Technology Adoption and Adaptation Model: A Study of Consumers' Digital Footprints

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By

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Abstract

Consumers' interactions with social media have become inescapable. The adoption and adaptation of these platforms are rapidly increasing. It is not known as to what underlying factors drive consumers' social media adoption, subsequent interactions with social media platforms and how they respond to the consequences of their digital footprints. Little attention is given to consumers' joint attitudinal components (cognitive and affective) as antecedents of a composite process of technology adoption and adaptation. Thus, this research aims to examine consumers' social media adoption, adaptation and behavioural outcomes as a composite process based on their joint attitudinal components.

An online survey strategy under a positivist research paradigm with a deductive research approach was undertaken. Under an explanatory quantitative research method, data was collected through a structured questionnaire, administered to a random sample of social media consumers. Data was analysed using Structure Equation Modelling. The findings confirm that consumers' joint attitudinal components are the antecedents of social media adoption, adaptation and behavioural outcome as a composite process that is influenced by cognitive (Perceived Opportunity, Perceived Social Influence and Perceived Control) and affective (Enjoyment, Self-Enhancement, Trust and Fear) attitudinal components. Consumers engage in adaptation behaviour of Exploration to Maximise or Exploitation to Satisfice Social Media Benefits if they have a favourable attitude towards the consequences of their digital footprints and Exploration to Revert from social media or Avoidance of Social Media adaptation behaviour if their attitude is unfavourable. Each adaptation behaviour leads to a specific outcome such as carelessness and carefreeness when consumers engage in exploration to maximise or exploitation to satisfice social media benefits and cautiousness and consciousness when they engage in social media avoidance and exploration to revert adaptation behaviour respectively.

This research makes the following contributions to literature. It develops a nomological model of technology adoption, adaptation and behavioural outcome as a composite process. It offers the joint attitudinal components (cognitive and affective) as antecedents to the composite process. It introduces consumers' adaptation behavioural efforts to cope with the consequences of their digital footprints and analyses the impact of technology adoption and adaptation on behavioural outcomes. The research helps marketers in segmenting, profiling and targeting customers. It allows marketers and information systems managers to focus on

consumers' joint attitudinal components by identifying and analysing the key antecedents of the technology adaptation which can provide useful insights for future product/service development. In addition, it enables marketers to analyse consumers' attitudinal response to their privacy and security of their digital footprints, and offers useful policy implications.

Declaration

I hereby declare that the thesis is based on my original work, except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Brunel University or other institutions. However, some parts of this thesis is presented in my research and conference papers. The details of the published research and conference papers are given on page XI of this thesis.

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1. Muhammad, S. S., Dey, B. L., and Weerakkody, V. (2018). Analysis of factors that influence consumers' willingness to leave Big Data digital footprints on social media: A systematic review of literature, *Information Systems Frontiers*, 20(3), 559-576.

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2. Muhammad, S. S., Dey, B. L., and Alwi, S. S. (2018). Analysis of Cognitive and Affective Factors that Influence Consumers' Willingness to Leave Big Data Digital Footprints on Social Media, paper accepted and presented at the *Academy of Marketing Conference*, Stirling, UK, July, 2018.

3. Muhammad, S. S., Dey, B. L., and Weerakkody, V. (2017). Analysing the Factors that Influence Consumers' (Un) Willingness to Leave Big Data Digital Footprints on Social Media: The Role of Privacy, Security and Psychological Dispositions, paper accepted and presented at the *Academy of Marketing Conference*, Hull, UK, July, 2017.

4. Muhammad, S. S., Dey, B. L., and Weerakkody, V. (2016). Analysis of Consumers' Perception of Big Data Digital Footprints on Social Media, paper accepted and presented at the *Academy of Marketing Conference*, Newcastle, UK, July, 2016.

5. Muhammad, S. S., Dey, B. L., and Weerakkody, V. (2016). Digital Footprint and Privacy Salient Consumers on Social Media, paper accepted and presented at the *British Academy of Management* Conference, Newcastle, UK, September, 2016.

Book Chapter

6. Examining the underlying attitudinal components driving technology adoption and adaptation behaviour in entirety (Accepted and reviewed by the editors and will be published in April 2019).

Chapter 1. Introduction

This chapter provides a brief background to consumers' technology adoption, adaptation and their digital footprints, which they share when they interact with technology (social media). It highlights the significant aspects of consumers' interaction and coping with technological disruptions. In addition, it highlights the critical issue of consumers' digital footprints in relation to social media adoption and adaptation. The chapter is structured as follows: The first section focuses on the background of technology adoption, adaption and consumers' digital footprints. The next section highlights the debate regarding consumers' attitudes, followed by the setting out of the research aim, objectives and research question. Finally, this chapter provides the layout of the thesis.

1.1 Background

The emergence of digitalisation and mobile applications has initiated a new era of technological innovation and use (Agarwal et al., 2017). The advent of social media and the exponential growth in mobile telephony, cloud computing, 4G and 5G networks have created innumerable technological touchpoints (website, phone, social media platforms etc.) to allow businesses to map consumers' journeys (Sharma, 2017; Roberts, 2018). These ubiquitous touchpoints have enhanced connectivity and flexibility (Chhonkeret al., 2017), enabling users to adopt and adapt technology and to be connected to technological devices 24/7. As a result, users interact virtually on these technological platforms using multiple devices such as tablets and smart phones (including smart devices like Alexa, Siri and Google Home), sharing their digital footprints. These digital traces are amassed into big data, due to which the digital universe is expanding, and it is estimated that 180 Zettabytes of data will be generated by 2025 (Kanellos, 2016). Digital footprints are digital DNA that consumers share on various digital platforms, including social media (Facebook, Twitter and Instagram etc.). Digital footprints are the records and traces that consumers leave while using technology (Internet Society, 2014). Such digital footprints are not just identities but also memories, moments and behaviour. Social media providers that collect and crawl these digital footprints can determine how and why consumers interact with and purchase on digital platforms (Fish, 2009). Even everyday objects, connected to the internet, collect personal digital footprints (Kuchler, 2017). Ramirez (2015) argued that connected devices, creating many digital touchpoints, collect, store, transmit and share digital footprints, thereby engendering privacy and security risks. Such technologies create three privacy and security challenges, namely ubiquitous data collection (e.g. likes, dislikes, habits, personal information and location), unexpected use of users' (who may often be consumers as well) data (use of data collected from smart phones, cars, TV, tablets, smart cities etc.) and security (access to personal data, misuse and breach of data, unauthorised access to personal information etc.) which can potentially shatter consumers' trust and may lead to inhibition and avoidance of advanced technological devices (Marakhimov and Joo, 2017; Ramirez, 2015).

There is immense growth in social media adoption worldwide and it is considered to be one of the major sources of the expansion of digital footprints. Social media is defined as collaborative online applications built on the technological foundation of the Web 2.0 platform to allow users to participate, connect and generate content (Henderson and Bowley, 2010; Kaplan and Haenlein, 2010). It is a big repository of digital footprints and considered to be a rich source of insights for marketers (Henderson and Bowley, 2010; Tuten and Solomon, 2015). Since the norms of reciprocity and interactions on technological platforms have increased, bringing consumers together, they reveal more intimate information by making the online relationship richer than face-to-face interactions (Mathwick, 2002). Furthermore, it is also interesting to notice how consumers drive out retailigence (technology shifting power to consumers) through the adoption and adaptation of social media by sharing digital footprints at the pace of zettabytes of data (Hendrix, 2014). Digital DNA is generated on social media platforms by sharing, for example, comments, photos, videos, blogs, bookmarks, reviews, ratings and social shopping etc. (Malhotra et al., 2012; Rosenberger et al., 2017).

These digital trails exhibit interests, social and cultural identities, and occupational and geographical attachments, which are essentially required by marketers and businesses (Charlesworth, 2014; Michael et al., 2014). Such digital traces help them to analyse consumers' shared contents and sentiments by using advanced analytics to gain deeper insights into their behaviour and develop their profiles (Charlesworth, 2014). Similarly, social media providers use personal data to track consumers and their behaviour through invasive and ubiquitous crawling by using advanced analytics and algorithms to generate rich and insightful information through data connections, inferences and data interpretations (DWork and Mulligan, 2013). Consumers' digital footprints are precious for social media providers and businesses, due to which they have given importance to data mining, machine learning and analytics to make the best use of consumers' digital footprints. Social media platforms provide free services (freemium business model) wherein the adoption and adaptation of such platforms have grown exponentially. Therefore, the managerial implications for digital footprints are immense, as they can create value for firms (Pulse, 2012). However, the pervasive adoption, adaptation of social media and the influx of digital footprints' traces on these platforms have raised privacy and security concerns amongst social media consumers.

Many countries have initiated measures to protect individuals' digital footprints, privacy and security as social media platforms and web technologies have become more intrusive, vulnerable to abuse and exploitation. It is understood that there is growing concern about how their digital footprints are accumulated, processed, and treated, and how third parties are given access to their digital DNA. The European Union (EU) recently introduced General Data Protection Regulation (GDPR) to ensure that personal data is secure and is not exploited (European Commission, 2018). Data privacy and security is a burning issue, as major social media providers are breaching data protection regulations (Murphy, 2019). Similarly, privacy advocates in the USA allege that large internet service providers can potentially encroach upon consumers' privacy, as they have access to large volumes of personal data (Waters and Bond, 2017).

On the other hand, it is fascinating that consumers are undeterred from social media adoption, continuing to adapt and appropriate social media in their daily lives, and sharing huge digital traces on these platforms. Tuten and Solomon (2015) describe this disparate relationship as a privacy paradox. Similarly, there is often inconsistency of privacy attitudes and behaviour amongst social media users (Kokolakis, 2017). Despite privacy and security concerns, consumers continue to share big digital footprints on social media. This disparate relationship and privacy salience attitude towards consumers' social media adoption and adaptation behaviour as a composite process is not known.

Although consumers' engagement with social media has received much research attention (Al-Jabri et al., 2015; Charlesworth, 2014; Hajli, 2014; Hsu and Wu, 2011; Akar and Topçu 2011; Hau and Kim, 2010), there is a paucity of research that identifies and analyses the factors driving consumers' adoption and adaptation of social media digital footprint sharing and outcome behaviour. Furthermore, the current literature provides theoretical frameworks on technology acceptance, adoption and adaptation: for instance, the Theory of Reasoned Action (TRA), the Theory of Planned Behaviour (TPB), the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) and the Coping Model of User Adaptation (CMUA). These theories have identified several determinants of technology adoption and adaptation, such as usefulness, perceived opportunity, relative advantage, ease of use, innovation, social norms and compatibility (Al-Gahtani et al., 2007; Beaudry and Pinsonneault, 2005; Davis et al., 1989; Hsu and Wu, 2011; Venkatesh et al., 2003, 2012). However, they do not fully capture the dynamics and kinetics of the composite process of consumers' social media adoption, adaptation, behavioural outcomes and their attitudinal antecedents. They provide partial explanations for consumers' underlying attitudinal components that drive these composite interactions. The existing models mainly focus on consumers' cognitive appraisal of technology, such as usefulness, perceived opportunity, ease of use, relative advantage and perceived threat (Bala and Venkatesh, 2016; Chiu, 2002).

Moreover, Beaudry and Pinsonneault (2005) posit that technological disruptions create expected and unexpected outcomes for users. They developed the CMUA model, which suggests that technological disruptions can lead to various changes in users' environment and they can perceive such changes as both novel and disruptive. They can perceive those outcomes multifariously and induce different types of behavioural responses and outcomes (Beaudry and Pinsonneault, 2005; Louis and Sutton, 1991; Lyytinen and Rose, 2003). Based on interpretation and perception, individuals undertake different adaptation behaviours to cope with technological disruption (Beaudry and Pinsonneault, 2005; Fugate et al., 2008). Negative appraisals of technological disruption may lead them to underutilise technology or abandon it completely (Bala and Venkatesh, 2016).

As such, technology adoption and adaptation have been of increasing interest among academics and practitioners (Kane and Labianca, 2011; Vessey et al., 2002). However, users' composite non-linear (adoption and adaptation) interactions with social media despite privacy and security concerns along with their underlying determinants have not been examined previously. The issue has also gained currency in marketing literature. Dey et al. (2013) postulate that adoption models suffer from certain ontological and epistemological limitations, as the existing models do not guarantee continued adaptation. They argue that consumers may choose to disengage from technology after short trials. Therefore, technology use goes beyond adoption and involves a gradual integration into consumers' lives and work practices. As such, technology adoption is not an end in itself and needs to be studied as a component of the composite process of adoption, adaptation and behavioural outcomes. Hence, the existing models do not fully capture the dynamics and kinetics of technology adoption and adaptation as a composite process along with their behavioural outcomes. They do not address the interaction amongst adoption, adaptation and the underlying determinants, or how such interactions result in behavioural outcomes.

Similarly, Walsham (2010) argued that if technology is to make a real impact, it needs to be examined along with adaptation because adaptation constitutes non-linear interactions between technological applications and individuals' situated capabilities (Dey et al., 2013). Moreover, an individual's attitude toward a technology is formed over time: this means that engagement with technology goes beyond adoption into how it is adapted and adjusted (Straub, 2009). Hence, there is a need to study the interaction of consumers' social media adoption, adaptation and outcome as a composite process. To examine this, it is vital to take a brief look at the background of technology adoption, adaptation and attitude before they are examined more deeply in this research. Furthermore, existing models offer limited insights into consumers' attitudes towards technology (social media) adoption, adaptation and behavioural outcomes and how their joint attitudinal components shape this composite process and the interrelationships amongst various facets. While this research seeks to address this dearth in scholarship, it has chosen consumers' engagement with digital footprints as the context of study due to its topicality and business implications.

1.2 Technology Adoption

Technology use, acceptance and adoption have been researched extensively (Davis et al., 1989; Hsu and Wu, 2011; Lin and Anol, 2008; Lu et al., 2009; Venkatesh et al., 2003, 2012) and the adoption literature has made a good contribution to IS and Marketing scholarship over the years. Prior studies provided a landscape of theoretical frameworks: for instance, the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), the Decomposed Theory of Planned Behaviour (DTPB), the Motivation Model (MM), the Model of PC Utilisation (MPCU), Social Cognitive Theory (SCT), Innovation and Diffusion Theory (IDT) and the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) are widely cited theories and frameworks for assessing individuals' use, acceptance and adoption of technology (Hsu and Wu, 2011; Lin and Anol, 2008; Lu et al., 2009; Venkatesh et al., 2012). The key focus of these models is on changes in users' beliefs, attitudes, knowledge and skills towards technology: for example, the TRA identified attitude and subjective norms as determinants of technology adoption. Attitude was identified as the individual's positive or negative feelings towards certain behaviour, and subjective norm as the individual's perception of how others think an individual should use technology (Fishbein and Ajzen, 1975). Similarly, the TAM further developed the acceptance of technology by identifying the attributes of perceived usefulness (enhance job performance), ease of use (free of effort) and subjective norms in the same way as the TRA (Davis, 1989). The TPB, on the other hand, added a new cognitive construct of perceived behavioural control (the individual's self-evaluation of his/her inner capabilities and how easy or difficult one finds the use of technology) to the attitude and subjective norm constructs of TRA (Ajzen, 1991), whereas the MPCU identified constructs of job fit (enhanced job performance), complexity (innovation's difficulty to use), and affect (feeling of joy) towards acceptance and outcomes that would pay off in the future (Thompson et al., 1991). A similar stance was taken by Davis et al. (1992), who theorised the Motivation Model and postulated extrinsic (valued outcome) and intrinsic motivations as an explanation for adoption behaviour. In addition, the SCT proposed personal outcome expectation (self-esteem), anxiety (emotional reactions while using technology), self-efficacy (ability to accomplish certain task) and affect as liking certain behaviour (Compeau and Higgins, 1995). The IDT propounded relative advantage, ease of use, image, compatibility, voluntariness and result demonstrability. Nonetheless, Venkatesh et al. (2003), as a result, unified the commonalities amongst the above models and proposed the UTAUT model by combining the constructs having common themes into performance expectancy, effort expectancy, social influence and facilitating conditions as the key determinants of use and acceptance of technology. They subsequently added constructs of habit, price and hedonic motivation in the consumer context and proposed the UTAUT 2 (Venkatesh et al., 2012). Although the UTAUT was initially developed to explain employees' adoption of technology in organisational contexts (Venkatesh et al., 2003), it was later extended into consumer technologies and finally into a Multi-Level Framework for cross-context theorising (Venkatesh et al., 2016).

The UTAUT has been used in variety of contexts and has been applied, integrated with other models and extended to cater for the different contexts. The UTAUT takes into account the type of users such as consumers, employees and citizens (Gupta et al., 2008; Hong et al., 2011) and it was examined in different types of technologies (internet, IS, digital learning, e-government services) along with different tasks and times of technology adoption and use (Brown et al., 2010; Dasgupta and Gupta, 2011; Zhou et al., 2010; Venkatesh et al., 2011). Its main focus was on users' technology adoption decisions. Similarly, the UTAUT was integrated with other models to examine consumers' purchase intentions (Guo and Barnes, 2011), extended through exogenous constructs (trust, innovation, culture, self-efficacy, perceived risk etc.) (Brown et al., 2010; Casey and Wilson-Evered, 2012; Dasgupta and Gupta, 2011) and endogenous constructs (perceived benefits, perceived threats, perceived risk, self-efficacy, attitude and anxiety etc.) (Weerakkody et al., 2014; Xiong et al., 2013; Yuen et al., 2010). The UTAUT multilevel framework catered for new contexts and suggested contribution of context effects (understanding differences in context-specific technology acceptance and use) and contribution to context effects (Venkatesh et al., 2016). However, Venkatesh et al. (2016) argue that there is a lack of fundamental shift in technology adoption research that is the promising direction for future research on the acceptance and adoption of technology.

Most of the above models suggest that attitude has the strongest influence on adoption of technology. Models such as the TRA and the TPB focus on users' attitude to determine users' adoption of technology (Ajzen, 1991; Davis, 1989; Davis et al., 1989; Fishbein and Ajzen, 1975), whereas Venkatesh et al. (2003) argue that the impact of attitude on technology acceptance is spurious. Use and usability of technology is associated mainly with the ease of use and its practical acceptability, such as cost, usefulness and reliability (Nielson, 1993). Use of technology alone does not identify the universality of technology use, as different skills, experience and knowledge are required (Han et al., 2001). The TAM, UTAUT and UTAUT 2 analyse technology adoption predictors at the micro and individual level, whereas others, such as the IDT, look into the diffusion of technology at the macro level. The Task Technology Fit (TTF) model analyses technology use against specific task and job related issues. Subsequent models dealt with the factors that determine technology adoption. Some literature redefines some of the factors, while others have introduced fresh components to enrich and advance the understanding, such as the UTAUT2 model for consumer technologies (Venkatesh et al., 2012).

Hence, prior models have mainly focused on the use and performance of technology and have given little consideration to adaptation, emotions and the social environment (Dey et al., 2013). They have largely focused on the user's initial perception towards the attractiveness of technology, which leads to acceptance and use due to the utility and usefulness of technology in isolation, but meagre attention has been given to adoption, adaptation of technology and outcome as a composite process. Moreover, these scholarly works, predominantly based on quantitative modelling, have been criticised by a different stream of literature that deals with a parallel notion. Over the years, the likes of Orlikowski (1992), DeSanctis and Poole (1994), and Beaudry and Pinsonneault (2005) have worked on how technology is further adapted (applied, extended and appropriated). This stream essentially raises the question of whether or not technology adoption literature should be confined only to technology adoption and determining factors. Simultaneously, a stronger research stream within IS has developed in the last two decades that seeks to assess the impact of technology use. As such, adoption is not an end in itself and it needs to be studied as a component of the composite process of adoption, adaptation and outcome.

In line with this argument, this research undertakes a study on consumers' social media adoption, adaptation and behavioural outcomes, as the existing models do not explicate the composite process and also give meagre attention to the joint attitudinal components, as Alwi and Kitchen (2014) argue that attitude is not only about cognitive but also affective evaluation and behavioural responses.

