings verify the use of clear and good quality static imagery alongside optional dynamic product viewing leads to greater perceptual fluency. While Lee and Benbasat (2004, p.90) argue ‘mobile devices have inferior visual displays and thus are not suitable for subscribing to high information intensity content’, this study demonstrates this is no longer the case with changes in technology and consumer behaviour. However, it is important to note that a balance should be maintained; too much visual complexity can hamper processing efforts (Sohn, 2017b; Wu et al., 2016).

In previous literature, less was known about m-commerce attitudes and perceptions towards fashion product presentation. Qualitative findings account for differences in usage; the combination of well-designed static and dynamic imagery is beneficial when consumers have a high interest in the product, particularly at the point of purchase. This is dependent on the product category as some fashion products were considered more difficult to gauge than others. This included items with greater fit constraints, such as
dresses and trousers, or items that were less familiar. Conversely, there was greater preference and usage of static product imagery when generally browsing for fashion on a mobile device. This is consistent with changes in the decision-making process as well as mobile shopping behaviours. With busy lifestyles, the ability to shop anywhere, anytime and an extensive assortment of fashion products, consumers may pay less attention to product detail. Moreover, there is increasing exposure to imagery on social media platforms, such as Instagram (Wakabayashi and Frenkel, 2018), which encourages behaviour of swiping and scrolling left for images and videos (Griffin, 2017) that may also explain preference of viewing static product images in the same manner on mobile devices for young female fashion consumers. Individual differences were due to inconsistencies of this technology across online fashion websites as well as differences in awareness, experience and knowledge of product presentation on m-commerce sites and apps.

Notably, qualitative findings indicate the potential of gestural interactivity. Most participants stated shopping on a mobile device is convenient, easy and fast to use with gestural interaction described as “close”. With the ability to move the device closer to an individual’s field of vision, which can help to observe greater product detail, interacting with a product through a touchscreen gesturally can provide a shopping experience that feels closer to the individual.

Findings also demonstrate shopping on a mobile device is no longer considered a novelty nor is it risky for Generation Y and Z female consumers in the UK. Despite associated product risks, consumers rely on other factors, such as experience, brand familiarity and convenience offered by the online retailer (Duarte et al., 2018; Nepomuceno et al., 2014). Online fashion consumers also appear to be taking advantage of lenient return policies that ‘fuel unnecessary ordering and increase return rates’ (Saarirvi et al., 2017, p.284). Along with the findings from this study, this highlights the need for engaging and informative product imagery in making better purchase decisions and encouraging positive purchasing behaviours. While visualisation tools may not be used at every opportunity, this mixed-methods research phase confirms the importance of displaying an advanced level of static and dynamic product imagery in facilitating both browsing and task-based shopping motivations.
8.3 Theoretical Contributions

In order to understand emotional and behavioural responses towards product presentation on m-commerce, it was helpful to understand the effects of this stimuli on cognitive processing and how this impacts the overall shopping experience on fashion m-commerce. Theoretically, findings support the use of fluency theory as a relevant concept and contributes to the growing body of literature that has examined various aspects of the retail environment and its influence on consumers’ processing fluency (Sohn, 2017b; Hermann et al., 2013; Mosteller et al., 2014). Unlike previous literature, which focussed on imagery fluency or mental imagery to understand the effects of product presentation on information processing (Kim, 2018; Flavián et al., 2017; Orús et al., 2017; Yoo and Kim, 2014; Kim and Lennon, 2008), this study validates perceptual fluency as an underlying theory that explains the way fashion products are presented can lead to ease or difficulty in information processing.

Prior marketing research compare simple and complex stimuli in the retail environment, with the former generating more positive effects on perceptual fluency (Hermann et al., 2013; Orth and Wirtz, 2014; Sohn, 2017b). Although high product presentation is higher in information intensity, results from this study demonstrate the importance of providing a high level of product information to serve as a vital cue in consumers’ cognitive processing and product evaluation. This study makes a further distinction by exploring the influence of product presentation on mobile devices whereby smaller screen size may enhance difficulties in processing. With the option of viewing dynamic imagery when necessary, findings from both studies reveal a high level of product information on a mobile device does not lead to disfluent processing for young fashion consumers, but actually has the opposite effect resulting in higher perceptual fluency. As important visual stimuli, the eye tracking experimental study corroborates the “visual superiority effect” towards product imagery.

Consistent with consumer research studies that use the SOR framework to evaluate the effects of atmospheric stimuli on consumers’ approach or avoidance behaviour (Mosteller et al., 2014), this study also confirms the influence of product presentation on positive
affect and purchasing intent, with perceptual fluency as an important antecedent in this framework.

Moreover, this research extends research on product presentation by highlighting the role and usage of product presentation technology on fashion m-commerce. Findings highlight the significance of static imagery for general browsing as well as dynamic imagery (i.e. visualisation tools) when there is enough interest in the product to warrant a detailed view and/or detailed product information. Irrespective of whether the consumer is browsing generally or evaluating the product in more detail on the product page, providing a high level of product presentation via static and dynamic imagery can facilitate higher levels of perceptual processing. With the ability to shop on the go, at any time of the day as well as the consumer shift towards searching for information on a mobile device, providing a high level of product presentation has important implications. With a huge assortment of products on fashion m-commerce sites like ASOS, consumers may not have enough time or effort to evaluate visual product information on the product page on a device with screen size constraints. Thus, using a combination of static and dynamic product imagery plays a vital role in enabling consumers to acquire greater product information with ease at all stages of the decision-making processing.

This research also supports the use of a mixed-methods approach in understanding the differences in visual attention between a low and high level of product presentation. Not only did the results from the qualitative approach corroborate the quantitative data, the results also provide a greater insight of consumers’ perceptions towards product presentation technology from a m-commerce perspective.
8.4 Managerial Implications

Findings from this thesis provide useful insights and practical guidance for online fashion retailers to help improve consumers’ experience when shopping for fashion merchandise from the m-commerce platform. Implementation of product presentation should include both formats of static and dynamic imagery. Specifically, this includes the use of multiple product images that also includes alternative product views, good quality product imagery alongside the use of various visualisation tools. Consideration should also be given to the product category that may require the use of specific product images and/or visualisation tools to aid product viewing.

Due to the screen size of smartphone devices, it is therefore important fashion retailers utilise space effectively in displaying product images on the product page. For example, the use of a model view that is displayed in an artful way should be carefully considered to avoid interference when obtaining product information. With a huge selection of fashion products to browse from, it is important for product imagery to provide sufficient detail, but to also grab consumers’ attention when they may only have a few seconds to examine the product. In such a scenario, an increase in visual salience on the product page can help consumers to exert less cognitive resources. Product attributes are also noticed sooner. As a result, processing product information is more efficient on both the perceptual and conceptual level (Wu et al., 2016). Development of good quality visualisation tools is recommended in offering consumers the choice to view a product in more detail and are particularly useful when there is high interest, and/or when consumers are considering a purchase.

One way to enhance the experience on a mobile device is to allow consumers to manipulate product presentation by incorporating elements of gestural interaction to create higher levels of experiential value when shopping for fashion. Along with the development of virtual try-on for fashion apparel, there is greater potential to exploit capabilities further; to try products virtually and to offer a “closer” interaction by simulating touch experienced in offline shopping.
Although product risk may be less of an issue for fashion consumers with the ability to return items for free, thereby creating a culture of unnecessary ordering (Saarijärvi et al., 2017), it remains an issue for online fashion retailers evidenced by high product returns (Mintel, 2017). This demonstrates the need to innovate in order to engage consumers with product presentation technology to not only make better, informed decisions but to also encourage positive shopping behaviours. Consumers are also more likely to be satisfied when they receive a product that meets or exceeds their expectations.

While product presentation technology has many positives, online fashion retailers should be careful. A balance should be maintained to avoid overloading the consumer with too much information that can increase visual complexity and cognitive effort (Sohn, 2017b; Wu et al., 2016). This would reverse the positive influence of product presentation on consumer behaviour. Nevertheless, if used effectively, these tools can help to blur the differences between online and offline shopping experience.

While qualitative findings suggest majority of young female consumers shop on their mobile device, there was a small minority who preferred shopping on a PC. To attract young fashion consumers who frequently access social media on their mobile devices, which plays an important part in their personal lives (Sheldon et al., 2017), efforts should also be focussed on ensuring product imagery is well presented and dynamic to complement imagery commonly found on social media platforms, such as Instagram (Wakabayashi and Frenkel, 2018).

Today’s consumers are more knowledgeable and may return to the same website or app or even the same product several times prior to purchase. With a competitive online fashion market, it is therefore important for online fashion retailers to employ a high level of product presentation on m-commerce in order to accommodate consumers’ desire to shop at any stage of the decision-making process. In agreement with Sohn, (2017a), this study posits there is room for development and innovation on m-commerce to convince consumers of its perceived usefulness, of which information quality is considered an important element.
8.5 Research Limitations

Since the study was based on fashion m-commerce, findings may not be applicable towards other types of online websites or a different product category. Fashion products are typically more hedonic in nature (Hirschman and Holbrook, 1982; Im and Ha, 2011). In comparison to other products online, such as buying a computer, there may be greater cognitive processing involved than shopping for fashion apparel as Im et al. (2010, p.290) stipulate ‘consumers rely more on elaborate and deliberate cognitive processing than aesthetic evaluation for some products (e.g. computers), which may diminish the perceptual fluency effect’.