1.3 Technology Adaptation

Adaptation behaviours are the post-adoption acts that users perform to cope with the outcomes of new technology or changes to existing technology (Bala and Venkatesh, 2016). Adaptation behaviours are the acts that users undertake to cope with the perceived and emotional consequences or outcomes of the technological event(s). Adaptation acts are performed by individuals in response to a change and a disruptive event in their environment. Beaudry and Pinsonneault (2005), in their Coping Model of User Adaptation (CMUA), posit that individuals employ cognitive appraisal to the consequences of the technological disruptions that happen in their environment and they demonstrate certain adaptation behaviour to cope with such disruption. It may lead them to delve deeper into technological features and make the maximum use of technology at one end of the spectrum, or at the other end, to completely abandon it (Beaudry and Pinsonneault, 2005). A similar stance was taken by Bala and Venkatesh (2016), who suggest that individuals undergo two processes when they confront technological disruption (new technology or changes to existing technology). In the first instance, an individual makes a cognitive appraisal of the technological disruption and based on such appraisal they undertake specific adaptation behaviour to cope with such disruptions. If they perceive that the new technology has a positive outcome for them, they will explore ways to maximise or satisfice the benefits of technology. On the other hand, if they perceive the outcome of the technological disruption as a threat, they may completely abandon or revert from it. Therefore, their strategies for coping with technology depend on their cognitive appraisal and the degree of control that the technology provides to users (Folkman et al., 1986; Major et al., 1998). Such interactions of appraisals explain adaptation behaviour, which may restore users' emotional stability, resist or abandon the technology completely (Bala and Venkatesh, 2016).

Hence, adaptation behaviour is about different actions and coping efforts that an individual performs to cope with technological disruptions. They are a combination of cognitive and behavioural efforts. These behavioural efforts can be categorised as either problem-focused (that is, either managing the disruptive event or developing a new set of behaviours/learning new skills to cope with the technology: Lazarus and Folkman, 1984) or emotion-focused, which involves changing one's perception (e.g. regulating personal distress, maintaining a sense of stability etc.), rather than the event. The specific combination of problem- and emotion-focused coping depends on the individual's appraisal of the situation. They may choose a coping strategy that has a major chance of success. Similarly, Bala and Venkatesh (2016) suggest four different adaption behaviour strategies when individuals encounter a new technology, ranging from exploration to maximise (take full advantage of) or satisfice (take limited advantage of) the benefits offered by a technology. On the other hand, they may revert (minimise perceived negative consequences) from technology or abandon technology completely so as to restore personal emotional stability. A similar argument was made by Dey et al. (2013) that individuals may discontinue technology after a few trials or it may go beyond adoption and become fully integrated into their lives. They suggest that technological impact is more appropriately determined if it is adapted in a particular context, as technological adaptation behaviour is more fluid, interactive and non-linear (Walsham, 2010). Similarly, Carroll et al. (2002) suggest that technology appropriation is led by initial perception about a technology, which may lead to technology acceptance, followed by a deeper evaluation level wherein users adopt technology, exploring technological features, and finally by adaptation, when technology is integrated into their everyday practices and long-term use.

Nonetheless, prior studies based on use, appropriation and acceptance of technology models provide limited insight into consumers' adoption and adaptation of social media and their behavioural outcomes as a composite process. Therefore, looking to consumers' attitudes towards the consequences of their social media digital footprints, it is important to develop deeper understanding of consumers' social media adoption, adaptation and outcome as a composite process, as prior models fall short of explicating this phenomenon. In addition, prior models have not examined the joint attitudinal components driving the kinetics of composite process interactions. This research aims to study the dynamics of social media consumers' attitude about their digital footprints on social media platforms and how it influences their social media adoption, adaptation and behavioural outcomes. Using rigorous empirical enquiry, it seeks to test the key underlying attitudinal determinants of adoption, adaptation and behavioural outcomes.

1.4 Attitude

Existing models have not given due consideration to consumers' attitude in technology adoption and adaptation as a composite process. Consumers' attitude towards social media adoption and their digital footprint appropriation is more relevant. Dwivedi et al. (2017a) argue that technology adoption models need to re-introduce attitude into their models because attitude is the key perceptions and dispositions held by individuals regarding a technology. They argue that it is important for these models to reconsider the role of attitude in technology adoption. They further argue that even though the four exogenous constructs of UTAUT are based on technological (performance and effort expectancy) and contextual attributes (social influence and facilitating conditions), they are in fact perceptions held by individuals regarding a technology and a context. The key element missing from UTAUT is the individuals' dispositions, which are their attitudes explaining their technology adoption behaviour. Furthermore, researchers have re-introduced attitude into technology adoption models (Dwivedi et al., 2017a; Dwivedi et al., 2017b; Rana et al., 2017a; Rana et al., 2016b).

When consumers engage with technology, they develop cognitive and affective attitude towards technology, due to which they adopt and adapt technology for its functions, utilities and emotions (Dey et al., 2013). Psychology literature has delineated individuals' cognitive and behavioural responses when they face a problem (Marakhimov and Joo, 2017). In the technology adoption literature, attitude has received significant attention, as psychologists have researched it for decades. It is defined as overall judgements of an object (Fazio, 1986), but Thurstone and Chave (1929) highlighted it as an evaluative or affective response to the attitude object. Zajonc and Markus (1982) defined attitude as a two-component structure of cognition and affect, and Chiu (2002) argued that attitude consists of affect, cognition and connation (behaviour): the three responses to an object (Chiu, 2002). Ajzen (1975) suggested that actions are controlled by intentions, which are determined by attitude towards behaviour: that is, a personal positive or negative evaluation of performing the behaviour. Similarly, Chiu (2002) highlighted that the affect-based component of attitude consists of emotions and feelings, whereas the cognition-based component includes beliefs, judgments or thoughts associated with an object. Attitude towards behaviour can be determined by salient beliefs and/or affect about the behaviour, and each belief or affect links the behaviour with some valued outcome.

The current theoretical models (e.g. the TRA, TPB, TAM, UTAUT, UTAUT2 and CMUA) have identified cognitive and affective factors in technology adoption and adaptation, but they have treated them in isolation and either focused solely on users' evaluation of cognitive attributes, such as usefulness, ease of use, perceived opportunity, relative advantage and convenience, or affective attributes based on emotions such as joy, status, ego and fear (Beaudry and Pinsonneault, 2005; Chiang, 2013; Hajli, 2014; Kim et al., 2011; Pereira et al., 2014). Moreover, in most cases, both affective and cognitive components are highlighted with little distinction and many overlaps. They do not provide enough attention to joint attitudinal components, although Alwi and Kitchen (2014) argue that attitude comprises both cognition and affect. Looking to this line of argument, prior models have been indistinct in their identification of the attitudinal components of technology adoption, adaptation and behavioural outcome as a composite process. A similar stance was taken by Venkatesh et al. (2016) in their revised multi-level framework, which acknowledged that technology adoption models have reached practical limitations. They expounded that there was a lack of paradigm-shifting research in technology adoption. It is vital to consider both cognitive and affective attitudinal components for their joint impact on the composite process of consumers' adoption, adaptation and behavioural outcomes.

This chapter, based on the aforementioned gap in the literature, propounds a model to study consumers' social media adoption, adaptation and outcome as a composite process. From the above discussion on attitude, both cognitive and affective attitudinal components are considered (Edvardsson, 2005), as consumers' behavioural response is not only the outcome of cognitive but also affective attitudinal attributes (Chiu, 2002). Combining both attitudinal components provides more useful and comprehensive meaning to understand consumers' attitude in a particular context (Alwi and Kitchen, 2014).

1.5 Problem Statement

There is no doubt that the cult of 'Neophilia', surrounding technological advances such as artificial intelligence, robotics, machine learning and social media, has transformed lives. Marakhimov and Joo (2017) argue that the Internet of Things (IOT) brings transformative change to consumers' lives, which makes them worry about their privacy risks. It has become increasingly challenging if not impossible to avoid technological disruptions such as social media. Consequently, the power of data and social media have transformed consumers' lives more than ever before in the history of mankind. They have created a virtual universe which is expanding by powers of 10. It is estimated that there are approximately 2.77 billion social media users worldwide and this figure is expected to exceed 3 billion by 2021 (Statista, 2019). Facebook alone has woven 700 billion friendships across the globe (Shadbolt and Hampson, 2018). Consumers' interactions with social media platforms are rapidly increasing. It has enhanced opportunities for social media providers and others to analyse consumers' digital footprints to get deeper insights into their buying behaviour through advanced analytics and algorithms. However, concerns over the privacy and security of social media users' digital footprints are on the rise, as increasing evidence.

The recent Facebook scandal regarding the exploitation of digital footprints to facilitate political campaigns exhibits the challenges and caveats for consumers' social media engagement (Thomas, 2018). The sheer volume of data collected by social media providers and their alleged algorithmic abuse have caused huge privacy and security concerns. For social media users privacy and security of their digital footprints are major concerns as Kobie (2015) argue that consumers are more worried about their privacy and security than ever before. Similarly, the pervasive use of digital footprints has raised privacy and security concerns amongst social media users. Due to which USA and EU have initiated measures to protect individual privacy and security as social media platforms and web technologies have become more pervasive and a possible tool for abuse and exploitation. Consumers are concerned about how their digital footprints are accumulated, processed, and treated, and whether or not third parties are given unauthorised access to their digital footprints. Privacy advocates in the USA allege that large internet service providers can potentially encroach upon consumers' privacy, as they have access to large volumes of personal data (Waters and Bond, 2017). Even everyday objects connected to the internet are collecting personal digital footprints (Kuchler, 2017).

The aforementioned developments raise key questions around consumers' social media digital footprints privacy and security, as social media providers use digital DNA to track consumers and their behaviour by using algorithms to establish data connections, inferences, and data interpretations and generate powerful insight (Dwork and Mulligan, 2013). This unimaginably pervasive use of digital footprints has created unrest and concerns amongst consumers about their privacy and security; yet, on the other hand, they are undeterred to adopt, apply, extend and integrate social media into their everyday lives by sharing huge digital traces on a daily basis.

Looking to this burning issue, policy-makers have recognised that the latest technologies are using personal data without users' consent, which is a major privacy and security risks for consumers (Manyika, 2015). The EU recently introduced General Data Protection Regulation (GDPR) to safeguard how companies handle an individual's data. The regulation focuses on whether companies collect and process data fairly, securely and lawfully, and on how it is kept, and moreover, on what purpose companies have for data collection and how long the data is kept (European Commission, 2018). In addition, the USA has been asked recently to consider an Algorithmic Review Board to provide the necessary transparency for individuals. However, the dominant digital platforms, such as Facebook, Twitter and Instagram, already have potent algorithms (Bradshaw and Wells, 2018).

This area of research has its significance with the digital revolution and changing dynamics in consumer world that may in the coming days reshape the modalities and nature of interactions with social media and other technological advancements. It is vital for social media providers and businesses to know about consumers' social media adoption, adaptation and behavioural outcomes as a composite process.

Social media adoption is not an end in itself but a component of a bigger process of adoption, adaptation and behavioural outcomes of social media, giving consumers the impetus to share digital footprints. Prior studies offer limited understanding of social media adoption and adaptation and fall short of presenting a composite model of the whole process. In addition, prior studies, predominantly based on quantitative modelling, have been criticised by a different stream of literature that deals with a parallel notion. Over the years, the likes of

Orlikowski (1992), DeSanctis and Poole (1994), and Beaudry and Pinsonneault (2005) have worked on how technology is further applied, extended and appropriated. Limited quantitative work has been done (Fadel, 2012) to examine adaptation phenomena, as much attention is confined within the adoption part of this process. This essentially raises questions as to whether or not the technology adoption literature should be confined only to technology adoption and determining factors.

Furthermore, despite the existing knowledge around social media, there is little research around the underlying factors that drive consumers' social media adoption and adaptation as a composite process. Consumers' attitude, as Agarwal et al. (2017) argue, is more relevant in this dynamic world of digitalisation and mobile applications, which have provided consumers with an entirely different world of technological innovation and technological devices.

However, just like previous researchers, these researchers did not examine consumers' joint attitudinal components. Adoption and adaptation of technology involves not only cognitive (functional attitudinal attributes) but also more affective (emotional, symbolic and hedonic) attributes such as fun, enjoyment, and self-enhancement (Diffley et al., 2011; Park and Kim, 2014). Henceforth, it can be argued that prior models have given little attention to the attitudinal components, with partial explanation of individuals' attitude, and ignored the impact of joint attitudinal components. Moreover, so far there has been little discussion around the attitudinal components of fear and trust around consumers' social media digital footprints. This research aims to examine whether such factors can influence users' adoption and adaptation of technology (Boyd, 2008; Chew et al., 2008; Lee et al. 2013). Therefore, it is vital to consider both cognitive and affective attitudinal components for their joint impact and important to examine how consumers' attitude towards the consequences of their social media digital footprints influence their social media adoption and adaptation as a composite process.

1.6 Research Aim

The aim of this research is to examine consumers' social media adoption, adaptation and behavioural outcome as a composite process. In so doing, this research considers consumers' joint attitudinal components as antecedents to technology adoption and adaptation. The contribution to the existing literature is therefore threefold: a) extension of attitudinal components; b) measuring post-adoption behavioural outcomes; c) developing a composite model of adoption and adaptation with outcomes.

1.7 Research Objectives

The following objectives have been set for this research.

Objective 1.

- To examine what underlying attitudinal components (cognitive and affective) drive consumers' social media adoption, adaptation and behavioural outcomes as a composite process.

Objective 2.

- To critically assess the joint attitudinal components' (cognitive and affective) impact on consumers' social media adoption, adaptation and behavioural outcomes.

Objective 3.

- To analyse the adaptation behavioural efforts consumers undertake to cope with the consequences of their social media digital footprints.

Objective 4.

- To determine the behavioural outcomes of the adaptation behaviour based on consumers' attitudes towards the consequences of their digital footprints.

Objective 5.

- To develop a comprehensive model which focuses on consumers' adoption, adaptation and behavioural outcomes as a composite process.

1.8 Research Questions (RQ)

RQ1.

- What are the underlying attitudinal factors that drive consumers' social media adoption, adaptation and behavioural outcomes as a composite process?

RQ2.

- How do the joint attitudinal components impact consumers' social media adoption, adaptation and outcomes as a composite process?

RQ3.

- What adaptation behavioural efforts do consumers undertake to cope with the consequences of their social media digital footprints?

RQ4.

- What are the behavioural outcomes of the adaptation behaviour based on consumers' attitudes towards the consequences of their digital footprints?

1.9 Significance of Study

Consumers' digital footprints are of vital significance and have attracted the attention of numerous researchers and practitioners. This research has the specific purpose to examine the underlying significant factors determining consumers' social media adoption, adaptation and their behavioural outcomes as a composite process, and aims to:

- analyse consumers' key attitudinal components in sharing digital footprints, to allow marketers and IS managers to set priorities accordingly;
- make a theoretical contribution to the underlying factors driving consumers' social media adoption, appropriation and behavioural outcomes of their digital footprint sharing behaviour;
- extend technology adoption and appropriation models to better understand consumers' interactions with social media;
- delineate behavioural outcomes of social media consumers about their digital footprints;
- highlight the importance and significance of joint attitudinal components in social media adoption, adaptation and outcomes as a composite process;
- unearth the influence of cognitive and affective attitudinal components on consumers' adoption and adaptation behaviour;
- identify further research gaps and avenues for academics and practitioners;
- help social media providers, practitioners and marketers to alter their strategic priorities.

1.10 Thesis Structure

This thesis has seven chapters with the brief overview of each chapter is as follows.

Chapter 1.

Chapter 1 provides a background to the research topic and highlights the significant aspects of the research topic. It delineates the research aim, objectives and research questions. Finally it focusses on the significance of this research, thesis structure and provides the chapter summary.

Chapter 2.

Chapter 2 analysis the scholarly works on the underlying significant factors that drive consumers' social media adoption, adaptation and outcome and makes in depth critical review of the literature. This chapter relates and evaluates prior research in conjunction with the aim and objectives of this research. It provides a critical evaluation and analysis on consumers' social media adoption, adaptation and their digital footprints sharing behaviour. The chapter comes to a close by identifying a research gap and overview of the chapter.

Chapter 3.

This chapter develops the Theoretical Framework and highlights the base theories used to underpin this research to facilitate the development of the conceptual framework, Technology Adoption and Adaptation Model (TAAM). In addition, this chapter delineates the details of the causal relationships given in the model by setting hypothesis and dependent relationships for empirical testing.

Chapter 4.

Chapter 4 focusses on the research methodology explaining the research framework and design. It also highlights the technique of research analysis used to test hypothesis. Finally, this chapter provides discussion on the ethical consideration and research limitations.

Chapter 5.

This chapter focuses on data analysis and hypothetical relationship given in the developed TAAM model by examining the joint attitudinal components of attitude as antecedents of adoption and adaptation behaviour to understand consumers' different social media adaptation and behavioural outcome based on their joint attitudinal response towards the consequences of their digital footprints. This chapter focuses on the findings and delineates the Confirmatory Factor Analysis, Structural Equation Model, hypothesis testing and finally with an overview of the chapter.

Chapter 6.

This chapter provides discussion and analysis on the findings derived in the above chapter 5. In addition, this chapter provides and an in depth analysis, interpretation and discussion of the findings in the context of the relevant literature to make inferences for the TAAM model and establish the causal links in the model.

Chapter 7.

Chapter 7 brings to a close this thesis by focusing on the inferences and conclusions derived for the objectives set in this research and provides summary of theoretical and practical contributions. In addition, it provides recommendations based on the conclusions followed by research limitations, future research direction and summary of the chapter.

1.11 Conclusion

This chapter has provided a brief background to consumers' adoption and adaptation of technology and the digital footprints that they share on share media platforms. It highlighted the significant aspects of consumers' interaction and coping with technological disruptions by discussing the critical issue of consumers' digital footprints with social media adoption and adaptation. It also discussed the problem statement with the key issue of consumers' digital footprints and social media adoption, adaptation and outcomes. In addition, the chapter shed light on the background of technology adoption, adaptation and attitude. The chapter comes to a close with the articulation of the specific aim of the research, with research objectives and research questions. This chapter provides an introduction and background to the key concepts and issues which are under investigation in this research.

Chapter 2. Literature Review

2.1 Introduction

To examine the underlying significant factors that drive consumers' social media adoption, adaptation and outcome, direction and meaning have been sought from Information Systems, Marketing, and Social Psychology literature to delve deeper into consumers' social media adoption, adaptation and outcome as a composite process. This chapter is structured as follows. Initially, digital footprints and social media are briefly described followed by in depth critical review of the prior scholarly works and finally leads into a research gap.

2.2 Digital Footprints

Digital footprints are the digital activities and actions undertaken by individuals when they interact with digital technologies. They are traceable digital activities and information shared by someone on the internet and digital technologies (Dictionary.com, 2018). Digital footprints are defined as social big data created by users when they interact with devices. Such digital footprints are not just identities but memories, moments and behaviour and the service provider who controls the data can determine why and how users behave and purchase (Fish, 2009). Bodani (2012) describes digital footprints are traces and trails of an individual or an organization left behind when they interact on the digital and online technologies such as social media, emails, search tools, uploading videos and photos etc. Digital footprints can provide behavioural data, likes, dislikes, interests, geographical location and social groups etc.

Pulse (2012) argue that big data digital footprints can create social value and promote development to conduct sentiment analysis (computational study of opinions, emotions and sentiments expressed in text) helping to predict behaviour, disease outbreaks and job losses etc. It is a new class of economic asset declared by the World Economic Forum (Forum, 2012). Anderson and Rainie (2019) describe it as the new oil. Organisations that are able to mine digital footprints will have huge advantages over their competitors. It has the power to predict economic development (Agrawal and Choudhary, 2013) and is described to contribute £322 billion to the UK economy between 2015 and 2020 (Hogan et al., 2016).

The advent of Web 2.0 has given more control and freedom to users providing access to rich data. Similarly, internet is not confined to hardware or location and is more mobile with the help of innovative technologies (e.g. tablets, laptops, mobile phones and smartwatches etc.) and social media platforms. Web 2.0 has created a reputation economy, which empowers consumers to co-produce and co-create resulting in innovation and perpetual beta. (Tuten and Solomon, 2015).