Although an online survey was deemed to be a convenient method of survey data collection, it was difficult to implement the experimental procedure accordingly. Although efforts were made to remove participants who spent less time than required when browsing for fashion (on ASOS/Amazon) and answering the questions during the data screening stage, it was difficult to accurately monitor how long participants spent on the browsing activity before completing the online survey and whether each question was read and answered carefully. Nepomuceno et al. (2016) who studied perceived risk towards online shopping also excluded participants who completed the survey in a very short amount of time.

With the eye tracking experiment, participants were given 180 seconds to browse each condition. While qualitative findings show that using visualisation tools can be time-consuming, this study could be repeated with more time given to each treatment condition to determine attention to fashion m-commerce product presentation that is more realistic of actual browsing time. There may also be existing bias towards online retailers such as ASOS and Amazon that may have inflated positive or negative responses towards the survey questions as research indicates past usage with particular brands can influence attention and evaluation (Chandon et al., 2009).
8.6 Further Research

To overcome the bias towards existing fashion websites and increase internal validity, future research could use two mock websites to control other variables or use professional web designers to design an exact copy of an existing fashion m-commerce site, but with limited product presentation. This approach was conducted by Beuckels and Hudders (2016) who created a mock website of Saks Fifth Avenue. Integration of current visualisation tools with gestural technology such as ShoogleIt used by Cano et al. (2017) would be helpful in assessing the joint impact of using different types and different levels of product visualisation tools.

Neither the survey nor eye tracking experiment asked participants to engage in a specific task when shopping on the website except to browse generally. For the survey, it would be particularly useful to further understanding of these tools in a given task-based situation. For example, participants could be asked to select and evaluate a dress for a party and how this impacts consumer behaviour. This approach was conducted by Beuckels and Hudders (2016) who asked participants to use the product visualisation tools. For eye tracking, however, this approach would turn the eye tracking experiment into a top-down approach. To test the effect of a stimuli on visual attention, a bottom-up approach is advocated (Wedel and Pieters, 2008).

Only one construct (i.e. purchase intentions) was used to convey a behavioural intention. Future research could evaluate additional constructs such as attitudes and re-visit intentions. The latter is regarded to be ‘relatively risk-free, which may lead the participants to answer based on how they feel at the moment on the web site’ (Im et al., 2010, p.289). This would provide a greater understanding of consumers’ overall behavioural intentions towards the m-commerce website or app. It is also preferable to use actual purchase behaviour since consumers have more experience in shopping online, and therefore are likely to display high levels of purchase intentions (Chaparro-Peláez et al., 2016).

Questions in the interviews were approached to understand general attitudes towards product presentation on mobile devices including the use of gestural interaction. More research is required to assess the impact of gestural interactivity with visualisation tools.
specifically. A mixed-method approach with a qualitative phase followed by a quantitative phase based on the qualitative data would also help to provide a stronger basis for a quantitative based framework.

Examination of different consumer cohorts, such as male consumers or older female consumers, would be also useful in revealing consumer differences towards fashion product presentation. With evidence suggesting implementation of AR and VR shopping experiences to become more likely for online fashion retailers in the near future (Watson et al., 2018), assessing eye movements towards the use of virtual product presentation would reveal new and useful insights.

8.7 Conclusion

Using a two-phase mixed-method approach, this study contributes to a growing body of product presentation literature by presenting a holistic overview of product presentation technology currently embraced by online fashion retailers on the m-commerce platform. As an important element of the online fashion environment that aids consumers in acquiring product information visually, examining the effect on perceptual fluency as an underlying theory was relevant to determine whether a high level of product information via static and dynamic imagery results can increase the ease of information processing and approach behaviour.