2.3 Social Media

Social media is founded on Web 2.0 technologies connecting interdependent communities in which users trust others as a source of knowledge resulting into network effect (networked and co-created), it empowers consumers by giving them unparalleled access (discuss, collaborate, share, contribute) to brands and with each other. It also creates an earned media or e-Word of Mouth called influence impressions. Social media cross boundaries of both mass and personal media. The use of social media is divided into four phases. First is Social Community such as social networking sites (Facebook, LinkedIn, Vine, Instagram and Pinterest etc.), message boards, forums and wikis etc. used for relationships and sharing similar interests. Second is Social Publishing that consists of blogs, microsharing sites (Twitter), media sharing sites (YouTube, Flickr, and Instagram), bookmarking and news sites etc. Third is Social Entertainment that consists of channels and vehicles for play and enjoyment (entertainment communities and MySpace etc.) and Finally Social Commerce that consists of channels of reviews and ratings (Epinions and Yelp), deal sites (Groupon), social shopping markets (communicate with friends for online shopping), deal aggregators (Yipit, Daily Flock, 8coupons) and social storefronts (online retails stores with social capabilities to operate on Facebook) etc. (Tuten and Solomon, 2015).

The use of social media platforms give consumers ample opportunities to share digital footprints. They create content by interacting on these platforms and lead a digital social life when they share digital footprints through social community interaction (Facebook, Instagram), get involved in social commerce (Amazon), make social publishing (Flickr, YouTube) and enjoy social entertainment (play games online). Consumers' interactions with these platforms make a lifestream in the digital forest which are traced by savvy marketers. These digital footprints help marketers and vendors understand consumers' profile and get deeper insight of consumer behaviour. They crawl the Web and listen to social media consumers. Hence, they develop consumers' profiles through their digital life and behaviour of digital trails (Charlesworth, 2014; Dwork and Mulligan, 2013).

The literature around the use, acceptance, adoption and adaptation of technology is found in different disciplinary origins but Marketing and Information Systems are more in limelight. Both technology adoption and adaption have been studied extensively (Bala and Venkatesh, 2016; Beaudry and Pinsonneault, 2005; Davis et al., 1989; Hsu and Wu, 2011; Venkatesh et al., 2003; Venkatesh et al., 2016). However, there is limited understanding and dearth of scholarly works on technology adoption, adaptation and behavioural outcomes as a composite process and their underlying attitudinal antecedents. In the following sections this doctoral research reviews adoption and adaptation literature and the key elements of their antecedents.

2.4 Technology Adoption

Straub (2009) describes technology adoption is the acceptance or rejection of a technology or an innovation by an individual. Technology adoption has been researched extensively (Davis et al., 1989; Hsu and Wu, 2011; Lin and Anol, 2008; Lu et al., 2009; Venkatesh et al., 2003; Venkatesh et al., 2012). Prior studies provided a landscape of theoretical frameworks (Hsu and Wu, 2011; Lin and Anol, 2008; Lu et al., 2009; Venkatesh et al., 2012), for instance, Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), Decomposed Theory of Planned Behaviour (DTPB), Motivation Model (MM), Model of PC Utilisation (MPCU), Social Cognitive Theory (SCT), Innovation and Diffusion Theory (IDT) and the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) etc. are widely cited theories and frameworks for assessing individuals' use and adoption of technology. These models study the choices an individual makes to accept a technology (Straub, 2009).

The key focus of these models are changes in users' beliefs, attitude, knowledge and skills etc. towards technology. They provided several determinants for technology adoption such as TRA identified attitude and subjective norm as determinants of intention to adopt and use technology. TRA highlighted attitude as individual's positive or negative feelings towards certain behaviour, subjective norm as individual's perception of how others think an individual should use technology (Fishbein and Ajzen, 1975). Similarly, TAM identified the functional attributes of perceived usefulness (enhance job performance), ease of use (free of effort) and subjective norms identical as in TRA (Davis, 1989). TPB, on the other hand, added a new construct of perceived behaviour control (individual's self-evaluation of the inner capabilities and how easy or difficult one feels on the use of technology) to attitude and subjective norm constructs of TRA (Ajzen, 1991). In addition to the above factors, MPCU identified constructs of job fit (enhance job performance), complexity (innovation difficult to use), affect (feeling of joy) towards acceptance and outcome that would pay off in the future (Thompson et al., 1991). Similar stance was taken by Davis et al. (1992), who theorised the Motivation Model (MM) and postulated extrinsic (valued outcome) and intrinsic motivations as an explanation of adoption behaviour. In addition, SCT proposed personal outcome expectation (self-esteem), anxiety (emotional reactions while using technology), self-efficacy (ability to accomplish certain task) and affect as liking certain behaviour (Compeau and Higgins, 1995). Whereas IDT propounded relative advantage, ease of use, image, compatibility, voluntariness and result demonstrability. Nonetheless, as a result, Venkatesh et al. (2003) unified the commonalities amongst the above models and propounded a UTAUT model by combining the constructs having common themes into four constructs of performance expectancy, effort expectancy, social influence and facilitating conditions as the key determinants of acceptance and adoption of technology. UTAUT was developed further by adding constructs of habit, price and hedonic motivation in consumer context in UTAUT 2 (Venkatesh et al., 2012). Although UTAUT was initially developed to explain employees' adoption of technology in organisational contexts (Venkatesh et al., 2003), it was later extended into consumer technologies and finally into a Multi-Level Framework for cross context theorising (Venkatesh et al., 2016). UTAUT extended the model to study different type of use and acceptance of technology in different organisational and non-organisational settings (Venkatesh et al., 2003). In addition, UTUAT has been applied to different technologies i.e. mobile internet, Sykes, e-government etc. (Venkatesh et al., 2016).

Thus, it can be argued that the above models have made contributions to technology acceptance and adoption scholarship over the years. Most of the above models identified attitude as a key determinant of use and adoption of technology such as TRA and TPB (Ajzen, 1991; Davis, 1989; Davis et al., 1989; Fishbein and Ajzen, 1975). However, Venkatesh et al. (2003) argued that the impact of attitude on technology acceptance is spurious. Moreover, TAM, UTAUT and UTAUT 2 analyse technology adoption predictors at the micro level, other models such as IDT looks into the diffusion of technology at the macro level and TTF analyses technology use against specific task and job related issues. Subsequent models and concepts emanating from these classic frameworks mostly dealt with the factors that determine technology adoption. While some literature redefines some of the factors, others have introduced fresh constructs to enrich and advance the understanding such as UTAUT2 for consumer technologies by Venkatesh et al. (2012) and their subsequent Multi-Level Framework for cross context theorising (Venkatesh et al., 2016). Nevertheless, these scholarly works predominantly based on quantitative modelling have been criticised by a different stream of literature that deals with a parallel notion such as Orlikowski (1992), DeSanctis and Poole (1994), and Beaudry and Pinsonneault (2005) have worked on how technology is further applied, extended and appropriated. Similarly, Straub (2009) argues that technology adoption models have a microperspective as they focus on the parts of the whole but not on the whole itself. It essentially, raises question whether or not technology adoption literature should be confined only to technology adoption and determining factors. Simultaneously, stronger research stream within IS has developed in the last two decades that seek to assess the impact of technology use. As such, adoption is not an end in itself and it needs to be studied as a component of the composite process of adoption, adaptation and appropriation.

2.5 Technology Adaptation

Adaptation behaviours are the post adoption acts that users perform to cope with a technology (Bala and Venkatesh, 2016). Extant literature suggest that technology adaptation is linked to technological features, tasks individuals perform and their behaviour. It refers to how individuals modify technological features, adapt tasks as result of technology and behaviour to take advantage of a technology (Kashefi et al., 2015; Sun, 2012; Thomas and Bostrom, 2010). Whereas Beaudry and Pinsonneault (2005) argue that adaptation behaviour involves appropriation, resistance and avoidance of technology. In addition, adaptation has an integrative dimension to do things better or emergent dimension when individuals appropriate technology to do new things (Schmidt et al., 2010)

Beaudry and Pinsonneault (2005) proposed Coping Model of User Adaptation (CMUA), which posits that technological disruption creates various expected and unexpected outcomes in users' environment. Users perceive and interpret these outcomes in a number of ways by inducing different types of behavioural responses (Louis and Sutton, 1991; Lyytinen and Rose, 2003). These behavioural responses are the cognitive and behavioural efforts made by users to cope with the consequences of the technological disruptions in their environment. Based on such perceptions and interpretation, individuals undertake different adaptation behaviour to cope with a technology (Beaudry and Pinsonneault, 2005; Fugate et al., 2008). Similarly, Bala and Venkatesh (2016) suggest that individuals employ two processes when they face technological disruptions. First is the cognitive appraisal of the technological disruption and second is the adaptation behaviour which represents the cognitive evaluation to cope with the technological disruption. If they evaluate technological disruption as positive (has benefits), they will consider technology as an opportunity. Whereas, if they evaluate the outcome of the technological disruption as negative (harmful), they will consider technology as a threat (Folkman et al., 1986; Major et al., 1998). Such interactions of appraisals explain adaptation behaviour.

Similarly Majchrzak et al. (2000) argue that there are other technology adaptation models such as Adaptive Structuration Theory (AST), which posits that technology is adapted in the process of structures, appropriation and outcomes. Technology structure has three sources; technology features, nature of task and decision making process. Appropriation is the subtle immediate visible action, which invoke technology structures. If appropriation is aligned with the users' attitude, it will lead to successful outcomes. (DeSanctis and Poole, 1994). In addition, the Model of (successful) Adaptation Process posits that adaptation is seen as cycles of misalignments followed by alignment with further micro-misalignments evolving to a state in which technology and performance are aligned. Both these adaptation models define adaptation as a process to modify existing conditions in order to achieve an alignment (Majchrzak et al., 2000).

Similarly. Fadel (2012) argue that the benefits of technology materialise when users adapt technology by proactively changing themselves, their routines and technology itself. Stein et al. (2015) suggest that it is post-adoption use of technology functions to accomplish a task and post adoption may also result in users' resistance of a technology. Thus, it can be argued that adaptation behaviour is about different post adoption actions individuals performs to deal with the technological disruption. They are a combination of cognitive and behavioural efforts to manage the disruptive event or change oneself by developing new set of behaviour such as learning new skills to cope with a technology (Lazarus and Folkman, 1984) or emotion focused to change one's perception rather than the event and maintain a sense of stability to accept technology passively or avoid it altogether.

As discussed above, previous scholarly works developed several technology adoption (TRA, TPB, TAM and UTAUT etc.) and adaptation (CMUA and AST etc.) models with numerous factors leading to technology adoption and adaptation as extant literature suggests e.g. Al-Jabri et al., 2015; Bala and Venkatesh, 2016; Charlesworth, 2014; Hajli, 2014; Hsu and Wu, 2011; Akar and Topçu 2011; Beaudry and Pinsonneault, 2005; Hau and Kim, 2010. However, Thomas and Bostrom, (2008) argue that technology adoption, appropriation and task technology fit discovers collective adaptation practices. Therefore, as technology use goes beyond adoption and involves a gradual integration into consumers' lives and work practices, technology adoption and appropriation may provide success. Hence, it is the ongoing adoption and adaptation composite process which needs to be studied. There is paucity of research on the composite process and requisite antecedents especially when social media adoption and adaptation is growing exponentially. Prior models have not addressed this research gap especially in the context Web 2.0 technologies and consumers' digital footprints. Venkatesh et al. (2016) in their recent article highlighted the limitation of their models based on the use, acceptance and adoption of technology and argued that a new framework in the light of technological and contextual evaluation is needed.

2.6 Technology Adoption and Adaptation Factors

Both technology adoption and adaption have been studied extensively. Adoption has been examined in the context of why and how individuals accept a technology with many different streams of research. One stream of research focused on the antecedents of individual's acceptance and use of technology (Venkatesh et al., 2003) whereas the other stream focused on the antecedents of net benefits of technology to measure its success (users' satisfaction) or task technology fit (Dwivedi et al., 2017b). Similarly, different streams of research have focused on how individual react or adapt to technologies. First stream used mainly adoption antecedents for adaptation whereas the second stream of research focused on the adaptation behaviour and outcome (Bala and Venkatesh, 2016; Beaudry and Pinsonneault, 2005). Each of these streams have made significant contributions to adoption and adaptation literature. However, they focused on adoption and adaptation in isolation with almost similar antecedents and many overlaps. The details of antecedents used for adoption and adaptation are given in Figures 2.2, 2.3 and 2.4 respectively below. These antecedents have been found to have the following common themes or dimensions given in Figure 2.1. Prior models of technology adoption and adaptation used different constructs but mainly with these common themes or dimensions. These models have used similar concepts differently across studies with similar meanings and connotations. Themes given in Figure 2.1 are the key dimensions of technology adoption and adaptation and each one is discussed in detail below.

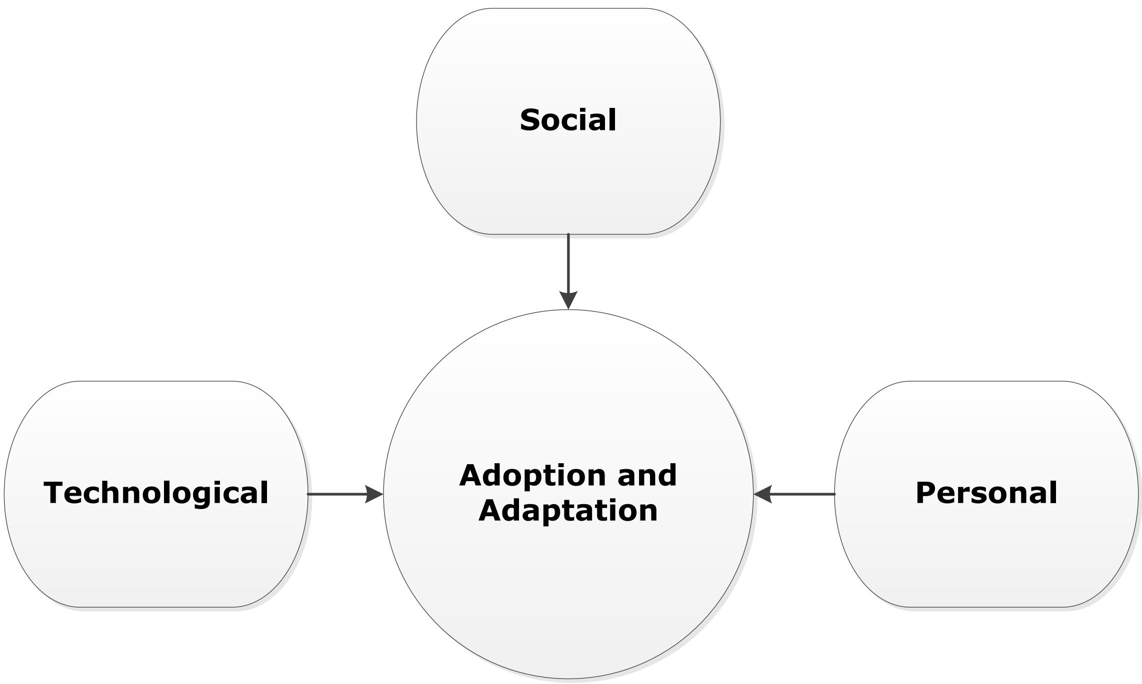

Figure 2. 1 Key Themes

Prior literature suggest both adoption (Straub, 2009) and adaptation (Beaudry and Pinsonneault, 2005) are complex processes as individuals have unique but malleable perceptions and feelings towards technology adoption and adaptation. Both has technological, personal and inherent social factors that influence their adoption and adaptation decisions.

2.6.1 Technological Factors

2.6.1.1 Perceived Opportunity, Performance and Effort Expectancy

Prior studies identified technological functional and utility factors (Figure 2.2) such as usefulness, performance expectancy, ease of use, mobility, convenience, compatibility, innovation and relative advantage as the determinants of technology acceptance, use and adoption (Ajzen and Fishbein, 1980; Al-Gahtani et al., 2007; Bhattacherjee, 2001; Lin and Anol, 2008). Perceived usefulness and ease of use have significant influence on the use and adoption of social media (Lu et al., 2010; Milewicz and Saxby, 2013). Hajli (2014) noted that perceived usefulness of social media transformed e-commerce into social commerce, facilitating consumer interaction to enhance trust which significantly influence consumers' behaviour. Similarly, Zhang et al. (2014) argue that technological functional features of utility influenced social media use and adoption. Whereas Thatcher et al. (2011) argue that usefulness and ease of use affects adaptation behaviour from the integrated view affecting both function specific and behaviour beliefs of individuals about a technology. However, Venkatesh et al. (2003) combined perceived usefulness, perceived utility, relative advantage and job fit into a single construct of performance expectancy (the belief that the system will enhance job performance). Similarly Al-Gahtani et al. (2007) and Lin and Anol (2008) argue that performance expectancy has a major influence on technology adoption.

Whereas Fadel and Brown (2010) examined the influence of performance expectancy on post adoption behaviour, adaptation of technology, and coping with technological disruptions. They argue that performance expectancy influence not only individuals' adoption but also technology adaptation behaviour as how their adaptation behaviour is influenced by adoption perception. Similar point was made by Beaudry and Pinsonneault (2005) that performance expectancy and task technology fit can influence users' adaptation. The same point was made by other researchers such as Bala and Venkatesh (2016) and Lazarus and Folkman (1984) in technology adaptation behaviour. They suggest that individuals undertake varied post-adoption response to technology based on their adoption appraisal. If they perceive the outcome of a new technology fits with the task they do, provides them success, they will perceived technology as an opportunity. They perceive technological features as benefits and utility to provide them growth, reward and success in their jobs. Therefore, they take full advantage of technological features. Beaudry and Pinsonneault (2001) describe that technology is multifaceted, based on individuals' perception of outcomes of a technology, they try out technological features for personal innovativeness, which in turn influence their adaptation process. Other researchers make similar argument that individuals develop their beliefs and understanding on different aspects of technology critical to functionality, which they perceive to be novel, provide compatibility, task technology fit and improve their performance (Agarwal and Prasad, 1998; Dishaw and Strong 1999; Venkatesh et al., 2003). Therefore, they would perceive technology as an opportunity. Perceived opportunity is described as the degree to which an individual believes that new technology would offer him or her success such that they may perceive new technology as providing personal growth opportunities, reward, improve performance etc. Technology users develop a holistic assessment of the opportunity of a technology. Venkatesh et al. (2003) suggest that when users adopt technology, they develop a sense of assessment that the use of a technology will enhance their job performance. They make cognitive appraisal of such outcome as how they would be personally and professionally affected. Such assessments determine their adaptation behaviour and they may tend to infer that the new technology is less tedious and more fun. It offers them more opportunities to learn new things and new skills. Hence, they consider it as a perceived opportunity in which gain is likely (Dutton and Jackson, 1987). Furthermore, Lazarus and Folkman (1984) describe that technology is multifaceted and can be assessed by individuals to have both positive and negative consequences. It depends on the relative importance of these consequences and based on such assessments individual adaptation behaviour will occur. Moreover, Bhattacherjee et al. (2008) suggest that such adaptation behaviour is not cognitive beliefs (performance expectancy, ease of use etc.) alone but also more affective reactions.

Furthermore, technological utility such as ease of use, convenience and complexity were combined into effort expectancy by Venkatesh et al. (2003) which is described as the degree of ease in relation to the use of system or using a system would be free of effort (Davis, 1989; Davis et al., 1989; Venkatesh et al., 2003). Acceptance of technology may be enhanced when users perceive that less effort is needed in the use of technology (Al-Gahtani et al., 2007; Lin and Anol, 2008; Venkatesh et al., 2003). Perceived ease of use is captured by effort expectancy. On the other hand, Zolkepli and Kamarulzaman (2015) suggest that technological innovation, relative advantage and compatibility has major impact on social media acceptance. Extant literature posit the same argument that relative advantage, innovation and compatibility have impact on social media acceptance and continuous usage (Chiang, 2013; Gironda and Korgaonkar, 2014; Wang et al., 2012; Zhang et al., 2014; Zolkepli and Kamarulzaman, 2015).

Chiang (2013) argue that the continuous usage of social media depends on innovation diffusion and gratifications of social media.

Venkatesh et al. (2003) incorporated these functional and utility attributes (perceived usefulness, ease of use, outcome expectation, innovation, relative advantage and complexity) from different theories into the constructs of performance and effort expectancy respectively as predictor of use and acceptance of technology. However, the later scholarly works identified technological innovation and relative advantage to include performance expectancy, effort expectancy, perceived usefulness, ease of use and compatibility affecting social media use and adoption (Chen et al., 2009; Chiang, 2013; Ho and Wu, 2011; Hsu et al., 2007; Kitchen and Panopoulos, 2010; Lean et al., 2009; Lee et al., 2011; Lin, 2011; Papies and Clement, 2008). Performance expectancy is described to comprise of perceived usefulness and utility of technology. Similarly, ease of use is described to include convenience and relative advantage, which involves the innovative compatibility of social media over other technologies (Al-Gahtani et al., 2007; Lin and Anol, 2008) and the adoption of technology (Carter and Weerakkody, 2008). It can be summarised that perceived usefulness, ease of use, relative advantage and innovation significantly influence social media adoption (Chiang, 2013; Hajli, 2014; Milewicz and Saxby, 2013; Zhang et al., 2014). Therefore, it can be argued that technological factors of usefulness, ease of use and relative advantage influence social media adoption (Gironda and Korgaonkar, 2014; Wang et al., 2012; Zolkepli and Kamarulzaman, 2015). Moreover, extant literature suggest that these users' perceptions of technology adoption identified in technology adoption models such as UTAUT play significant role in technology adaptation and ongoing technology sense making behaviour (Boudreau and Seligman 2005; Fadel and Brown, 2010; Jasperson et al., 2005).

Adaptation behaviour starts as soon as individuals become aware of the consequences of the adoption of technology, they evaluate the new technological disruption in terms of personal and professional relevance and importance. They may adapt technology depending on their assessment and their individual characteristics such as personal tendency to try new technology and being more innovative etc. Whereas Louis and Sutton (1991) argue that those individuals who have stronger belief, may have adaptation sooner. Coping literature and CMUA posit that individuals develop their assessment of technology based on certain features of technology or functional characteristics that they perceive to be novel. Such assessment leads to their perceived compatibility with technology, expected task and technology fit which they perceive as an opportunity. Prior literature suggest that when individuals believe strong task technology fit, they will perceive technology as an opportunity to improve their performance and will be assessed positively (Karahanna et al., 1999; Venkatesh et al., 2003;

Zigurs and Buckland 1998). Similar argument was made by Agarwal and Prasad (1999) that individuals will perceive technology more positively if they have high personal innovativeness.

It can be argued that individual may assess the outcome of a technology as an opportunity due to its perceived performance, relative advantage, ease of use and convenience (Zolkepli and Kamarulzaman, 2015; Venkatesh et al., 2003). Similar stance was taken by other scholarly works for technology acceptance and adoption that perceived utility, perceived usefulness, perceived ease of use and relative advantage influence technology acceptance and adoption (Compeau and Higgins, 1995; Davis et al., 1989; Moore and Benbasat, 1991; Plouffe et al., 2001; Thompson et al., 1991).

Hence, based on the similarities of the themes, subsequent scholarly works had combined the constructs with common themes and dimensions. This is evident not only in the subsequent works of Venkatesh but also other empirical studies (Zolkepli and Kamarulzaman, 2015). Arguably, the technological functional and utility factors constitute the themes of relative advantage, perceived opportunity, performance and effort expectancy (cognitive attributes) as they determine how an individual perceives technology to enhance his/her job performance (perceived usefulness, job fit), achieves valued outcome (utility), is free of effort (ease of use) and better than its precursor (relative advantage). Thus, these individual cognitive functional beliefs embody perceived usefulness, performance expectancy, effort expectancy, ease of use and relative advantage influencing adoption and adaptation of technology as extant literature suggests (e.g., Beaudry and Pinsonneault, 2005; Bala and Venkatesh, 2016; Chen et al., 2009; Chiang, 2013; Davis, 1989; Jan and Contreras, 2011; Kitchen and Panopoulos, 2010; Lean et al., 2009; Lee et al., 2011; Lin, 2011). It can be argued that previous stream of scholarly research identified perceived opportunity and technological innovation to comprise of functional attributes of relative advantage, utility, usefulness and ease of use etc.

2.6.1.2 Perceived Control

Extant literature suggests that users' acceptance of technology depend on the level of control they have on technological features (Culnan, 2000; Eastlick et al., 2006; Hoffman et al., 1999; Kang et al., 2007; Morgan and Hunt, 1994). Malhotra et al. (2004) argue that when individuals are vested with control on processes, they tend to accept and view those processes and disclosure of information as fair. They want to exercise control on procedures, technologies and sharing personal data on technological platforms. Control on technology becomes a crucial issue when opportunistic behaviour exists in online transactions. There is immense evidence in the literature that the ability to control technology determines their adoption of technology and sharing personal information. If online technologies offer individuals flexible means to control technology and their personal information, they will be less worried about their data collection (Malhotra et al., 2004).

Similarly, prior research noted that users' acceptance of social media depend on the level of control social media platforms and online vendors give to users. It is the level of control on their privacy, security and information disclosure (Li et al., 2006; Wu et al., 2010). Moreover, Dinev et al. (2013) made a similar point that the element of control is the most important factor on technological platforms. They describe control as individuals' belief in their ability to determine how much they share information on social media platforms. When they have high sense of control, they will tend to have less privacy concern on social media platforms. Tucker (2014) argue that social media consumers react positively when web platforms give control to users. In addition to social media platforms, brands need to relinquish control to their consumers if they want consumers' engagement with technological and web 2.0 platforms. Whereas, many IS researchers have discussed the role and significance of control in technology adoption and around their privacy and security e.g. Culnan and Armstrong 1999; Malhotra et al., 2004; Tucker; 2014; Xu et al., 2012. They argue that perceived control on technology and privacy can enhance positive responsiveness to technology and interactions on technological platforms.

Similarly, in adaptation literature, Kashefi et al. (2018) describe perceived control as the options individuals have to exert control on the situation to prevent harm or gain benefits from technology. Perceived control is described to have three dimensions that is control over technology (features or functionalities of technology), self (adapt to new technology) and task (able to modify tasks). Beaudry and Pinsonneault (2005) argue that individuals' adaptation of technology is based on their evaluation of the level of control they have on technology. It is the degree to which individuals perceive that they have the ability and resources to control a technology. Bala and Venkatesh (2016) argue that perceived control has conceptual similarities with technology adoption literature. It has similar dimension as perceived behaviour control in TPB and facilitating conditions in UTAUT. Thus, perceived control is found to be a common construct in technology adoption and adaptation literature. Cheung et al. (2015) argue that if technology provides control to users, they will have positive attitude towards technology acceptance. Whereas, Bala and Venkatesh (2016) highlight that individuals' level of competence and ability to leverage resources determine their technology adaptation behaviour. Therefore, it can be argued that individuals react positively when technological platforms give them control (Cheung et al., 2015; Krasnova et al., 2010). The technological functional and utility factors are given in Figure 2.2.

Figure 2. 2 Technological Factors

2.6.2 Social Factors

Previous research mainly focused on technological factors of usefulness, performance expectancy, perceived opportunity and ease of use etc. on technology adoption and adaptation. However, Junglas et al. (2013) argue that recently researchers recognised the social aspect that incorporates the pleasure users get by interacting and socialising with others through technology. This has become more common in virtual environment especially on Web 2.0 technologies such as social media platforms. Due to technological advancements, technologies have evolved immensely giving individuals more opportunities of adoption, engagement, interaction and socialisation (Junglas et al., 2013). Social influence is identified by previous studies as the degree to which one believes that important others view that one should adopt and use technology and subjective norms as a social influence by referent group (friend, family etc.) to accept and adopt technology (Ajzen, 1991; Dholakia et al., 2004;

Fishbein and Ajzen, 1975; Talukder and Quazi, 2011; Venkatesh et al., 2003). Social factors are given in Figure 2.3.

Venkatesh (2003) describes that social factors, subjective norms and social image are related terms and combines them into social influence. Social media users are found to feel pressured from peers and family to accept social media (Grace et al., 2015). In adaptation literature, social status is described to influence technology adaptation behaviour. Individuals may perceive technology as an opportunity and therefore explore to innovate or may perceive it as a threat to their social status. Therefore, resist or abandon technology (Bala and Venkatesh, 2016; Beaudry and Pinsonneault, 2005). Due to Social networks, individuals may tend to exhibit different adaptation behaviour. Social ties, both positive and negative influence adaptation behaviour and has impact on deep technology use and performance (Sykes and Venkatesh, 2017). Furthermore, Beaudry and Pinsonneault (2005) highlight that social influence has an impact on individuals' primary appraisal of a technological disruption which lead to different adaptation behaviour.

Consumer behaviour can be determined by social influence that enhances social media acceptance (Hsu and Wu, 2011; Lin and Anol, 2008; Venkatesh and Morris, 2000; Wei et al., 2009). Gironda and Korgaonkar (2014) identified social norms as antecedents to attitude of consumer on social media. Equally, Hsu and Wu (2011) highlighted that social influence determines the use and acceptance of social media. Social factor is based on consumers' perceived psychological social influence, comprising social interaction, social ties and social support. They represent consumers' overall judgement of the key social factors (social interaction, social ties and social support) to influence consumers' psychological needs (Liang et al., 2011; Zhang et al., 2014). Social influence results in consumers' total impression of social media stored in their memory and shared by other social media members (peers, friends and family). It construes an overall impression of social media resulting in mutual understanding of a mental map, shaped by beliefs set by previous experiences based on memory and feelings forming an overall mental map.

Social interaction is highlighted as an important factor to influence the acceptance of social media and is described as the desire to communicate, interact with others and build relationship (Al-Jabri et al., 2015; Ko et al., 2005). It is human nature to socialize and interact with others (Dyson, 1998). Social media is perceived by individuals to enhance social interaction, connect people almost anywhere and give control of interaction with others (Park et al., 2009; Papacharissi, 2009; Rosen, 2007). Dalla Pozza, (2014) suggest that social media users are influenced more by social motivation than utilitarian motivation. De Valck et al. (2009)

posit that social interaction (informational, recreational and relational) influence consumers' purchase decision on social media. Similarly, Chang and Chuang (2011) argued that social interaction and reciprocity influence users' behaviour on social media. In addition, it is found that individuals are led by psychological goals to develop and maintain social relations with others, release anxiety and depression, increase social motivation, companionship, interpersonal utility, which in turn enhance their social interaction. Users desire to adopt and use social media to meet new people that gratify their socialisation needs (Amichai-Hamburger et al., 2002; Ellison et al., 2007; Grieve et al. 2013; Oldmeadow et al., 2013; Papacharissi and Rubin, 2000; Park et al., 2009; Whiting and Williams, 2013). Similarly, individuals interact on social media to have pleasurable experience (Junglas et al., 2013).

Furthermore, social ties between individuals, emotional relationships and contacts with social circles are found to be the other key factor to influence the adoption and use of social media. Ellison et al. (2007) argues that there is a strong association between social ties and acceptance of social media. They suggest that social ties establish emotional bonding amongst individuals, close relationships such as friends and family, and maintain contacts to stay in touch. Arguable, individuals perceive these social relations within social media community to enhance social bonds and social trust which increases social belonging to the community (Blanchard and Markus, 2004; Hau and Kim, 2010). Social media communities are formed to have shared goals. These goals encourage them to assist each other and share information on social media platforms (Chiu et al., 2006; Chow and Chan, 2008).

The other key factor identified is social support that Shumaker and Brownell (1984) defines as an exchange of resources between the provider and recipient with the intention to enhance the well-being of the recipient. Social support is more a personal aspect of exchange with the functional attribute to share information with the ones who are loved or cared for within the communication network (Ali, 2011). Social support is a major social value for social media users from the online community (Obst and Stafurik, 2010; Shaw and Gant, 2002). Social support can satisfy psychological cognitive needs ensuing good willingness to help and share with others. It fulfills social needs and results in warmth online relationship (Liang et al., 2011; Zhang et al., 2014). Social support is functional that is informational (solution, advice and recommendation) on social media. If social support is present, it is natural for social media users to share commercial information (Crocker and Canevello, 2008; Taylor et al., 2004). In addition, Ali (2011) identified social obligations and sacrifice as major factors influencing the level of support received by consumer on social media. Liang et al. (2011) further argue that in addition to social support (emotional and informational), it is the quality of relationship based on social commitment, trust and satisfaction that play a critical role in influencing users' future participation in social commerce on social media.

From the above discussion, it can be argued that social interaction is the desire to communicate, interact with others and build relationship. Social media is perceived by consumers to enhance social interaction, connect them anywhere and complement their offline relationship. Social ties are social relations within social media community to enhance social bonds. They are led by psychological goals to develop social relations to gratify their socialisation needs and they feel pressured from others that affect their technology adoption and adaptation behaviour. Social support is a personal aspect of exchange on social media. Therefore, consumers' attitude is positively associated with social strengths determined by social influence comprising the above aspects that enhances their social media adoption and adaptation behaviour. Arguably, social influence is users' cognitive psychological pressure from external factors to interact, establish social ties and exchange to help others on social media.

Thus, consumers adopt social media due to social influence, which includes social interaction, social ties and social support (Bharati et al., 2014; Grace et al., 2015; Talukder and Quazi, 2011; Venkatesh et al., 2003). These factors drive them to have social interaction, which is a desire to connect, collaborate and communicate with others (Hussain, 2012; Trivedi et al., 2018). They perceive technology (social media) to enhance their social interaction that connect them with people almost anywhere in the world, give them control over interaction and maintain social relations. Social media provide them platforms to release anxiety, increase companionship, interpersonal utility (Ellison et al., 2007; Grieve et al. 2013; Oldmeadow et al., 2013), establish social ties, build and maintaining relationships (Rishika et al., 2013; Wang et al 2012). Similarly, social support provides them to help others and share anything that would assist others on social media (Liang et al., 2011; Zhang et al., 2014). Thus perceived social influence enhance adoption and adaptation behaviour. The same stance was taken by Sánchez et al. (2014) that the adoption of technology can best be predicted by social influence as technology users tend to comply with whom they share interests.

Figure 2. 3 Social Factors

2.6.3 Personal Factors

Personal intrinsic motivations are highlighted as the key factors of technology adoption and adaptation behaviour. It is the personal intrinsic factors such as pleasure, enjoyment, self-enhancement (Tuten and Solomon, 2015), fear, anxiety and trust (Beaudry and Pinsonneault, 2005) etc. that influence technology adoption and adaptation behaviour. Personal factors are illustrated in Figure 2.4.

Hau and Kim (2011) noted sharing on social media is due to intrinsic hedonic motivation. Consumers are driven by their perceived intrinsic experiential and hedonic benefits, sensory pleasure (Park and Kim, 2014) and self-enhancement (self-esteem and ego) that satisfy hedonic needs. Consumers seek social media to fulfill their needs of entertainment and relaxation that lead to their ultimate gratifications (Whiting and Williams, 2013). Their engagement with social media is based on features of self-image and self-disclosure that affect social media adoption (Campbell et al., 2014; Grace et al., 2015). Al-Jabri et al. (2015) suggested that enjoyment and self-presentation are the key factors of social media acceptance.

Whereas, personal factors of fear, anxiety and stress in adaptation literature is described to influence beliefs about a technology. It is the fear of technological disruption that may have huge impact on individuals' adaptation behaviour. They may fear that a new technology might eliminate social ties and may change their work processes. As a result, individuals may perceive technology to have negative consequences for them (Beaudry and Pinsonneault 2005). Likewise, Bala and Venkatesh (2016) argue that individuals may be less motivated when they perceive that the outcome of technological disruption is not beneficial. They will not be engaged in technology adaptation behaviour.

It may be argued that both technology adoption and adaptation literature identified personal factors (enjoyment and fear etc.) as determinants of technology adoption and adaptation behaviour. However, it is noted that it mainly consists of intrinsic motivation such as experiential benefits, sensory pleasure (hedonic and emotional: Park and Kim, 2014), self-enhancement, self-esteem, ego (Diffley et al., 2011; Hau and Kim, 2011), which satisfy their hedonic needs and factors of fear and trust.

Intrinsic hedonic factors are important affective attitudinal components. Chen et al. (2014) posit that emotional attachments are good predictors of adoption and use of social media. Equally, Kim et al. (2011) suggest that consumers' affective factors had more significant effect on purchase intention over the functional values for social media consumers. Consumers' emotional state affect the online purchase behaviour (Dennis et al., 2009). Positive words from users affect other users' emotional state leading to 'Emotional Contagion' unbeknown to technology users (Schroeder, 2014). In addition, self-efficacy and self-enhancement are suggested by prior studies to motivate the acceptance of social media (Chen et al., 2014; Hsu et al., 2007; Presi et al., 2014). Hence, self-focused dimensions, intrinsic affective elements of joy and enjoyment, self-efficacy, self-esteem are found to drive individual acceptance and use of social media (Füller et al., 2007; Hau and Kim, 2010).

Nov et al. (2010) and Lin et al. (2008) posit that enjoyment is intrinsic hedonic motivation that encourages social media users to share information, participate in discussion and engage in a sensation. Playfulness is highlighted to constitute of intrinsic motivation of enjoyment, fun and pleasure that enhance social media interaction and satisfy users (Chiang, 2013). Also, Kim et al. (2011), suggested playfulness as intrinsic enjoyment, fun and interest resulting in pleasure and satisfaction. Thus, enjoyment is found to constitute of pleasure and flow (Hsu and Wu, 2011; Wu and Chang, 2005). Likewise, pleasure is described as playfulness, fun and an intrinsic acceptance of technology (Moon and Kim, 2001; Sledgianowski and Kulviwat, 2009; Van der Heijden, 2004; Zolkepli and Kamarulzaman, 2015).

Equally, hedonistic factors of self-esteem and self-enhancement are found to enhance self-presentation and self-image expression on social media. Self-enhancement and self-esteem are the positive feelings about oneself (Hepper et al., 2011; Sedikides and Gregg, 2008). High self-enhancers have high self-esteem due to which they overwhelmingly update and present their self-focused status online, share information regarding themselves and anything that they feel would enhance their status and image to attract attention from others (Hennig-Thurau et al., 2004). Self-status and self-esteem gratify social media users' psychological needs of self-esteem and self-presentation to portray the desired impression (Ali and Lee, 2010; Sas et al., 2009; Terry et al., 2007).

However, other factors such as perceived economic benefits, information quality and social media experience were also highlighted to motivate consumers' acceptance of social media such as Chow and Shi (2015) argued that consumers' use and satisfaction of social media depend on their perception of economic benefit, entertainment, information quality and social presence, whereas, Leung et al. (2015) suggest that consumers' attitude towards social media sites and brands are influenced by social media experiences. Nonetheless, enjoyment, self-enhancement, fear and trust are found to be the key factors in technology adoption and adaptation behaviour. They are discussed briefly below.

2.6.3.1 Enjoyment

Park and Kim (2014) posit that enjoyment constitutes of users' intrinsic emotional factors driving their intrinsic pleasure (hedonic and emotional) that satisfy their hedonic needs of enjoyment. Similar point was made by Vroom (1964) that individuals' target behaviour can be determined based on certain hedonic benefits that satisfy their needs. Consumers are driven by their intrinsic sensory elements of joy and enjoyment, hedonic and emotional self-focused dimensions originated from self-interest that drives their attitude (Hau and Kim, 2010). It can be argued that enjoyment is intrinsic motivation that encourages consumers to share information, participate in discussion and engage in a sensation (Lin et al., 2008; Nov et al., 2010).

Pleasure is described as playfulness, fun and an intrinsic acceptance of technology (Moon and Kim, 2001; Sledgianowski and Kulviwat, 2009; Van der Heijden, 2004; Zolkepli and Kamarulzaman, 2015). Users fully immerse in online activities that lead them to culmination of enjoyment ensuing more online activities with significant impact on their behaviour (Domina et al., 2012; Huang, 2012). Arguably, enjoyment drives consumers' attitude on social media. Pleasure results in greater enjoyment, revisit of social media, prolong usage and purchase products (Cyr et al., 2005; Hsu and Wu, 2011; Lu et al., 2009; Wu and Chang, 2005). Hence, it can be argued that consumers' affective needs are intrinsic by nature, arousing from within, and ensuing pleasant hedonic motivation of joy, fun and pleasure (Chiang, 2013; Füller et al., 2007; Hau and Kim, 2010). Similar, point was echoed by Kim et al, (2011) that enjoyment is intrinsic fun, which results in pleasure and satisfaction from a playful experience.