Findings establish the importance of a high level of static and dynamic imagery in contributing to perceptual processing, which mediates the effects of positive affect and purchase intentions towards the online fashion retailer. Despite higher levels of information intensity that may increase attentional effort on a small screen size, high product presentation increases information quality that reduces cognitive resources and also helps product detail to be noticed sooner. Combining objective and subjective measures, empirical findings establish the influence of product presentation on all three types of consumer responses i.e. cognitive, affective and behavioural, as well as significant differences in visual attention towards product presentation, perceptual fluency and purchase intentions.
Qualitative data also demonstrates the importance of product presentation in providing detailed product information that is an essential part of the decision-making process. There is also greater potential with gestural interactivity; it is possible for consumers to exert higher levels of control when manipulating the product image or visualisation tool that can provide a greater experiential and sensorial effect when shopping for fashion online. Coupled with the evidence above and the fact that mobile devices are increasingly used at the information stage as well as purchasing stage (Faulds et al., 2018), which is particularly true of young consumers (Fuentes and Svingstedt, 2017), there is a need for well-developed product presentation on the mobile platform to assist consumers in providing greater product information when required or to acquire adequate information when casually browsing. This can help minimise product returns when shopping online.

Due to mobile shopping growth and the issue of high online returns, focused efforts on displaying fashion apparel images using innovative technology on the mobile platform is likely to benefit both the consumer and fashion retailer. In sum, implementation of product presentation technology is a useful technology to both the consumer and retailer - whether they have existing, developing or yet to develop an app or an optimised mobile site as such a channel would help online fashion retailers to ultimately increase sales and revenue. Essentially, there is a need to emulate the store experience online with product presentation technology as a strong contributor of enhancing this experience.
References


Marlow, N. and Jansson-Boyd, C.V. (2011). ‘To touch or not to touch; that is the question. Should consumers always be encouraged to touch products, and does it always alter product perception?’, *Psychology & Marketing, 28*(3), pp. 256-266.


Appendices

Appendix 1: Online Survey (Surveygizmo.com)
Shopping for Fashion on ASOS using a Smartphone

Welcome to the survey!

SID Action: Hidden Value
Value: [url("SID")]

Please click Next to continue

About this Survey

This survey is part of a PhD study at The University of Manchester.

Aim

With your help, the aim of this survey is to understand consumer behaviour towards product presentation on fashion clothing websites/app when using a smartphone. The results of this survey will be published in a PhD thesis and will provide an academic contribution on how to improve the mobile interface for consumers who shop on this platform. Outcomes may also be published in a peer-reviewed academic journal, in a book, at a conference presentation or other published outlets (i.e. EPSRC).
What you will do (3 parts)
1. ANSWER questions about yourself.
2. BROWSE on a fashion website/app via your smartphone.
3. ANSWER a series of questions about the browsing activity.

The survey can be completed on a desktop, laptop, tablet or a smartphone. The duration is approximately 10-15 minutes.

Participation
You will need:

A SMARTPHONE with 3G/Wi-Fi for the browsing activity.

Participation is voluntary and you are free to change your mind at any time.

Data Confidentiality
All data collected will be treated with complete confidentiality. Data will remain anonymised and will be stored in an encrypted folder on the university server. Access to the data will only be permitted by the researcher and the project supervisor. Please note that the data may be stored for up to 5 years.

Enquiries
For enquiries, please contact the primary researcher and/or the project supervisor.

Primary researcher: Sobia Khan
Email: sobia.khan-2@manchester.ac.uk
Project supervisor: Dr Delia Vazquez
Email: delia.vazquez@manchester.ac.uk

This project has been reviewed by the The University of Manchester's Research Ethics Committee [UREC reference number: 16357], but should you wish to make a formal complaint please email the Committee on research.complaints@manchester.ac.uk or call 0161 275 2674.
Consent

Page description:
Before you begin, please answer the following questions on consent below.

Page exit logic: Skip / Disqualify Logic
IF: Question "I voluntary consent to participate in this online survey. "
#3 is one of the following answers ("No")
THEN: Redirect to: r.oneopinion.com/r/sid?o=2

Page exit logic: Skip / Disqualify Logic
IF: Question "I agree to have data collected in this online survey. "
#2 is one of the following answers ("No")
THEN: Redirect to: r.oneopinion.com/r/sid?o=22

Page exit logic: Skip / Disqualify Logic
IF: Question "I confirm that I have read and understood all the information about participation in this online survey. "
#1 is one of the following answers ("No")
THEN: Redirect to: r.oneopinion.com/r/sid?o=22

ID 12
1. I confirm that I have read and understood all the information about participation in this online survey. *
   - Yes
   - No
13
- I agree to have data collected in this online survey. *
  - Yes
  - No

14
- I voluntary consent to participate in this online survey. *
  - Yes
  - No

About You

Page description:
This section explores a little bit more about you, your shopping behaviours and your experience.
Please note the phrase "shopping" includes browsing and/or purchasing.

Page exit logic: Skip / Disqualify Logic
IF: Question "Do you have experience of purchasing fashion clothing online?" #7 is one of the following answers ("No") THEN: Redirect to:
r.oneopinion.com/r/sid?o=22

Page exit logic: Skip / Disqualify Logic
IF: Question "Are you British?" #6 is one of the following answers ("No") THEN: Redirect to:
r.oneopinion.com/r/sid?o=22

Page exit logic: Skip / Disqualify Logic
IF: Question "What is your age group?" #5 is one of the following answers ("Under 18","25-34","35-44","45-54","Above 55") THEN: Redirect to:
r.oneopinion.com/r/sid?o=22

Page exit logic: Skip / Disqualify Logic
IF: Question "What is your gender?" #4 is one of the following answers ("Male") THEN:
Redirect to: r.oneopinion.com/r/sid?o=22
4. What is your gender? *
   - Female
   - Male

5. What is your age group? *
   - Under 18
   - 18-24
   - 25-34
   - 35-44
   - 45-54
   - Above 55

6. Are you British? *
   - Yes
   - No

7. Do you have experience of purchasing fashion clothing online? *
   - Yes
   - No
# A Bit More About You

<table>
<thead>
<tr>
<th>19</th>
<th>8. Are you a student? *</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>☐ Yes</td>
</tr>
<tr>
<td></td>
<td>☐ No</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>20</th>
<th>9. On average, how often do you shop for fashion clothing? This includes shopping from a PC, laptop, smartphone, tablet and/or in-store shopping. *</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>☐ At least once a day</td>
</tr>
<tr>
<td></td>
<td>☐ Several times a week</td>
</tr>
<tr>
<td></td>
<td>☐ Several times a month</td>
</tr>
<tr>
<td></td>
<td>☐ Several times a year</td>
</tr>
<tr>
<td></td>
<td>☐ Rarely</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>120</th>
<th>Below are a number of statements regarding mobile shopping usage.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Please read each one and indicate to what extent you agree or disagree with each statement.</td>
</tr>
<tr>
<td></td>
<td>Please note the phrase &quot;shopping&quot; includes browsing and/or purchasing.</td>
</tr>
</tbody>
</table>
10. I am familiar with mobile shopping. *
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

11. I frequently use mobile devices to shop from. *
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

12. I visit retail mobile websites and/or apps to gather product information. *
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree
Your Shopping Task for this Survey

1. Using your smartphone, access the internet app (such as Safari or Google Chrome) and type in the website address listed below:

   www.asos.com/women/

   N.B. If downloaded, you may also use the ASOS app instead.

2. From the menu bar, select DRESSES.
3. Spend **more than 5 MINUTES** browsing dresses

Select **at least ONE** dress that you like to view in more detail. This will help you to answer questions in the following sections.
IMPORTANT: Please return to the survey and answer the following questions when you have finished browsing ASOS on your smartphone.

Page exit logic: Skip / Disqualify Logic
IF: Question "Have you spent at least 5 minutes browsing dresses on ASOS?" #13 is one of the following answers ("No") THEN: Jump to page 6 - Your Shopping Task for this Survey

13. Have you spent at least 5 minutes browsing dresses on ASOS? *
   - No
   - Yes

Ease of Processing Information

Page description:
Below are a number of statements regarding how easy it is to process information in the product picture on the product page.

An example of a product page is shown below.

Please read each statement and indicate to what extent you agree or disagree.

14. The product picture attracts my attention instantly.*
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree
15. The product picture stands out on the product page. *

- [ ] Strongly Agree
- [ ] Agree
- [ ] Somewhat Agree
- [ ] Neutral
- [ ] Somewhat Disagree
- [ ] Disagree
- [ ] Strongly Disagree

16. Information presented in the product picture is easy to view. *

- [ ] Strongly Agree
- [ ] Agree
- [ ] Somewhat Agree
- [ ] Neutral
- [ ] Somewhat Disagree
- [ ] Disagree
- [ ] Strongly Disagree
17. It is easy to identify information (such as quality) from the product picture.

* 

- Strongly Agree
- Agree
- Somewhat Agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly Disagree

**Cognitive Effort**

*Page description:* Below are a number of statements regarding mental effort required when looking at clothing images.