2.6.3.2 Self-Enhancement

Prior literature shows that self-enhancement and self-esteem are the positive feelings about oneself for self-fulfillment (Hepper et al., 2011; Sedikides and Gregg, 2008). High self-enhancers have high self-esteem due to which they overwhelmingly update and present their self-focused status online, share information about themselves and anything that they feel would enhance their self-status, image and attract attention from others (Hennig-Thurau et al., 2004). Self-status and self-esteem are the important factors that gratify social media users' self-fulfilling hedonic needs of self-esteem behaving and presenting themselves to portray the desired impression (Ali and Lee, 2010; Sas et al., 2009; Terry et al., 2007). Similarly, self-presentation, which Boyd and Ellison (2007) argue is a key element for technology adoption. Consumers reveal desirable information on social media to formulate the impression they wish to produce on others (Krasnova et al., 2010) and they also apply positive self-presentation strategies to reveal information for their subject well-being (Kim and Lee, 2011).

2.6.3.3 Fear

By adopting social media, users create public profile, connect and share personal information and preferences with others. These revelations lead to fear of personal privacy and security risks (Cheung et al., 2015, Krasnova et al., 2010; Tan et al., 2012). Privacy in this ubiquitous technological environment means how information is accumulated, treated and shared based on individuals' location, communication and information privacy by vendors and social media providers (Karyda et al., 2009; Lanier and Saini, 2008). Two key dimensions of privacy and security are found in previous studies; privacy is described as consumers' fear of personal information risk and security is described as trust in the protection against the threat from unauthorised access to their personal information. Moreover, privacy is described as an individual's right to be left alone, the ability to control and select to divulge personal information (Eastlick et al., 2006; Ha and Stoel, 2009; Warren and Brandeis, 1890). It is defined as an individual's fear on the consequences of disclosure of personal information, the fear of identity theft, cyber harassment, and personal record for scrutiny by the public, the disruption when personal information goes viral. It is the fear of the threat from the disclosure of information, abuse or unauthorised access to their personal information. Hence, it causes fear and anxiety amongst consumers (Karyda et al., 2009; Lanier and Saini, 2008).

Akar and Topçu (2011) suggest that users' fear has a huge impact on the acceptance and use of technology. Consumer behaviour in the virtual world is affected by consumers' fear of privacy and security (Cheung et al., 2015). Extant literature suggests that the fear of privacy risks has negative relationship with the sharing of personal information online (Boyd, 2008; Chew et al., 2008; Featherman and Pavlou, 2003; Gross and Acquisti, 2005; Im et al., 2008; Krasnova et al., 2009; Lee et al. 2013; Rosenblum, 2007). Ghosh et al. (2014) argues that consumers' fear and sense of risk has an impact on purchase intention and credibility influencing their decision making on social media. Yulihasri et al. (2011) also suggests that online shopping is influenced by privacy and security. Similarly, Jiang et al. (2013) have shown that intrusiveness affects privacy concern and many users use misrepresentations to protect privacy on social media. In contrast, Cheung et al. (2015) argues that risk of privacy does not have an impact on self-disclosure on social media. Unlike Cheung et al. (2015), Krasonikolakis et al. (2014) suggests that consumer behaviour in the virtual world is affected by the fear of privacy and security. Similar stance was taken by Belanger et al. (2002) that the fear of privacy risk determines consumers' willingness to share information online.

Liang and Xue (2009) highlight that individuals' make emotional appraisal when coping with technological threats. When individuals feel that they are susceptible to a malicious technology and the consequences of such technological disruptions are severe, they will feel threatened by the technology. Similar argument was made by Bala and Venkatesh (2016) that the degree to which individuals believe that a technological disruption or a new technology brings about harm to their well-being, success or growth, they will perceive it as a threat. They may feel that technology influences their performance, downgrades their status and reputation in the organisation and amongst friends. They may perceive technology as a threat (Beaudry and Pinsonneault, 2005). Other researchers have a similar notion that individuals develop an overall feeling of threat from a technological disruption in their environment (Liang and Xue 2009; Lapointe and Rivard 2005). Bala and Venkatesh (2016) argue that if individuals develop anxiety about a technology, it will generate more anxiety. This develops an overall feeling of threat in individuals which influence their technological adaptation behaviour. As a result, they may perceive that the technology is incompatible with them and they will develop negative feelings about the technology (Dishaw and Strong 1999; Venkatesh et al., 2003; Zigurs and Buckland 1998). From the above discussion, it can be argued that when individual have a technological disruption in their environment, they may feel threatened of such technological event.

2.6.3.3.1 Privacy and Security

Privacy is described as an individual's right to be left alone, the ability to control, select to divulge personal information and willingness to share online (Belanger et al., 2002; Eastlick et al., 2006; Ha and Stoel, 2009; Warren and Brandeis 1890). It consists of users' sense of risk on the consequences of disclosure of information (sensitivity and transparency) and perceived information control about their identity management (secrecy, anonymity and confidentiality) (Dinev et al., 2013) whereas security is the protection against the threat from the disclosure of information, abuse or unauthorised access to personal information. Furthermore, privacy in this ubiquitous digital environment means how information is accumulated and treated based on individuals' location, communication and information privacy (Karyda et al., 2009; Lanier and Saini, 2008). It is identified as the fear of identity theft, cyber harassment, and personal record for scrutiny by the public when personal information goes viral. It is the fear of privacy risk that has negative relationship with the sharing of personal information on technology (Boyd, 2008; Chew et al., 2008; Im et al., 2008; Krasnova et al., 2010; Lee et al. 2013; Rosenblum, 2007). Although most social media users are aware of their privacy options and risks, they reveal personal information (Acquisti and Gross 2006; Boyd, 2008). It is identified by some studies as their subjective evaluation of cost and benefit (privacy calculus) analysis (Chou et al., 2009; Hann et al., 2007; Smith et al., 2011).

Consumers' digital footprints have given rise to key debate of their privacy and security. Both businesses and governments with the help of technology are taking advantage to conduct digital surveillance (Dodd, 2011). In the Personal Democracy Forum 2011, Boyd (2008) highlighted that the current laws are focused on data collection and not on the usage of data wherein the violation of privacy takes place. Big players such as Google, Facebook, Yahoo and Apple are busy making billions of dollars collecting and selling user information fueled by consumers' data and they can be considered as contributing in violating individual privacy. The privacy settings of these giants have been engineered to the consumers' online behaviour which is public by default and private by effort (Boyd, 2008).

Privacy salience is described as the extent to which one worries about sharing too much digital footprints on social media. This impacts their online behaviour. However, it is noticed that despite privacy and security concerns, consumers share big digital footprints on social media. This disparate relationship is called as privacy paradox (Tuten and Solomon, 2015). The underlying consumers' attitude towards the consequences of their digital footprints sharing behaviour and social media adoption and adaptation is not known.

From the above discussion of fear, privacy and security, it can be argued that these factors play a significant role in consumers' social media adoption, adaptation and behavioural outcomes.

2.6.3.4 Trust

In addition to fear, trust has been discussed to play a key role in the adoption and adaptation behaviour of a technology. Trust is posited as the reliance of users on online service providers and vendors with whom they share information. It is users' feeling of uncertainty or confidence in the features of social media to provide them protection or improve their performance (Cheung et al., 2015; Cheung and Lee, 2006; Gefen et al., 2003; Krasnova et al., 2010; McKnight et al., 2002; Metzger, 2004). Trust is identified as an important factor in both technology adoption and adaptation literature. Prior literature on technology acceptance posit that technology acceptance is the product of consumers' assessment of usefulness and ease of use of technology. However, Gefen et al. (2003) argue that this assessment includes consumers' trust in technology as it is an important and widely accepted antecedent of technology acceptance. Whereas, Thatcher et al. (2011) argue that trust reflects predictability in post-adoption use of technology. It is favourable object specific and behavioural beliefs about technological attributes determining predictability due to which they are related to postadoption behaviour. McKnight et al. (2002) argue that trust is multidimensional concept.
Trust is described as the ability of service provider to protect and monitor personal information or reduce users' uncertainty on the use of the service (Cheung and Lee, 2006; Gefen et al., 2003; Krasnova et al., 2010; McKnight et al., 2002; Metzger, 2004). Prior studies suggest that online transaction integrity and transaction decision depend on users' trust in the integrity and reliability of website vendors (Culnan, 2000; Eastlick et al., 2006; Hadjikhani et al., 2008; Hoffman et al., 1999; Kang et al., 2007; Li et al., 2006; Morgan and Hunt, 1994; Wu et al., 2010). Arguably, trust plays a significant role in consumer's outcome of disclosure of information (privacy) and their confidence in the protection against the threat from the unauthorised access to their identity management (security). Social media users' protection of privacy and security positively influences trust (Shin, 2010). Equally, Pentina et al. (2013)

argue that consumers trust influences continued use of Twitter and social media brands which has a positive relationship with the patronage intention (visit websites, purchase and recommend to others).

Consumers' attitude towards social media depends on the feeling of trust they have in social media (Szmigin, 2018). Trust refers to how confident they feel on the reliability of social media. Feeling of trust depends on technology's ability and reliability in handling users' expectations (Moorman et al., 1993). Some researchers such as Mayer (1995) noted confident expectation as key component of trust, which is the belief of an individual that others would not exploit his/her vulnerabilities and that they would not exploit or harm the individual. Trust in consumer studies is described as consumers' expectation that the service provider is both reliable and dependable. It is conceptualised as a propensity to depend on others (Moorman et al., 1992; Terres et al., 2015). Higher protection and confidence in technology will enhance consumers' feeling of trust in technology (Cheung et al, 2015).

Rousseau et al. (1998) suggests that trust could be relational, calculus and deterrence based while Jones and George (1998) highlights conditional and unconditional states of trust. Extant literature posit both cognitive and affective dimensions of trust (Rousseau et al., 1998; Cummings and Bromiley, 1996; Zaheer et al., 1998). They describe trust as a very complex psychological state, undergoing cognitive processes and affective influences. Nonetheless, Kramer (1999) argue that treating trust as a rational paradigm would be too narrowly cognitive rather trust is more emotionally dependent because for an individual to trust someone/situation does not require awareness of that individual or situation. The cognitive trust undergoes a careful, methodical thought process whereby there are good reasons and empirical evidence that someone or an organisation is trustworthy. It goes through a cognitive process and careful evaluation of the evidence. In contrast, affect based trust consists of one's feeling and instincts, which is more emotional bonds established to believe that someone or an organisation etc. is trustworthy (McAllister, 1995; Rousseau et al., 1998). To establish trust, one suspends the belief because of the lack of evidence to make a cognitive evaluation, therefore, an individual will rely more on the affective based trust which is instinct and feelings based trust to determine if the other party is trustworthy (Morrow et al., 2004). Johnson and Grayson (2000) argue that consumers trust is influenced by affective aspects of emotions, care and attention. In addition, their trust is influenced by service providers' respect, empathy and caring. McAllister (1995) argue that emotional attachment provide a basis for trust development and such trust is not only more intense but also has the strongest effect. The affective aspect of trust has rarely been given due attention in consumer research (Terres et al., 2015).

Consumers rely on affective signals given by service providers to establish affective trust in the quality of their service provision (Alford and Sherrell, 1996). It is the confidence on the basis of feelings generated by the level of care the service provider (social media) demonstrates and it is the feeling of security. Similarly, Johnson and Grayson (2005) posit that the deepening of emotional connections, enhance trust in the service provider beyond the available justified knowledge or awareness. Thus, it can be argued that emotional driven trust plays a key role in technology adoption and adaptation behaviour.

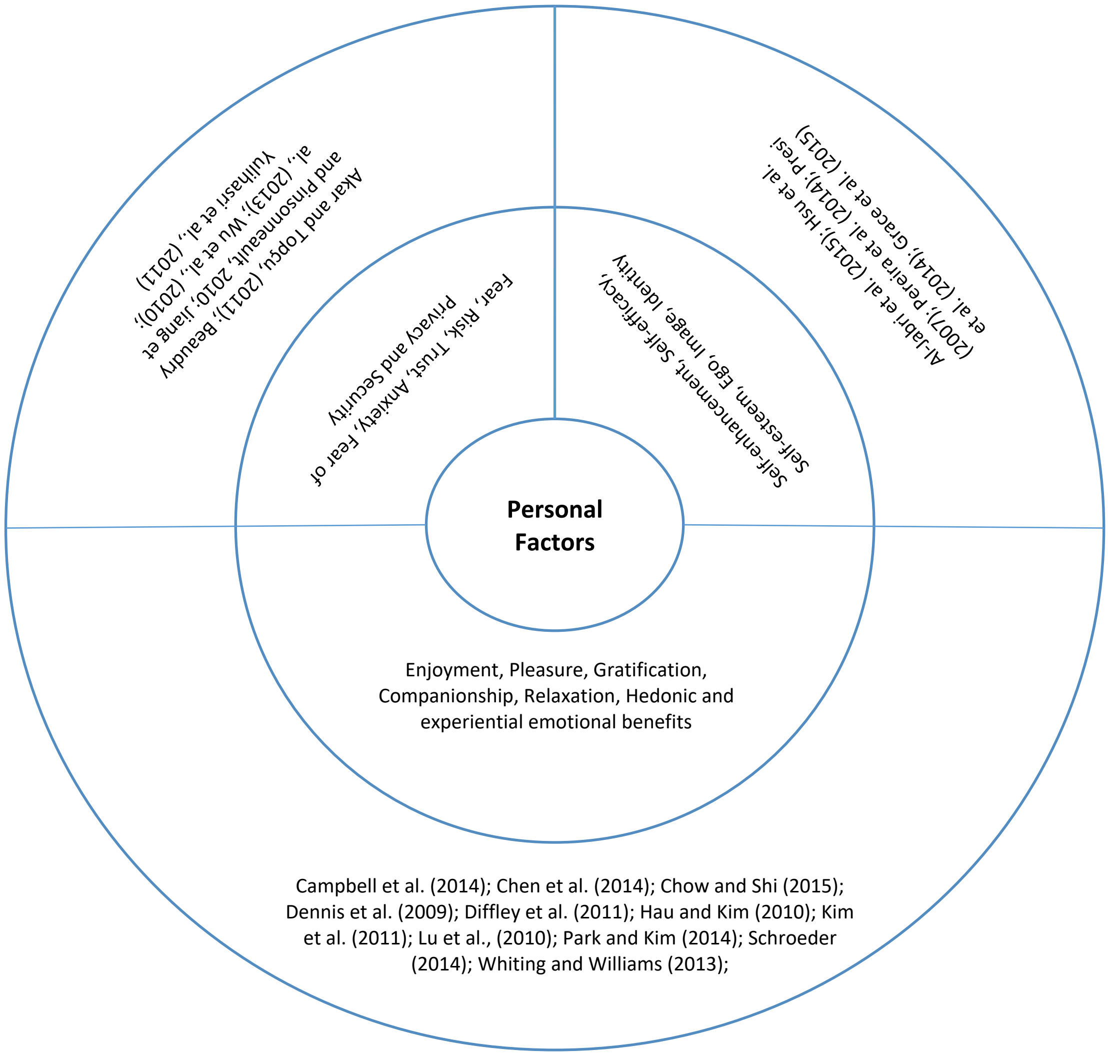

Figure 2. 4 Personal Factors

2.7 Technology Adaptation Behaviour

As discussed above, prior models have excessively focused on adoption. Therefore, Bruque et al. (2008) suggest that an alternative approach is needed to study beyond adoption to understand technology user behaviour. Technology adoption models analysed several technology adoption factors but they have not given much attention to consumers' adaptation behaviour. Similarly, many aspects of social media adaptation behaviour at consumers' level are unknown.

Prior literature highlight the importance of users' adaptation behaviour. Kashefi et al. (2018) argue that as technological advancement enhances, organisations, users and consumers dependence on technologies amplify. Therefore, it is essential to understand how consumers adapt these technologies and appraise the outcomes. Such adaptation behaviour is of immense significance to both researchers and practitioners.

In order to take benefits of a technology, users engage in adaptation behaviour by proactively changing themselves, technological features and the task they want to perform (Kashefi et al., 2018). Bruque et al. (2008) describe that adaptation is a dynamic process that is in constant evolution; whereas, Dey et al. (2013) describe adaptation as technology use, which goes beyond adoption and involves a gradual integration into consumers' lives and work practices. They suggest that technological impact is more appropriately determined if it is adapted in a particular context as technological adaptation behaviour is fluid, interactive and non-linear (Walsham, 2010).

Prior models, both adoption and adaptation, gave little attention to the composite process of technology adoption, adaptation and outcomes which this study aims to examine in the context of consumers social media digital footprints. This is to provide a broader perspective to the composite process and avoid the dichotomous approach towards adoption or adaptation. It is to provide a shift in the study of technology adoption and adaptation by propounding a nomological richer model that takes into account the antecedents of the composite process and behavioural outcomes. The following section analyses the common technology adaptation behavioural efforts used in prior models and literature and evaluates their relevance to the current study.

Coping Model of User Adaptation (CMUA) describe that technology users undertake cognitive and behavioural efforts based on their primary and secondary appraisal of the consequences of the technological disruptions in their environment. They describe adaptation behaviour as cognitive and behavioural efforts to cope with technological disruptions. Their focus is mainly on cognitive appraisal of the outcome of a new or change in the existing technology and they describe adaptation behaviour as different acts technology users perform to cope with the outcome of a technological disruption. CMUA posits a discrete set of adaptation responses ranging from benefits maximising and satisficing to disturbance handling to avoiding technology altogether. They argue that individuals employ cognitive appraisal and adaptation behaviour when they face technological disruptions (Beaudry and Pinsonneault, 2005). Similar stance is taken by Bala and Venkatesh (2016) in their study of adaptation to information technology. They suggest that individuals employ two processes when they face technological disruptions. First is the cognitive appraisal of the situation and second is the adaptation behaviour representing the cognitive and behavioural efforts to cope with the technological disruption. If individuals perceive that technological disruption is positive, they will consider that as an opportunity. However, if they perceive that technological is harmful for their well-being, they will consider it as a threat (Folkman et al., 1986; Major et al., 1998). Such interactions of appraisals explain their adaptation behaviour (Bala and Venkatesh, 2016).

From the above discussion it can be argued that adaptation behaviour is about different actions and coping efforts individuals perform to deal with a new or change in the existing technology. Adaptation behaviour is described as a combination of cognitive and behavioural efforts categorised as problem focused that is to manage the disruptive event or change oneself by developing new set of behaviour such as learning new skills to cope with the technology (Lazarus and Folkman, 1984) or emotion focused that is to change one's perception rather than the event e.g. regulate personal emotions and distress; maintain a sense of stability (minimising the consequences of threat); maintain hope; accept technology passively or avoid it completely (Beaudry and Pinsonneault, 2005). Similar argument is made by Bala and Venkatesh (2016) that individuals adapt problem focused and emotion focused coping strategies when they face technological disruption. They suggest four technology adaption behaviour. First is about maximizing personal benefits by taking full advantage of the opportunities offered by a technology. Second is about benefit satisficing that is taking limited advantages offered by a technology. Third is about disturbance handling that is to minimise perceived negative consequences of technology and restore personal emotional stability. Fourth is about self-preservation and restoring personal emotional stability with no impact on individuals' performance of a technology. These adaptation efforts are analysed and discussed below.

2.7.1 Benefit Maximisation

CMUA suggests that the introduction of a new technology or change in the existing technology brings about changes in adaptation behaviour, such adaptation behaviours are the acts that individuals undertake to cope with perceived and emotional consequences of the technological event. Furthermore, adaptation behaviour is about individuals actions which they appropriate to technological features and adapt technological behaviour for instance they explore and exploit technological benefits, explore to revert or avoid technology completely. Beaudry and Pinsonneault (2005) describe that it is also about the coping options available to an individual as to how he or she can cope with a technological event. It is about different actions (coping efforts) individuals perform to deal with the consequences of the technological event. These are a combination of cognitive and behavioural efforts categorised as either managing the disruptive event for instance alleviating, altering the technological functions or changing oneself by developing new set of behaviour such as learning new skills or procedures and finding new channels of gratification (Lazarus and Folkman 1984) or managing self, changing individual perception rather than the event for instance regulating personal distress, making a positive comparison, passive acceptance and minimising the consequences of threat that is avoidance of technology.