Please read each one and indicate to what extent you agree or disagree with each statement.
18. Looking at an individual clothing item required time. *

- [ ] Strongly Agree
- [ ] Agree
- [ ] Somewhat Agree
- [ ] Neutral
- [ ] Somewhat Disagree
- [ ] Disagree
- [ ] Strongly Disagree

19. Looking at an individual clothing item required effort. *

- [ ] Strongly Agree
- [ ] Agree
- [ ] Somewhat Agree
- [ ] Neutral
- [ ] Somewhat Disagree
- [ ] Disagree
- [ ] Strongly Disagree
20. Looking at an individual clothing item was complex. *

- Strongly Agree
- Agree
- Somewhat Agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly Disagree

21. Looking at an individual clothing item was frustrating. *

- Strongly Agree
- Agree
- Somewhat Agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly Disagree

**Positive Affect**

**Page description:**
Below are a number of statements regarding emotions felt during the browsing activity.

Please read each one and rate each statement according to how you felt on a scale of 1-7.
22. While visiting this mobile website or app, I felt... *
1=Happy  2  3  4  5  6  7=Unhappy

23. While visiting this mobile website or app I felt... *
1=Happy  2  3  4  5  6  7=Unhappy

24. While visiting this mobile website or app I felt... *
1=Happy  2  3  4  5  6  7=Unhappy

25. While visiting this mobile website or app I felt... *
1=Happy  2  3  4  5  6  7=Unhappy

Aesthetic Evaluation

Page description:
Below are a number of statements regarding the aesthetic appeal of the product page.

Please read each one and indicate to what extent you agree or disagree with each statement.
26. The product pages look attractive. *

- Strongly Agree
- Agree
- Somewhat Agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly Disagree

27. The product pages look organised. *

- Strongly Agree
- Agree
- Somewhat Agree
- Neutral
- Somewhat Disagree
- Disagree
28. There is proper use of graphics (i.e. product pictures). *
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

29. There is proper use of visualisation tools (such as zoom function or catwalk video). *
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

**Purchase Intent**

**Page description:**
Below are a number of statements regarding purchasing intent.

Please read each one and indicate to what extent you agree or disagree with each statement.
30. It is likely that I would purchase clothing from this mobile website or app.

- [ ] Strongly Agree
- [ ] Agree
- [ ] Somewhat Agree
- [ ] Neutral
- [ ] Somewhat Disagree
- [ ] Disagree
- [ ] Strongly Disagree

31. At the price shown, I would consider buying clothing from this mobile website or app.

- [ ] Strongly Agree
- [ ] Agree
- [ ] Somewhat Agree
- [ ] Neutral
- [ ] Somewhat Disagree
- [ ] Disagree
- [ ] Strongly Disagree
32. It is probable that I would consider buying clothing from this mobile website or app. *

- Strongly Agree
- Agree
- Somewhat Agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly Disagree

33. I am willing to buy clothing from this mobile website or app. *

- Strongly Agree
- Agree
- Somewhat Agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly Disagree

Access

Page exit logic: Skip / Disqualify Logic
IF: Question "Please indicate how you accessed ASOS during this shopping task." #34 is one of the following answers ("The ASOS app","Mobile optimised website") THEN: Redirect
to: r.oneopinion.com/r/sid?o=FXZ0GBAL&sid=%3csid
34. Please indicate how you accessed ASOS during this shopping task.

☐ The ASOS app

☐ Mobile optimised website

Thank You!

Thank you for taking our survey. Your response is very important to us.

For enquiries or if you would like to receive the results of the survey, please contact the primary researcher Sobia Khan (email: sobia.khan-2@manchester.ac.uk).
Appendix 2: Example of Interview Transcript

Interview 9 (ASOS Website)
[Duration: 04:05]

So, first question, when you shopped on the mobile website of ASOS today, where did you mostly look and why?
On the tops, I looked at the left side more. Left side of the screen.
Can you explain why?
Umm, I dunno I think the items on that side caught my eye more than the ones further to that side. I don’t know why.

How does your shopping experience on the tablet compare to shopping on a computer or laptop?
I found it easier because you can hold it yourself. Er, it’s more mobile, you can take it everywhere. It’s quicker to scroll with your finger than using a mouse or mouse pad on a laptop.

What are your thoughts on the product pages on ASOS?
Erm, the prices are quite noticeable, but like the rest of the information wasn’t really. You had to scroll down to get the extra information, like the care and stuff like that.
Ok, how does that make you feel?
I’d rather be able to see it more clearly and quicker. Like you know what you’re getting straightaway.

What are your thoughts on the images on ASOS, so the product pictures?
They’re all really clear and there were obviously different angles, which is good to see. There was one on the top, it had like writing on the top that wasn’t that clear I don’t think. But the rest of them you could see everything. You could see the inside of the bags as well.