Lazarus and Folkman (1984) describe that when individuals appraise the consequence of technological disruption as an opportunity, they will take full advantage of the technology and will maximise personal benefits. Bala and Venkatesh (2016) highlighted maximizing personal benefits as the first adaptation behaviour which is taking full advantage of the opportunities offered by a technology. Similarly, Boudreau and Robey (2005) argue that individual will maximise their efforts to technology and explore new technological features which improves their work and provide them opportunities to accomplish their job in most innovative and creative ways. The same point was echoed by Thatcher et al. (2011) that exploration of feature exploration of technology is tantamount to maximising innovative ways to use technology and maximise benefits of such technological features. Likewise, Bala and Venkatesh (2016) suggest that individuals who explore new technological features cognitively engage in technology benefit maximising strategy to take a full advantage of technology. Furthermore, it is argued that if individuals perceive new technology as an opportunity for instance improve their performance, brings success or growth in their job, they will both maximise the use of technology and take full advantage of technological features (Lapointe and Rivard, 2005). Thus, in line with this discussion around technological adaptation behaviour, it can be argued that if the outcome of social media is assessed to be positive, consumers will be motivated to explore and maximise social media benefits and take full advantage of social media features.

2.7.2 Benefits Satisficing

Beaudry and Pinsonneault (2005) argue that when individuals perceive the outcome of a technological disruption as an opportunity (positive appraisal of technological features), they will take maximum use of technological benefits. However, if they perceive that they have limited control on technological features, they will have minimal adaptation acts, which means their adaptation efforts will reduce and they will engage in benefits satisficing adaptation behaviour. It is due to individuals' beliefs that the lack of perceived control on new technology limits their exploitation of technological features as they believe that they cannot avail the technological benefits (Folkman and Moskowitz 2000). Due to which individuals engage in benefits satisficing behavioural efforts by taking limited benefits technology offers. Bala and Venkatesh (2016) have a similar stance that when individuals perceive that they have limited control on technological functions, they will engage in exploitation to satisfice technological benefits as a routine use of technology rather than explore to maximise technological benefits. Individuals will make use of those technology features which are used on a regular basis (known habitual features) to accomplish their tasks. It means they will not be able to exploit additional benefits because of the lack of perceived control technology offers and individuals' inability to go beyond such technological features. Hence, in such a situation individuals will engage in limited satisficing adaptation behaviour. Zuboff (1988) described that minimal adaptation was carried out when the new control system introduced in an organisation provided interesting opportunities to enhance employees' job performance but provided limited autonomy to employees to change their work and technological features. Furthermore, Bala and Venkatesh (2016) argue that if individuals are aware of the positive outcome of technology, they would perceive this as an opportunity rather than a threat but if they believe that they have limited capability and resources, they will resort to limited benefits satisficing or they will stick to the known technological features. They will not be able to exploit additional technological benefits because of their inability to go beyond technological features they learnt to exploit. Therefore, it can be argued that technology users' may tend to engage in limited adaptation efforts because of their inability to derive further benefits or go beyond technology features they learnt to exploit. Thus, their adaptation will be minimal and confined to the limited ability they have.

2.7.3 Exploration to Revert

Individuals perform different adaptation efforts when they evaluate the outcome of a technological disruption as a threat. Such efforts are either problem or emotion focussed adaptation behaviour (Lazarus and Folkman, 1984). Problem focussed adaptation efforts are a combination of cognitive and behavioural efforts, these efforts focus to manage the external event by alleviating and altering the technological disruption. Whereas, in emotion focused adaptation behaviour they change their individual perception by regulating personal emotions, personal distress to bring a sense of stability and minimise the consequences of threat. The combination of problem and emotion focussed dimensions depend on individuals' appraisal of the event and the level of control they perceive to have on the technological disruption. If the threat is appraised as problem focussed whereby they assess that threat can be managed well by managing the technological disruption (external event), they will engage in problem focussed adaptation behaviour. However, if the threat is appraised as an emotion focussed, they will engage in adaption behaviour to minimise the inner emotional distress and anxiety rather than in managing the external technological disruption. Similar argument is made by CMUA, which posits that when individuals assess a technological event as a threat they will rely on both problem and emotion focused adaptation efforts depending on their perceived controllability of the event. Hence, their focus would be to minimise the negative outcome of the event and restore emotional stability. Their adaptation efforts will be focused on managing self, technological feature and task they perform (Beaudry and Pinsonneault, 2005). In case of self-focused adaptation efforts, individuals may seek more training to cope with the technological disruption (Majchrzak et al., 2000). If the focus is on technology, individuals would look to revert from technology and make the efforts to decrease the negative features of technology. Similarly, if their focus is orientated to task, they will change their work procedures so as to better fit with the technology.

From the above discussion, it can be argued that when individuals appraise the consequences of a technological disruption, they will tend to restore emotional stability and minimise the negative outcome of the technological disruption in their environment. They will engage in exploration to revert adaptation behaviour by searching old ways of performing tasks (Beaudry and Pinsonneault, 2005). Similarly, Bala and Venkatesh (2016) argue that when individuals perceive that new technology is harmful for their well-being or may hinder their growth or damage their reputation, they will explore ways to minimise the harmful consequences of such technological event. In such a scenario wherein they appraise the consequence of the technological disruption as a threat and at the same time they have high perceived controllability on the situation, they will have the strongest exploration to revert behaviour. It is because they believe that their old ways of doing things give them more control on the technology and they have the ability and resources to accomplish tasks without having any negative consequences. It can be argued that when individuals believe that technology is causing harm to their well-being or damage their reputation, they will explore ways to minimise the harmful consequences and revert from the technology.

2.7.4 Avoidance of Technology

Beaudry and Pinsonneault (2005) describe that when individuals assess a technological disruption as a threat and they have limited control on the situation, they will opt to avoid technology altogether. It is because individuals' adaptation efforts will be mainly emotion focused. They would want to come out of the distress and their main focus would be restoring emotional stability (Folkman, 1992; Lazarus and Folkman 1984). Individuals would also have strong intention to avoid technology if they find that there is high task and technology misfit. In addition, where individuals perceive that a new technology deskills or eliminates their job, they will avoid technology completely (Patrickson's, 1986). Bala and Venkatesh (2016) conceptualise the avoidance of technology adaptation behaviour as emotion focused adaptation when individuals evaluate technology as a threat and they have no control on technology, they will avoid technology altogether to eliminate psychological distress. They will resort to self-preservation adaptation effort and reduce distress caused by the technological disruption. Similar argument is posited by CMUA and IS literature that individuals will completely abandon technology if they perceive that a technological disruption is characterised to be threatening. If they perceive that it brings about harmful consequences or decreases their performance, they will make efforts to minimise the negative consequences and avoid technology to restore emotional stability. Unlike exploration to revert adaptation behaviour, in the case of avoidance of technology adaptation behaviour individuals will resort to self-preservation strategy to restore emotional stability (Liang and Xue, 2009). It can be argued that if individuals assess the outcome a technological disruption has harmful consequences for them, they will minimise the negative consequences and avoid technology altogether.

2.8 Attitude

To analyse consumers' attitude towards social media and their digital footprints in social media adoption and adaptation, it is vital to shed some light on attitude. Prior studies suggest that attitude accurately captures the motives that determine actual behaviour (Armitage and Conner 2000; Gupta and Pirsch 2006; Vogt et al., 2005). Leading researchers highlighted and used cognitive and affective attitudinal components to determine individuals' attitude towards an object or entity (e.g., Armitage and Conner 2000; Gupta and Pirsch 2006; Lwin et al., 2002; Pike and Ryan 2004).

Consumer psychology begins from attitude and their behaviour is determined by attitude (Alwi and Kitchen, 2014). Therefore, it is vital to understand consumers' attitudinal components to social media adoption and adaptation as a composite process in the context of the consequences of their bid data digital footprints on social media platforms. In technology adoption and adaption literature, attitude has received most attention as psychologists have researched it for decades. It is defined as an overall judgement to an object (Fazio, 1986). Extant literature posits that attitude is formed on the basis of cognitive, affective and behavioural components with numerous conceptualisations of attitude (Chiu, 2002; Eagly and

Chaiken 1993; Ford and Smith 1987; Lazarus, 1982; Rosenberg and Hovland, 1960). Thurstone and Chave (1929) describe it as an evaluative or affective response to the attitude object. Whereas Zajonc and Markus (1982) define attitude as two component structure of cognition and affect. The popular definition of attitude is proposed by Chiu (2002) that attitude consists of affect, cognition and connation (behaviour), the three responses to an object. Tri-component model of attitude implies that attitude consists of the interactions of three attitudinal components namely cognition, affect and conation (Rosenberg and Hovland, 1960). Cognitive element refers to beliefs and knowledge, affect is about feeling towards something or someone and conation refers to action based on those beliefs and feelings (Chiu, 2002). However, it is noted that in prior literature, there is a huge debate amongst psychologist on the components of attitude whether attitude is the overall judgement to an object or it refers to cognitive and affective response to an object or it is more affective component based on cognition (Fishbein and Ajzen, 1975).

One line of argument is that individuals' actions are controlled by attitude towards a behaviour that is personal positive or negative evaluation of performing the behaviour (Ajzen, 1975). Eagly and Chaiken (1993) argue that a cognitive attitudinal component exists when an individual processes information about the attitude object, which forms into beliefs. Similarly, Ajzen and Fishbein (1980) argue that attitudes are formed of beliefs that get accumulated during an individual's lifetime. Due to which the individual perceives the outcome of his/her action either positive or negative based on his/her beliefs. If the individual has a positive belief towards the outcome of an object or behaviour, they will have a positive attitude towards that object or vice a versa (Ajzen and Fishbein, 1980). Moreover, Lazarus (1982) suggests that cognition is a necessary condition of emotion.

Contrary to this line of argument, Kwon and Vogt (2010) argue that it is the affective attitudinal components that drive attitude towards an object or behaviour favourably. They posit that affective attitudinal components are emotional experiences or preferences. Both positive (e.g. enjoyment) and negative (e.g. fear) emotional influences can arise from positive and negative experiences of the attitude object such that a positive emotional reaction to an experience are more likely to evaluate an attitude favourably (adopt and appropriate social media) and vice a versa. Kwon and Vogt (2010) claim that attitude is composed of affective components such as delight, satisfaction and fear etc. whereas behavioural response is the actions that an individual exhibit in relation to the attitude object. Moreover, Eagly and Chaiken (1993) highlight the tripartite distinction of cognitive, affective and behavioural components and suggest that the evaluation of attitude can be manifested through all three components.

Nonetheless, there is inconsistent viewpoints on the different components of attitude in the literature. Some scholars identified one component of attitude (e.g. Thurstone and Chave, 1929; Fishbein and Ajzen, 1975); whereas, others proposed two components, cognition and affect (Zajonc and Markus, 1982) and Breckler (1984) suggested three components of attitude namely cognition, affect and conation (behaviour) to predict behaviour.

Prior studies also expounded the strength and order of the cognitive and affective attitudinal components. Ryan and Cave (2005) identified cognitive attitudinal components as antecedents to affective components. Similarly, Mackenzie (1986) suggests that cognition and knowledge about an object primarily influence attitude towards that object compare to affective attributes. Similar argument was made by Vinhas and Faridah (2006) and Franzen and Bouwman (2001) that emotional components germinate from cognitive elements that is the cognitive process precedes the emotional components, leading affective response. On the contrary Zajonc (1980) propounds affect as an antecedent to cognitive attitudinal components. He posits that affect has primacy in the formation of attitude that is affect precedes cognition and also at times functions autonomously. Whereas, Alwi and Kitchen (2014) argue that attitude towards an object is driven by the joint cognitive and affective attitudinal components.

Thus, from the above discussion, it can be argued that some scholars used cognition as antecedent of affect and others identified affect as antecedent of cognition. Whereas, other scholars highlighted the significance of the joint attitudinal components towards an object or behaviour such as Alwi and Kitchen (2014) and Chiu (2002), who argue that affect based component of attitude consists of emotions, feelings whereas the cognition based component includes beliefs, judgments or thoughts associated with an object. Attitude towards an object or behaviour can be determined by the joint attitudinal components of salient beliefs and affect about the object or behaviour. Each belief and affect links the behaviour with some valued outcome. The latter, joint attitudinal components, is found to be more common in consumer studies (Alwi and Kitchen, 2014). Therefore, it is vital to examine attitude consumers hold towards social media adoption, adaptation and behavioural outcomes as a composite process in the context of their digital footprints on social media. It is vital as Szmigin (2018) suggests that consumers' attitude has a link to their behaviour which provide a predisposition to behave in a certain way. Similar notion is highlighted Alwi and Kitchen (2014) that understanding a consumer's response to an object or entity begins from attitude (Alwi and Kitchen, 2014). Therefore, this research focuses on the joint underlying attitudinal components that determine consumers' adoption and adaptation as a composite process.

In technology adoption and adaptation literature, Venkatesh et al. (2003) define attitude as a user's overall affective reaction to accept and use technology. They posit that the attitude construct was significant only in the presence of specific cognition that is the presence of performance and effort expectancy which made its impact non-significant and therefore they considered the impact of attitude on behavioural intention as spurious. On the contrary, attitude was found to be the main determinant in TRA and TPB. Furthermore, Venkatesh et al. (2003) initially treated attitude as mainly affective component with similar treatment in TRA and TPB as intrinsic motivation and affect towards use by model of PC Utilisation (MPCU). In their later works UTAUT2 (Venkatesh et al., 2012) and revised Multi-Level Framework (Venkatesh et al., 2016) along with other technology adoption and adaptation models treated cognitive attitudinal components as affect or vice versa with little or no distinctions. In addition, in technology adaptation model of CMUA, little attention has been given to affective attitudinal components and their focus has been mainly on cognitive appraisals. CMUA posits that an individual undertakes primary and secondary cognitive appraisals to undertake adaptation behaviour towards the consequence of a technological disruption. These models have given no attention to the joint attitudinal components. Moreover, in recent scholarly works, the likes of Dwivedi et al. (2017a) and Rana et al. (2017a) have re-introduced attitude into technology adoption models. They posit that attitude is the key perceptions and dispositions held by individuals towards a technology. They argue that the constructs used in models such as UTAUT are based on technological (performance and effort expectancy) and contextual attributes (social influence and facilitating conditions) and they are in fact perceptions held by individuals regarding a technology and a context. The key element missing from UTAUT is the individuals' dispositions, which is their attitude explaining their technology adoption behaviour. Therefore, technology adoption models need to re-introduce attitude into their models. Similarly, these scholarly works also gave meagre attention to the joint attitudinal components. Thus, it is vital to examine the joint impact of cognitive and affective components on consumers' social media adoption, adaptation and behavioural outcome as a composite process.

As discussed, in previous sections of this chapter that the current literature provides a landscape of theoretical frameworks on use, adoption and adaptation of technology (Bala and Venkatesh, 2016; Hsu and Wu, 2011; Lin and Anol, 2008; Lu et al., 2009; Venkatesh et al., 2012. They identified different technological, social and personal attributes which determine the acceptance, adoption and adaptation of technology such as usefulness, ease of use, perceived opportunity, social pressure, relative advantage and compatibility etc. (Al-Gahtani et al., 2007; Bala and Venkatesh, 2016; Davis et al., 1989; Hsu and Wu, 2011; Venkatesh et al., 2003; Venkatesh et al., 2012) but they gave little attention to attitude and its joint attitudinal components of cognitive and emotional attributes. As highlighted above, Alwi and Kitchen

(2014) suggest that attitude is not only about cognitive but also affective attributes and behavioural responses.

Therefore, based on the above discussion, this doctoral research proposes that consumers' social media adoption and adaptation are both cognitive (rational and functional attributes) and emotional (symbolic and affective) attributes such as fun, enjoyment, self-enhancement and self-presentation. Similarly, social influence is based on consumers' perceived psychological social pressure, comprising social interaction, social ties and social support, which represents consumers overall judgement of the key social factors of social interaction, social ties and social support to influence consumers' psychological needs. Social influence results in consumers' total impression of social media stored in their memory and shared by other social media members (peers, friends and family). It construes an overall impression of social media resulting in mutual understanding of a mental map, shaped by feelings and previous experience based on memory forming an overall mental map. Hence, it is consumers overall impression driven by both cognitive and affective attitudinal components referring to consumers overall attitude based on previous experience. Therefore, this research aims to examine the joint attitudinal components and it is vital to consider the joint attitudinal components (cognitive and affective) for their joint impact on the composite process of consumers' social media adoption, adaptation and behavioural outcomes. Thus, it can be argued that social media attraction for consumers is potentially based on two attitudinal components, which this doctoral research aims to investigate. It is the functional attributes related to tangible benefits such as usefulness, relative advantage, ease of use, control and convenience etc. considered to be a perceived opportunity or emotional attributes such as joy, happiness, self-enhancement, status, ego, fear and trust etc. manifest in consumers' feelings towards social media as discussed in the aforementioned sections. Focussing solely on the functional elements may lead to a more cognitive orientation, which may ignore the emotional components. Similarly focussing on feelings alone may omit the cognitive components (Alwi and Kitchen, 2014). Therefore, the joint attitudinal components impact on technology adoption, adaptation and outcomes needs to be examined.

Having discussed the significance of attitude in consumer studies, it is evident that attitude plays a vital role to determine consumers' behaviour. Looking to the above discussion, prior models have not addressed this research gap. Therefore, this research aims to develop a model to study consumers' attitude towards social media adoption, adaptation and behavioural outcomes as a composite process.

2.9 The Research Gap

Prior research focused on the acceptance, adoption, use and adaptation of technology in isolation (Dey et al., 2013) and little consideration is given to adoption, adaptation and outcome as a composite process. They have either focused on the initial perception of a user towards the attractiveness of a technology which leads to acceptance and use due to utility and usefulness of the technology but meagre attention has been given to how the technology is further adapted (applied, extended and appropriated). It should not be confined only with technology adoption and determining factors as such, adoption is not an end in itself and it needs to be studied as a component of the composite process of adoption, adaptation and outcome. Prior models provide limited insight on the composite process.

Moreover, there is a dearth of scholarly works on the joint underlying cognitive and affective attitudinal component that determine consumers' adoption, adaptation and outcome as a composite process. Similarly, consumers' attitude towards the consequences of their digital footprints and their key underlying patterns of behaviour and psychological impulses have not been addressed. Therefore, looking to consumers' attitude towards the consequences of their social media digital footprints, it is important to develop deeper understanding of consumers' social media adoption, adaptation and outcome as a composite process. There is limited insight around such a composite process and little attention is given to the joint attitudinal components driving the composite process. Prior studies have either focused solely on users' evaluation of cognitive attributes or treated affective attributes as cognitive. In addition, both affective and cognitive components are used with little distinctions and many overlaps. They have provided partial explanation of consumers' attitude and have not considered the joint attitudinal components. It is vital to consider both cognitive and affective attitudinal components for their joint impact on consumers' adoption, adaptation and outcomes as a composite process.

Venkatesh et al. (2016) argue that there is a lack of fundamental shift in technology adoption and that fundamental shift is the promising direction for future research. In line with this argument, this research undertakes a similar direction on consumers' attitude towards social media adoption, adaptation and outcome as a composite process as Alwi and Kitchen (2014) argue that attitude is not only about cognitive but also affective attributes and behavioural responses. This doctoral research aims to address this research gap and contributes to the body of knowledge by developing a composite technology adoption and adaptation model for current and future research and practice.

2.10 Conclusion

This chapter introduced briefly digital footprints, social media and provided an in depth critical review and evaluation of prior scholarly works on technology adoption, adaptation and attitude. In addition, it focused on a critical evaluation and analysis on consumers' social media adoption, adaptation determinants and their digital footprints sharing behaviour. In addition, it discussed the leading factors which developed good impetus for this research by determining the cognitive functional and social attributes vis a vis the affective intrinsic personal emotional attributes. The literature review provided a good understanding to the rudimentary underlying technology adoption and adaptation determinants, which provides sufficient knowledge and understanding to accomplish the aim and objectives of this research. Moreover, the critical review of the literature identifies the research gap and the dearth of scholarly works in consumers' social media adoption and adaptation as a composite process. This chapter touched upon different aspects of the research themes and made a thorough review of the scholarly works. The next chapter develops the conceptual framework and the hypothesised relationships in the proposed framework.