So, retailers often use visualisation tools. The tools mays include a zooming in function, a catwalk video, or a 360 degree rotation. I noticed you did not use any of these tools, can you explain why?
Er, I don’t think it’s that noticeable you can use or that they are there to use. But I think the pictures are pretty clear, you saw what you’re getting, so it’s not always necessary I suppose.

So, final question. In general, what are your thoughts towards these tools?
I think they are good, maybe not for general shopping but if you're looking for something in particular, it's nice to see what items for it to go with or something like that. Erm, to see finer details, but if you're just having a general browse I don’t feel like it’s necessary, only if you’re looking into detail or if you’re looking at something in particular. I think it’s quicker to go normally and just scroll.

Ok. Thank you very much for your time.

[End of interview]
### Appendix 3: Initial Communalities: ASOS

<table>
<thead>
<tr>
<th></th>
<th>Initial</th>
<th>Extraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>PF1</td>
<td>0.588</td>
<td>0.496</td>
</tr>
<tr>
<td>PF2</td>
<td>0.569</td>
<td>0.49</td>
</tr>
<tr>
<td>PF3</td>
<td>0.451</td>
<td>0.312</td>
</tr>
<tr>
<td>PF4</td>
<td>0.352</td>
<td>0.272</td>
</tr>
<tr>
<td>CE1</td>
<td>0.418</td>
<td>0.447</td>
</tr>
<tr>
<td>CE2</td>
<td>0.569</td>
<td>0.746</td>
</tr>
<tr>
<td>CE3</td>
<td>0.482</td>
<td>0.499</td>
</tr>
<tr>
<td>CE4</td>
<td>0.514</td>
<td>0.511</td>
</tr>
<tr>
<td>PA1</td>
<td>0.706</td>
<td>0.74</td>
</tr>
<tr>
<td>PA2</td>
<td>0.735</td>
<td>0.783</td>
</tr>
<tr>
<td>PA3</td>
<td>0.725</td>
<td>0.753</td>
</tr>
<tr>
<td>PA4</td>
<td>0.667</td>
<td>0.668</td>
</tr>
<tr>
<td>AE1</td>
<td>0.568</td>
<td>0.56</td>
</tr>
<tr>
<td>AE2</td>
<td>0.563</td>
<td>0.558</td>
</tr>
<tr>
<td>AE3</td>
<td>0.553</td>
<td>0.58</td>
</tr>
<tr>
<td>AE4</td>
<td>0.438</td>
<td>0.359</td>
</tr>
<tr>
<td>PI1</td>
<td>0.656</td>
<td>0.629</td>
</tr>
<tr>
<td>PI2</td>
<td>0.51</td>
<td>0.49</td>
</tr>
<tr>
<td>PI3</td>
<td>0.843</td>
<td>0.901</td>
</tr>
<tr>
<td>PI4</td>
<td>0.822</td>
<td>0.877</td>
</tr>
</tbody>
</table>

Extraction Method: Maximum Likelihood.
### Appendix 4: Model Fit of the Modified Measurement Model (1): ASOS

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>249.253, p = 0.000</td>
<td>Small $\chi^2$ and p &gt; 0.05 (Hair et al. 2014)</td>
</tr>
<tr>
<td>Normed Chi-Square ($\chi^2$/df)</td>
<td>2.543</td>
<td>&lt; 2 (Tabachnick and Fidell, 2013) &lt; 5 (Kelloway, 1998)</td>
</tr>
<tr>
<td>GFI</td>
<td>0.880</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>NFI</td>
<td>0.887</td>
<td>Value close to 1 (Hair et al. 2014) &gt; 0.95 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.927</td>
<td>&gt; 0.95 (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.083</td>
<td>≤ 0.06 (Hu and Bentler, 1999) &lt; 0.10 (Browne and Cudeck, 1993)</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>0.000</td>
<td>&gt; 0.05 (Jöreskog and Sörbom, 1996a)</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.833</td>
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</tr>
<tr>
<td>PGFI</td>
<td>0.634</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.0758</td>
<td>≤ 0.08 (Tabachnick and Fidell, 2013)</td>
</tr>
</tbody>
</table>

### Appendix 5: Model Fit of the Modified Measurement Model (2): ASOS

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>180.025, p = 0.000</td>
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<tr>
<td>Normed Chi-Square ($\chi^2$/df)</td>
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<tr>
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</tr>
<tr>
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</tr>
<tr>
<td>CFI</td>
<td>0.960</td>
<td>&gt; 0.95 (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.063</td>
<td>≤ 0.06 (Hu and Bentler, 1999) &lt; 0.10 (Browne and Cudeck, 1993)</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>0.073</td>
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<tr>
<td>AGFI</td>
<td>0.874</td>
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</tr>
<tr>
<td>PGFI</td>
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<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.0638</td>
<td>≤ 0.08 (Tabachnick and Fidell, 2013)</td>
</tr>
</tbody>
</table>
Appendix 6: Modified Measurement Model (1): Amazon