Chapter 3. Theoretical Framework and Hypothesis Development

3.1 Introduction

This chapter highlights the theories that are used to underpin this research and also examines how these theories are integrated to facilitate the development of the conceptual framework. The CMUA and the UTAUT (Base Model) are chosen for this research. From the review of the literature in the previous chapter, it can be argued that many models have been developed on the use, acceptance, adoption and adaptation of technology but potentially no identifiable model has addressed the underlying factors driving consumers' social media adoption, adaptation and behavioural outcomes as a composite process. Moreover, the UTAUT not only omitted some relationships in the model but also excluded attitude, which is a vital construct in explaining the adoption of technology (Dwivedi et al., 2017a), and little attention has been given to the joint attitudinal components. Thus, no specific theory has been found to have addressed the above research gap.

This chapter provides details of the model on the chosen base theories of the UTAUT and the CMUA to underpin and demonstrate a relationship model to address the research aim. Considering consumers' digital footprints, a conceptual framework is developed which explains consumers' cognitive and affective attitude, adoption and adaptation behaviour patterns and behavioural outcomes based on structural equation modelling. Subsequently, the hypotheses defining the interrelationships between various constructs of the framework are developed.

The UTAUT is chosen because it is a widely used framework on technology adoption, whereas the CMUA is chosen because it explicates adaptation behaviour and coping with the consequences of social media digital footprints. These models focus on technology adoption and adaptation in isolation and both models are driven mainly by cognitive utilitarian attributes (usefulness, ease of use, complexity, convenience, social norms, performance etc.) and less by affective attributes (enjoyment, self-enhancement, fear etc.). The UTAUT, on the commonalities of the constructs, summarised them into unified constructs of performance expectancy, effort expectancy, social influence and facilitating conditions, along with four moderators of gender, age, experience and voluntariness. UTAUT2 extended the model by adding habit, price, and hedonic motivation, whereas the multi-level framework did not change the basic structure of the UTAUT.

Similarly, the CMUA mainly focused on individuals' cognitive appraisals in adaptation behaviour (discussed in Chapter 2). Individuals either maximise or satisfice technological benefits or revert or abandon technology completely based on their cognitive appraisal of the consequences of technological disruptions (Beaudry and Pinsonneault, 2005; Lyytinen and Rose, 2003).

Nonetheless, both the CMUA and the UTAUT have ignored the joint attitudinal components, as understanding a consumer's response to social media and their digital footprints in consumer psychology begins from attitude, and their response is driven by both cognitive and affective attitudinal components, referring to consumers' overall attitude. These models have not paid attention to the joint attitudinal components. Thus, based on consumers' joint attitudinal components towards the consequences of their digital footprints, this doctoral research examines the antecedents of adoption and adaptation composite patterns and behavioural outcomes by developing a model which offers predictive power and accounts for the composite process of adoption, adaptation and behavioural outcome. Aligned with the arguments of Dwivedi et al. (2017a) and Venkatesh et al. (2012), due to the UTAUT's limitations, this doctoral research has dropped the moderators because they do not add any variations for the adoption and use context.

3.2 Conceptual Framework

Technology Adoption and Adaptation Model (TAAM)

The existing adoption models have reached their practical limitations (Venkatesh et al., 2016). In order to understand consumers' attitude towards social media adoption and adaptation as a composite process, a paradigm-shifting joint attitudinal based framework is developed, informed by three major streams of literature: consumers' attitudinal construction, technology adoption and finally technology adaptation.

3.2.1 Technology Adoption and Adaptation as a Composite Process

Many technology adoption models have been proposed based on psychological studies. The TAM was developed from the TRA, and subsequently the TPB reinforced social influence and facilitating conditions, acknowledging factors such as perceived behaviour control and perceived usefulness. The TPB received significant attention from a wide range of scholarly disciplines, leading to reconsideration of the constructs of technology acceptance. As such, the subsequent models of technology acceptance – the TAM2, TAM3 and UTAUT – consider factors such as usefulness, ease of use, performance and effort expectancy, attitude, self-efficacy, playfulness, anxiety and social influence (Venkatesh and Davis, 2000; Venkatesh and Bala, 2008). Simultaneously, the popularity of the IDT (Rogers, 1995) introduced a new dimension to these technology adoptions, albeit at a macro level. In addition to taking individual technology acceptance to the social/communal diffusion stage, the IDT also triggered semantic debates surrounding some of these constructs, as discussed in the literature review: relative advantage was proposed as an alternative to perceived usefulness, and eventually was accommodated in the widely applied UTAUT model. The TAM3 incorporated factors such as experience, indicating that technology adoption is not an end in itself: it goes beyond adoption and involves a gradual integration into consumers' lives and work practices (Dey et al., 2013). It needs to be studied as a composite process of adoption and adaptation. Based on the above discussion, it can be argued that there is a considerable academic debate in relation to semantic aspects and the appropriateness of various constructs leading to technology adoption and adaptation.

Although the original TAM and its more recent versions and various derivatives, such as the UTAUT and UTAUT2, have been widely criticised in the Information Systems, General Management and Marketing literature (Agarwal and Prasad, 1999; Casey and Wilson-Evered, 2012; Bagozzi, 2012; Slade et al., 2015; Sumark and Sorgo, 2016; Van Raaij and Schepers, 2008), the usefulness and relevance of these models in future IS models cannot be understated, as more recent scholars continue to extend and develop models in various contexts. For instance, Dwivedi et al. (2017a) revised the UTAUT model and argued for the re-introduction of attitude into the model because attitudinal components are the key perceptions and dispositions held by individuals regarding a technology. They argue that even though the four exogenous constructs of the UTAUT are based on technological (performance and effort expectancy) and contextual attributes (social influence and facilitating conditions), these are perceptions held by individuals regarding a technology. The key element that is missing is the individuals' dispositions, which are their attitudes explaining technology adoption behaviour (Dwivedi et al., 2017a; Rana et al., 2017a). Furthermore, one of the key scholars championing various forms of technology acceptance models, such as the UTAUT (Venkatesh et al., 2003), the UTAUT2 (Venkatesh et al., 2012) and the Multi-Level Framework (Venkatesh et al., 2016) recently coined a new model of Adaptation to Information Technology (Bala and Venkatesh, 2016). In that particular model, performance expectancy and perceived usefulness have been termed as perceived opportunity.

Moreover, so far these particular technology adoption models have been analysed by interpretivist researchers who have been quite critical about the quantitative modelling of technology adoption. That was also cited as a weakness of the TAM and other models (Baron et al., 2006; Dey et al., 2013; Snowden et al., 2006). As discussed in the literature review, Bala and Venkatesh (2016) initiated a paradigmatic shift in the technology adoption and use literature by incorporating various adaptation strategies within quantitative modelling. Concurring with their argument and in the light of the above discussion surrounding technology adoption and adaptation, this doctoral research develops the TAAM model and offers insight on the composite and non-linear process of consumers' adoption and adaptation. This research proposes that consumers' joint attitudinal components (cognitive and affective) influence their social media adoption and adaptation as a composite process. It identifies the antecedents of the composite process and postulates that social media adoption is not an end in itself but involves various adaptation strategies leading to the ultimate nature of use. Adoption and adaptation are a composite process rather than being compartmentalised and treated separately. The constructs are developed as follows.

3.2.2 Attitude as an Antecedent to Adoption and Adaptation

In the consumer studies and IS literature, attitude has been identified as a strong antecedent to behavioural intention in general, which also leads to specific behaviour such as technological adoption. It is also understood that attitude is an outcome of belief, indicating cognition of consumer attitude. Nevertheless, psychologists widely argue that the emotional or affective part of attitude also has a significant part to play in this process. As such, in the literature review, a number of affective components such as enjoyment, self-enhancement and fear (Chen et al., 2014; Hau and Kim, 2011; Nov et al., 2010) have been identified and discussed as constituents of affective components of attitude. Thereby, it is essential to consider these affective attitudinal components along with the cognitive component, which is identified as an evaluative response to the attitude object (positive or negative evaluation of the performing behaviour). It has also been noticed (as discussed in Chapter 2) that the consideration of both components together as antecedents to the composite process of technology adoption and adaptation has not been central in many of the scholarly works in relevant disciplinary areas, calling upon further investigation to ascertain the comparative influence of these components on technology adoption and adaptation. In relation to the core conceptual underpinning of this doctoral research, the influence of affective attitudinal components cannot be underemphasised due to the myriad emotional attributes that have been discussed in consumer studies (Nov et al., 2010; Park & Kim, 2014). It even becomes salient for consumer engagement with social media, as suggested by relevant scholarly works. Therefore, following from the literature review, this doctoral research develops the following conceptual framework and hypothesises the joint attitudinal components as antecedents of the composites of technology adoption and adaptation.

As delineated in detail in the previous chapters, consumers often continue to adopt and adapt social media despite their concern over their digital footprints. Such adoption and adaptation behaviours are not just cognitive but also affective emotional attributes that influence their attitude towards the consequences of their digital footprints. Venkatesh et al. (2003) argue that attitude has the strongest influence in TRA and TPB theories. Similarly, Dwivedi et al. (2017a) argue that attitude needs to be re-introduced into technology adoption models. This doctoral research has the same argument but postulates the joint attitudinal components (cognitive and affective) as antecedents to the composite process of technology adoption and adaptation. Therefore, this research is parsimonious towards the antecedents for the composite process and develops a predictive conceptual framework of the Technology Adoption and Adaptation Model (TAAM) (Figure 3.1). It postulates that Perceived Opportunity, Perceived Social Influence and Perceived Control are the cognitive utilitarian attitudinal components, and enjoyment, self-enhancement, fear and trust are the affective attitudinal components. Furthermore, this research suggests that affective components of trust and fear have a direct impact on the behavioural outcomes. Both cognitive and affective constructs are discussed below.

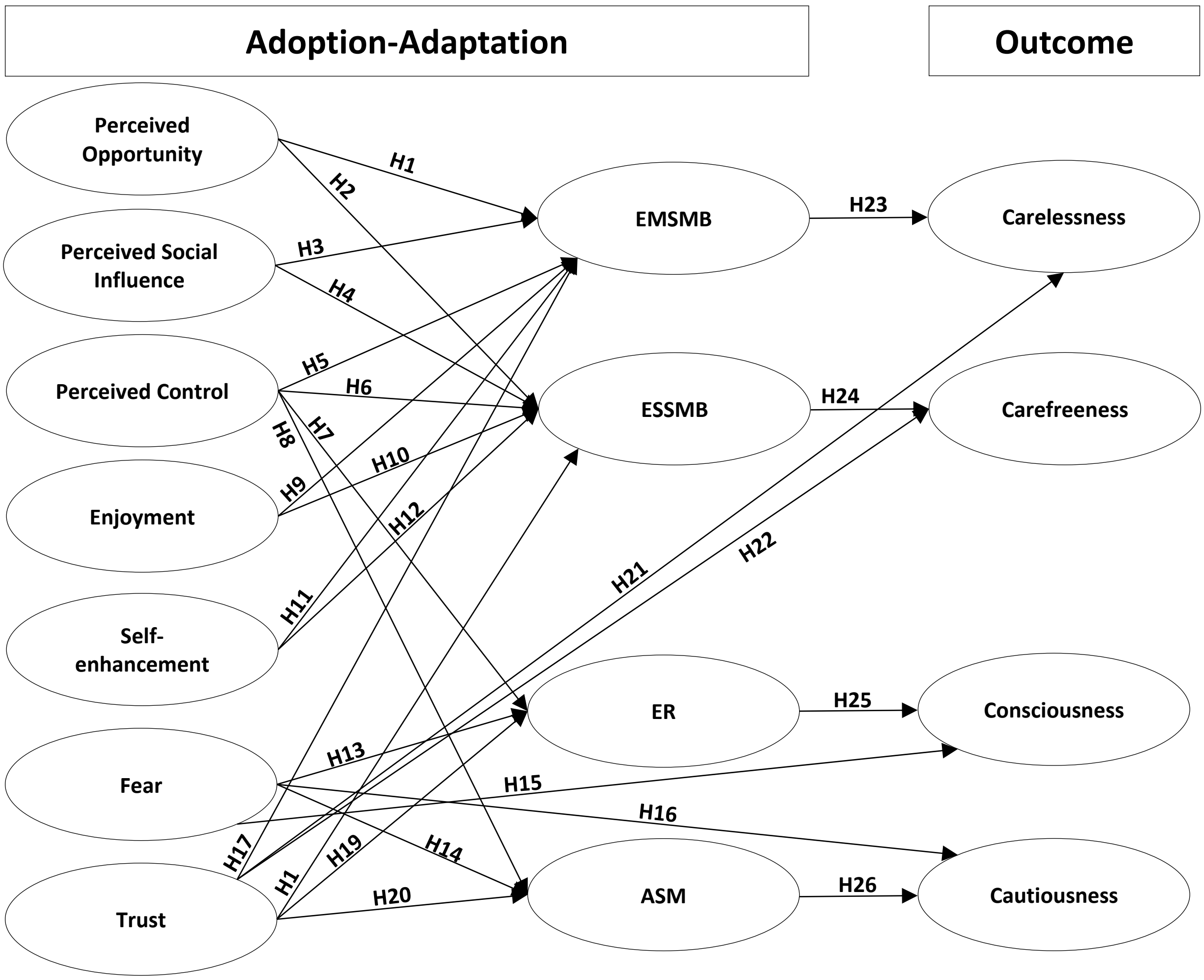

Figure 3. 1 Conceptual Framework

3.2.2.1 Cognitive Attitudinal Components (CAC)

Eagly and Chaiken (1993) argue that attitudinal cognitive components exist when individuals process information about an object, which forms into beliefs. Similarly, this doctoral research postulates that Perceived Opportunity, Perceived Social Influence and Perceived Control are the cognitive beliefs that determine consumers' cognitive utilitarian attitude towards social media digital footprints. Table 3.1, below, provides the details about the cognitive attitudinal components, source and their contributions to hypotheses.

Cognitive Attitudinal Components	Themes/Concepts	Source	Contribution to Relevant Hypothesis
Perceived Opportunity	Relative Advantage, Usefulness, Ease of use, Innovativeness, Performance Expectancy, Effort Expectancy etc.	Beaudry and Pinsonneault, 2005; Gironda and Korgaonkar, 2014; Venkatesh et al., 2003; Bala and Venkatesh, 2016	Cognitive utilitarian elements of perceived usefulness, perceived ease of use, relative advantage, reward, reduce efforts and improve performance etc.
Perceived Social Influence	Social Pressure, Subjective Norms, Social Interaction, Social Support, Social Ties and Social Relationship etc.	De Valck et al., 2009; Hsu and Wu, 2011; Ellison et al., 200); Grace et al., 2015; Venkatesh et al., 2012	Cognitive utilitarian elements of individuals' perception about subjective norms, social image, social pressure from referent group (friends, family etc.) and social support to develop and maintain social relations with others and enhance interpersonal utility.
Perceived Control	Control, Controllability, Privacy Control, Internal Autonomy, Locus of Control, Perceived Behaviour Control	Beaudry and Pinsonneault, 2005; Bala and Venkatesh., 2016; Cheung et al., 2013; Dinev et al., 2013; Gironda and Korgaonkar, 2014; Tucker, 2014	Cognitive utilitarian elements of the level of control technology provides (influence on technological features), self-evaluation of the inner capabilities and how easy or difficult one feels on the use of technology (strong locus of control), perceived behaviour control, control of interaction etc.

Table 3. 1 Cognitive Attitudinal Components' Contribution to Hypotheses

3.2.2.1.1 Perceived Opportunity (PO)

Perceived opportunity is the degree to which consumers believe that social media offers them usefulness, ease of use, reduced efforts, and success, has a relative advantage and improves their performance (Bala and Venkatesh, 2016; Venkatesh et al., 2003; Zhang et al., 2014). They develop a holistic assessment of the opportunities offered by social media such that its adoption will enhance their performance and they will need to make less effort (Venkatesh et al., 2003). These are the cognitive functional elements of their perceived usefulness to enhance performance, perceived ease of use to be free of effort and relative advantage, such that social media is perceived to be better than its precursor (Chiang, 2013; Wang et al., 2012; Zhang et al., 2014; Zolkepli and Kamarulzaman, 2015). Perceived opportunity is a positive situation for consumers, and this doctoral research postulates that customers develop their assessment of social media features and functional characteristics that they perceive as novel. Social media provides compatibility with their needs and the functional features offer good fit to the tasks they want to accomplish. Similar to the CMUA and the UTAUT, this doctoral research posits that consumers believe that social media is a strong fit with what they want to accomplish, as consumers with high personal innovativeness will perceive social media as an opportunity to improve their effectiveness and will assess it positively. Thus, this research suggests that perceived opportunity embodies performance and effort expectancy along with the theme of utility for social media. Consumers would perceive social media as an opportunity due to its functional attributes of performance, relative advantage, ease of use and convenience (Table 3.1). Therefore, their attitude towards the consequences of their digital footprints would be positive, and they will adopt and maximise social media benefits. The following hypothesis is formulated.

H1– Perceived Opportunity (PO) has a positive effect on exploration to maximise social media benefits.

As discussed above, perceived opportunity is a positive situation for consumers that customers develop their assessment of social media features and functional characteristics that they perceive as novel. Social media provides compatibility with their needs and the functional features offer good fit to the tasks they want to accomplish. Consumers believe that social media is a strong fit with what they want to accomplish, as consumers with high personal innovativeness will perceive social media as an opportunity to improve their effectiveness and will assess it positively. Consumers would perceive social media as an opportunity due to its functional attributes of performance, relative advantage, ease of use and convenience (Table 3.1). Therefore, their attitude towards the consequences of their digital footprints would be positive, and they will adopt and exploit to satisfice social media benefits. The following hypothesis is formulated.

H2– Perceived Opportunity (PO) has a positive effect on exploitation to satisfice social media benefits.

3.2.2.1.2 Perceived Social Influence (PSI)

It can be argued that perceived social influence is consumers' perceived social pressure, which denotes their cognitive psychological goals to develop and maintain social relations with others on social media platforms. Such perceived social pressure drives social interaction (desire to connect, collaborate and communicate), and establishes social ties (with friends, colleagues, family etc.: Hau & Kim, 2010) and social support (social exchange to help and share information with others: Ali, 2011). Hence, this doctoral research hypothesises that PSI is consumers' perceived cognitive social pressure for social interaction, social ties and social support (Table 3.1), which gives them psychological pressure to adopt social media (Grace et al., 2015) and maximise or satisfice social media benefits. PSI has a direct relationship with social media adoption (Hsu and Wu, 2011) and exploration to maximise social media benefits, as it offers social links to engage, support and share information. Therefore, the following hypothesis is suggested.

H3– Perceived Social Influence (PSI) has a positive effect on exploration to maximise social media benefits.

Similarly PSI is the desire to communicate, interact with others and build relationship. Social media is perceived by consumers to enhance social interaction, connect them anywhere and complement their offline relationship. Consumers are led by psychological goals to develop social relations to gratify their socialisation needs and they feel pressured from others that affect their technology adoption and adaptation behaviour (Bharati et al., 2014; Talukder and Quazi, 2011; Venkatesh et al., 2003). Consumers' attitude is positively associated with social strengths determined by social influence. It is consumers' cognitive psychological pressure from external factors to interact, establish social ties and exchange to help others on social media. Hence, this doctoral research hypothesises that PSI is consumers' perceived cognitive social pressure for social interaction, social ties and social support (Table 3.1), which gives them psychological pressure to adopt social media and satisfice social media benefits. It has a direct relationship with social media adoption and exploitation to satisfice social media benefits. Therefore, the following hypothesis is formulated.

H4– Perceived Social Influence (PSI) has a positive effect on exploitation to satisfice social media benefits.