Appendix 7: Model Fit of the Modified Measurement Model (1): Amazon

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$) and P-Value for Model</td>
<td>$242.344$ (p = 0.000)</td>
<td>Small $\chi^2$ and $p &gt; 0.05$ (\text{(Hair et al., 2014)})</td>
</tr>
<tr>
<td>Normed Chi-Square ($\chi^2$/df)</td>
<td>$2.498$</td>
<td>$&lt; 2$ (\text{(Tabachnick and Fidell, 2013)})</td>
</tr>
<tr>
<td>GFI</td>
<td>$0.891$</td>
<td>Value close to 1 (\text{(Tabachnick and Fidell, 2013)})</td>
</tr>
<tr>
<td>NFI</td>
<td>$0.901$</td>
<td>Value close to 1 (\text{(Hair et al., 2014)}) $&gt; 0.95$ (\text{(Tabachnick and Fidell, 2013)})</td>
</tr>
<tr>
<td>CFI</td>
<td>$0.937$</td>
<td>$&gt; 0.95$ (\text{(Hu and Bentler, 1999)})</td>
</tr>
<tr>
<td>RMSEA</td>
<td>$0.079$</td>
<td>$\leq 0.06$ (\text{(Hu and Bentler, 1999)}) $&lt; 0.10$ (\text{(Browne and Cudeck, 1993)})</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>$0.000$</td>
<td>$&gt; 0.05$ (\text{(Jöreskog and Sörbom, 1996a)})</td>
</tr>
<tr>
<td>AGFI</td>
<td>$0.848$</td>
<td>Value close to 1 (\text{(Jöreskog and Sörbom, 1993)}).</td>
</tr>
<tr>
<td>PGFI</td>
<td>$0.636$</td>
<td>Value close to 1 (\text{(Tabachnick and Fidell, 2013)}) $&lt; 0.10$ (\text{(Hair et al., 2014)})</td>
</tr>
<tr>
<td>SRMR</td>
<td>$0.0839$</td>
<td>$&lt; 0.05$ (\text{(Schumacker and Lomax, 2016)})</td>
</tr>
</tbody>
</table>
Appendix 8: Modified Measurement Model (2): Amazon

Appendix 9: Model Fit of the Modified Measurement Model (2): Amazon

<table>
<thead>
<tr>
<th>Model Fit Index</th>
<th>Model Fit Values</th>
<th>Suggested Thresholds and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square ($\chi^2$)</td>
<td>188.868 p = 0.000</td>
<td>Small $\chi^2$ and $p &gt; 0.05$</td>
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<tr>
<td></td>
<td></td>
<td>(Hair et al. 2014)</td>
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<tr>
<td>Normed Chi-Square ($\chi^2$/df)</td>
<td>1.967</td>
<td>&lt; 2 (Tabachnick and Fidell, 2013)</td>
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<tr>
<td>GFI</td>
<td>0.913</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
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<td></td>
<td>&gt; 0.95 (Hair et al. 2014)</td>
</tr>
<tr>
<td>NFI</td>
<td>0.923</td>
<td>Value close to 1 (Hair et al. 2014)</td>
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<tr>
<td></td>
<td></td>
<td>&gt; 0.95 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.960</td>
<td>&gt; 0.95 (Hu and Bentler, 1999)</td>
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<tr>
<td>RMSEA</td>
<td>0.063</td>
<td>≤ 0.06 (Hu and Bentler, 1999)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&lt; 0.10 (Browne and Cudeck, 1993)</td>
</tr>
<tr>
<td>PCLOSE</td>
<td>0.053</td>
<td>&gt; 0.05 (Jöreskog and Sörbom, 1996a)</td>
</tr>
<tr>
<td>AGFI</td>
<td>0.877</td>
<td>Value close to 1 (Jöreskog and Sörbom, 1993).</td>
</tr>
<tr>
<td>PGFI</td>
<td>0.645</td>
<td>Value close to 1 (Tabachnick and Fidell, 2013)</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.076</td>
<td>&lt; 0.10 (Hair et al. 2014)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&lt; 0.05 (Schumacker and Lomax, 2016)</td>
</tr>
</tbody>
</table>