3.2.2.1.3 Perceived Control (PC)

As discussed in Chapter 2, consumers evaluate social media platforms positively if they have more control over these platforms. Similarly, this research postulates that consumers evaluate the outcomes of their digital footprints in terms of personal and professional relevance and importance. Consumers' sharing of digital footprints depends on the level of control that social media platforms provide. Consumers are likely to maximise social media benefits if they perceive that social media gives them a strong locus of control, which is their personal belief, autonomy and information control (Table 3.1). Therefore, they adopt and maximise social media benefits. This research suggests that perceived control is customers' cognitive attitude and enhances their positive attitude towards maximising or satisficing social media benefits. It builds their confidence, integrity and reliability (Cheung et al., 2015; Krasnova et al., 2010) in sharing their digital footprints. This research formulates the following hypothesis.

H5– Perceived Control has a positive effect on exploration to maximise social media benefits.

Similarly, this research posits that cconsumers' adoption and adaptation of social media is based on their evaluation of the level of control they have on these platforms. It is the degree to which they perceive that they have the ability and resources to control social media. Consumers are likely to satisfice social media benefits even if they perceive that social media does not give them a strong locus of control (Table 3.1). Therefore, they would tend to engage in exploitation to satisfice adaptation behaviour despite having little control on social media platforms. The following research hypothesis is formulated.

H6– Perceived Control has a positive effect on exploitation to satisfice social media benefits.

Bala and Venkatesh (2016) argue that perceived control has conceptual similarities with technology adoption literature. They argue that if technology users' perceive that a technology brings them harm even if they have high controllability, they will explore to revert from technology to old ways so as to minimise the negative consequences of the technology.

Consumers appraise the consequences of a technological disruption, they may tend to restore emotional stability and minimise the negative consequences of the technological disruption in their environment (Beaudry and Pinsonneault, 2005). Similarly, if social media consumers perceive that the consequences of their digital footprints bring them harm, they may revert from social media to old ways of sharing information. They may perceive that they lack controllability and ability on social media platforms. Therefore, they may tend to engage in exploration to revert adaptation behaviour by searching old ways of sharing information. This research postulates the following hypothesis.

H7– Perceived Control has a positive effect on exploration to revert from social media.

Unlike exploration to revert adaptation behaviour, if consumers perceive that social media have harmful consequences towards their digital footprints, they may make the efforts to minimise the negative consequences and avoid social media in order to restore emotional stability. Bala and Venkatesh (2016) argue that if individuals evaluate technology as a threat and they have no control on technology, they will avoid technology altogether to eliminate psychological distress. They will resort to self-preservation adaptation effort and reduce distress caused by the technological disruption. They will completely abandon technology and will resort to self-preservation strategy to restore emotional stability (Liang and Xue, 2009). Similarly, this research postulates that if social media consumers perceive that sharing digital footprints on social media platforms has harmful consequences for them and they have no control, they will tend to minimise the negative consequences and avoid technology altogether. This research formulates the following hypothesis.

H8– Perceived Control has a positive effect on avoidance of social media.

3.2.3 Affective Attitudinal Components

This research suggests that consumers' social media adoption and adaptation are not only determined by cognitive attitudinal attributes but also by their positive or negative affective attitudinal components. Affective components are emotional experiences or preferences composed of affective components such as enjoyment, delight and fear (Kwon and Vogt, 2010). Positive emotions such as enjoyment, pleasure and self-enhancement arise from positive social media experiences, which make consumers' attitudes more favourable. Negative emotions such as fear arise from negative social media experiences, which make consumers' attitudes unfavourable towards the consequences of their social media digital footprints. Table 3.2, below, provides details about the affective attitudinal components, their sources and their contributions to the hypotheses.

Affective Attitudinal Components	Themes/Concepts	Source	Contribution to Relevant Hypothesis
Enjoyment	Happiness, joy, pleasure, fun, playfulness, flow,	Al-Jabri et al., 2015; Domina et al., 2012; Hau and Kim, 2010; Hsu and Wu, 2011; Park and Kim, 2014	Intrinsic hedonic elements of joy, pleasure, fun, playfulness and flow (full immersion in an online activity leading to culmination of enjoyment).
Self-Enhancement	Self-esteem, self-status, image, self-presentation, self-fulfilment	Al-Jabri et al (2015); Hau and Kim, 2010; Campbell et al., 2014; Hepper et al., 2011	Affective hedonic and emotional self-focused dimensions originated from self-interest, elements of self-esteem, status, image, and self-presentation to portray the desired impression.
Trust	Reliance, integrity, reliability, credibility, confidence, trustworthiness	Krasnova et al., 2010; Moorman et al., 1993; Pentina et al., 2013; Szmigin, 2018; Wu et al., 2010;	Affective emotional instincts (emotional bonds) based trust, attributes of reliability, dependability, feeling of (un)certainty, reliance and confidence in technology to provide protection or improve performance.
Fear	Harm, anxiety, feeling threatened, fear of privacy and security	Bala and Venkatesh, 2016; Cheung et al., 2015; Dinev et al., 2013; Liang and Xue, 2009	Affective emotional feelings of susceptibility to malicious consequences of technology, fear on the consequences of disclosure, feeling threatened.

Table 3. 2 Affective Attitudinal Components' Contribution to Hypotheses

3.2.3.1 Enjoyment

This research postulates that consumers are driven by their intrinsic sensory elements of pleasure, enjoyment and flow, with hedonic and emotional self-focused dimensions originating from self-interest driving their attitude (Hau & Kim, 2010). Enjoyment comprises consumers' intrinsic emotional factors driving their intrinsic hedonic and emotional pleasure, which satisfies their hedonic needs for enjoyment, encouraging them to adopt and adapt social media platforms. Pleasure is fun and playfulness, and flow is their immersion in social media activities, which culminates in enjoyment (where nothing else seems to matter). As a result, they may engage more with social media platforms. This research posits that enjoyment comprises pleasure and flow (optimal social media experience) resulting in greater enjoyment to adopt and maximise social media benefits and formulates the following hypothesis.

H9– Enjoyment has a positive effect on exploration to maximise social media benefits.

As discussed above, this research postulates that enjoyment is pleasure, fun and an intrinsic acceptance of social media (Zolkepli and Kamarulzaman, 2015). Consumers immerse in social media platforms that give them enjoyment with significant impact on their behaviour (Huang, 2012). If social media offer limited benefits to consumers, consumers would still tend to engage in exploitation to satisfice adaptation behaviour due to enjoyment. This research posits that when consumers feel that social media platforms offer them limited benefits, they would still tend to engage in exploitation to satisfice social media benefits. The following hypothesis is formulated.

H10– Enjoyment has a positive effect on exploitation to satisfice social media benefits.

3.2.3.2 Self-Enhancement (SE)

Self-enhancement is consumers' positive feelings about themselves. Self-status, self-image, self-presentation and self-esteem are their self-fulfilling hedonic needs of self-enhancement to portray the desired impression on social media platforms. In order to attract attention, their self-fulfilling emotions would enhance their self-status and image, and they would overwhelmingly engage with social media platforms and share information about themselves, which they feel would enhance their self-status and image (Ali and Lee, 2010). They reveal desirable information on social media platforms to formulate the impression they wish to convey to others (Krasnova et al., 2010). This research suggests that consumers' affective attitude is enhanced when hedonic factors of self-enhancement goals of self-esteem operate on social media, which in turn drive social media adoption and adaptation to maximise social media benefits. It postulates the following hypothesis.

H11– Self-enhancement has a positive effect on exploration to maximise social media benefits.

Emotional attachments are good predictors of adoption of social media. Positive words from users affect other users' emotional state (Chen et al., 2014; Schroeder, 2014). Self-esteem and self-enhancement enhance self-presentation and self-image expression on social media. This research postulates that consumers' self-enhancement and self-esteem are the positive feelings about themselves. High self-enhancement of consumers will enhance their self-esteem and they would tend to overwhelmingly update and present their status online, share information and anything that they feel would enhance their image to attract attention from others (Hennig-Thurau et al., 2004). However, in exploitation to satisfice minimum social media benefits engagement behaviour, despite limited social media benefits, consumers may feel that they still have high self-enhancement opportunities on social media platforms. This research formulates the following hypothesis.

H12– Self-enhancement has a positive effect on exploitation to satisfice social media benefits.

3.2.3.3 Fear

Consumers share and reveal their digital DNA (profile, information, interests, likes, dislikes, opinions, comments, recommendations and preferences etc.) on social media platforms. These revelations lead to fear of privacy and security risks (Cheung et al., 2015; Tan et al., 2012). Social media providers accumulate, use and share (collection, processing, storing, giving access to) consumers' digital footprints. It is the fear of disclosure of digital footprints, susceptibility to malicious social media disruptions (with harm to their well-being), abuse or unauthorised access to their digital footprints that may cause fear and anxiety (Karyda et al., 2009) amongst consumers. This research postulates that consumers' fear and anxiety towards the consequences of their digital footprints may give rise to negative social media experiences, such that they feel threatened to revert from social media to old ways of sharing information. The following hypothesis is suggested.

H13– Fear has a positive effect on exploration to revert from social media.

Consequences of disclosure of personal information, the fear of identity theft and personal record for scrutiny by the public on social media cause fear amongst social media consumers. It influences consumers' adoption of social media platforms (Cheung et al., 2015) and has a negative impact on sharing information and online buying (Ghosh et al., 2014; Lee et al. 2013). Beaudry and Pinsonneault (2005) argue that individuals would avoid technology altogether if they assess a technological disruption as a threat and have limited control on the technology. Similarly, this research postulates that consumers' avoidance of social media behavioural efforts are emotion focused as a threat to their digital footprints may cause them emotional distress. When they feel their digital footprints are at risk and they have the fear of the consequences of their privacy and security risks, they would tend to avoid social media altogether to eliminate emotional distress and restore emotional stability. Therefore, this research formulates the following hypothesis.

H14– Fear has a positive effect on avoidance of social media.

As discussed above, social media consumers may feel that the consequences of sharing digital footprints on social media may affect their status, reputation and personal record for scrutiny by the public. It may cause fear amongst social media consumers and influence their adoption and adaptation of social media. However, they may feel that their digital footprints are not secure (i.e. that they are exploited and unauthorised access is granted to third parties). Their consciousness towards the consequences of their digital footprints would increase and they may tend to give more attention and enhance their awareness of sharing digital footprints on social media. As they give more attention towards their digital footprints, their feeling of fear would decrease. They may tend to give considerable attention to their digital footprints. They would tend to be vigilant towards their digital footprints due fear of privacy and security. They would consciously interact with social media platforms with focus attention. Therefore, this research suggests that as consumers' become conscious towards their digital footprints, their fear towards the consequences of their digital footprints would decrease, and formulates the following hypothesis.

H15– Fear has a negative effect on consumers' consciousness towards their data digital footprints on social media.

Prior studies suggest that individuals develop an overall feeling of threat from a technological disruption in their environment (Liang and Xue 2009). When consumers feel that the consequences of sharing digital footprints are severe, they will feel threatened by social media. This research postulates that consumers develop overall feeling of threat towards the consequences of their digital footprints on social media. They may feel that their privacy and security is at stake when they share digital footprints on social media platform. Due to which they may develop negative feelings and become cautions towards sharing digital footprints on social media. They may tend to be suspiciously alert towards sharing digital footprints on social media platforms. This research postulates the following hypothesis.

H16– Fear has a positive effect on consumers' cautiousness towards their digital footprints on social media.

3.2.3.4 Trust

Trust, for the context of this research, is consumers' feelings of uncertainty and protection against the unauthorised access to their data digital footprints on social media platforms. A wealth of data is accumulated, stored and accessed by social media providers. Consumers' attitude towards sharing digital footprints depends on the integrity and reliability of these platforms (Szmigin, 2018). This refers to how confident they feel about the reliability, credibility and integrity of social media platforms. The lack of these key characteristics may make them emotionally sensitive to their privacy and security (Cheung et al., 2015; Krasnova et al., 2010) and reluctant to share digital footprints. This research posits that trust is consumers' affective attitudinal component rather than a rational paradigm in the context of their digital footprints, as they may not be aware of every aspect of their digital footprints (privacy paradox). Therefore, consumers' trust in sharing digital footprints on social media platforms does not undergo a careful and methodical thought process; rather, it is more affect-based, comprising consumers' emotions, feelings and instincts. They rely on affective signals from other social media users, such that these emotional connections enhance their trust in social media platforms beyond beliefs and awareness of the consequences of their digital footprints and they engage in exploration to maximise social media benefits adaptation behaviour. This research formulates the following hypothesis.

H17– Trust has a positive effect on exploration to maximise social media benefits.

This research posits that cconsumers' adoption and adaptation of social media is based on their feeling of trust in social media platforms. It is how confident they feel about the reliability, credibility and integrity of social media platforms. They rely on the emotional connections from other social media users. They are likely to engage in exploitation to satisfice social media benefits even if the trust or emotional connection from other social media users is not so high. This research suggest the following hypothesis.

H18– Trust has a positive effect on exploitation to satisfice social media benefits.

Trust is social media providers' ability to protect consumers' personal information and reduce their feelings of uncertainty of their digital footprints on social media. Trust plays a vital role in consumer's sharing of digital footprints on social media and their feeling of trust in the protection against the unauthorised access to their digital footprints. Consumers' trust influences continued sharing of digital footprints. When consumers feel that the outcome of their digital footprints is harmful, they may tend to restore emotional stability and engage in exploration to revert adaptation behaviour by searching old ways sharing information. This research posits that in such a situation, consumers tend to rely on affective-based trust, which is the affective signals from other social media users. If consumers' feelings of trust enhance in social media providers' ability to protect their digital footprints, they will not revert from social media to old ways of information sharing. Thus, this research postulates the following hypothesis.

H19– Trust has a negative effect on exploration to revert from social media.

Consumers' attitude towards the consequences of their digital footprints depends on their feeling of trust in social media platforms. It is their feeling of trustworthiness in the reliability of social media providers. It is consumer's sharing of digital footprints on social media and their feeling of trust in the protection of their privacy and security. When individuals assess a technological disruption as a threat, they will opt to avoid technology altogether. It is because individuals' adaptation efforts are mainly emotion focused. They would want to come out of the distress and their main focus would be restoring emotional stability (Beaudry and Pinsonneault, 2005). Similarly, this research postulates that if consumers feel that the sharing digital footprints on social media brings them harm, they will tend to minimise the negative consequences and avoid social media altogether to restore emotional stability. However, if consumers' feel that social media providers are trustworthy, they will not avoid social media. Thus, this research postulates that if consumer feelings of trust enhance in social media providers' reliability, they will not avoid social media and suggest the following hypothesis.

H20– Trust has a negative effect on avoidance of social media.

Trust is the basis of feelings generated by the level of care social media providers demonstrate. Emotional connections enhance trust in the service providers beyond the available justified knowledge or awareness (Johnson and Grayson, 2005) posit that the deepening of. Thus, it can be argued that emotional driven trust plays a key role in technology adoption and adaptation behaviour. This research postulates that consumers attitude towards the consequences of their digital footprints determine their adaptation behaviour. Simultaneously, some of the affective attitudinal attributes such as trust has a direct impact on behavioural outcomes. Consumers may have favourable or unfavourable attitude towards the consequences of their digital footprints. As their feeling of trust in social media providers increases, their carelessness towards digital footprints decreases. It means consumers would tend to have careless engagement with their digital footprints. This research formulates the following hypothesis.

H21– Trust has a negative effect on consumers' carelessness towards their digital footprints on social media.

Johnson and Grayson (2000) argue that consumers trust is influenced by affective aspects of emotions, care and attention. In addition, their trust is influenced by service providers' respect, empathy and caring. Emotional attachment provide a basis for trust development and such trust is not only more intense but also has the strongest effect (McAllister, 1995). As discussed above, consumers' attitude towards the consequences of their digital footprints determine their adaptation behaviour and this research posits that the affective attitudinal attribute of trust has a direct impact on behavioural outcomes. As consumers feeling of trust in social media providers increases, their carefreeness towards digital footprints decreases. It means consumers would tend to have carefree engagement with their digital footprints such that they would tend to be indifferent, easy going and free from care about their social media digital footprints. The following research hypothesis is formulated.

H22– Trust has a negative effect on consumers' carefreeness towards their digital footprints on social media.

3.2.4 Adaptation behaviour

Both cognitive and affective components are considered together in this doctoral research as their comparative level of influence, various components of attitude on adoption and subsequent decisions cannot be understated. Firstly, it posits that technological advances such as social media have made lives more transformational (Marakhimov and Joo, 2017). It is increasingly ever challenging to avoid social media and consumers' interactions with these platforms and other innovative technologies (Kuchler, 2017; Shadbolt and Hampson, 2018). Secondly, it is the composite process that involves complex decisions which is inextricably weaved with our day to day lives and at the same time can have myriad economic, social and psychological cost (stress and risks). It can be like a car purchase or a mortgage but the subtleness in social media is personal and social well-being at stake. As such in a complex decision making process, where consumers often get involved such as social media. The relative influence of various attitudinal factors is a novel area of investigation. It is about both adoption and adaptation, which has not been properly investigated as part of a composite modelling. Partial understanding can be obtained from Bala and Venkatesh (2016) while the model has a commendable contribution in terms of defining the adaptation components. However, there is a lack of clarity in relation to their direct inter-relationship with adoption components and also due to the nature of that investigation which is posited in organisational dynamics, the constructs and the model itself do not fully capture consumer adoption and adaptation of technology. Finally, to the best knowledge of the researcher, there is paucity in academic literature where consumer adoption, adaptation and subsequent outcome of technology use have been considered as a composite process, captured within a scientific model. The advantage of having all in one single model is its ability to exhibit relative influence and relational interlink between various components and ascertain the outcomes characterised by both emotional and cognitive attributes.

Adaptation acts are performed by consumers in response to social media adoption such adaptation behaviours are the acts that consumers undertake to cope with the consequences of their digital footprints. Adoption and adaptation are intertwined and cannot be isolated from each other (Isaac et al., 2006). This doctoral research has a similar stance and posits that social media adoption and adaptation is a composite process and cannot be separated. Consumers' adapt social media features on these platforms to explore or exploit technological benefits, revert or avoid social media. The following table 3.3 provides the details about adaptation behaviour, source and their contributions to hypothesis.

Adaptation Behaviour	Themes	Source	Contribution to Relevant Hypothesis
Exploration to Maximise Social Media Benefits	Take full advantage, explore technological benefits	Bala and Venkatesh, 2016; Bar et al., 2007; Beaudry and Pinsonneault, 2005; Dey et al., 2011; Isaac et al., 2006	Efforts and actions undertaken to maximise benefits, explore new features, non-linear and iterative process in exploring social media features, fully integrate social media into consumers' lives.
Exploitation to Satisfice Social Media Benefits	Take limited advantage, exploit technological benefits	Bala and Venkatesh, 2016; Beaudry and Pinsonneault, 2005; Bar et al., 2007; Dey et al., 2011	Exploit minimum benefits, reduced efforts and limited benefits satisficing, non-linear and iterative process in limited social media features exploitation.
Exploration to Revert	Revert from technology	Bala and Venkatesh, 2016; Beaudry and Pinsonneault, 2005; Dey et al., 2013	Revert from social media, minimise the negative outcome, explore to minimise the harmful consequences and revert from social media, less integration into their lives.
Avoid Social Media	Abandon technology	Bala and Venkatesh, 2016; Beaudry and Pinsonneault, 2005; Dey et al., 2013	Abandon social media completely due to fear and threat, do not let social media integrate into their lives at all.

Table 3. 3 Adaptation Behaviour Contribution to Hypotheses

3.2.4.1 Exploration to Maximise Social Media Benefits (EMSMB)

This research, unlike CMUA, postulates that the consequences of social media digital footprints bring about changes in consumers' adoption, adaptation and behavioural outcomes as a composite process. Consumers respond to such consequences through their joint attitudinal components. Thus, consumers will explore ways to maximise social media benefits and they will be careless towards the consequences of their digital footprints if they perceive that social media is an opportunity, and that they have social pressure and control over these platforms. Likewise, they have strong emotional attachment with social media, such that these platforms provide them with self-enhancement, enjoyment and trust. Thus, this research suggests the following hypothesis.

H23– EMSMB has a positive effect on consumers' carelessness towards their digital footprints on social media.

3.2.4.2 Exploitation to Satisfice Social Media Benefits (ESSMB)

As discussed above, consumers' attitudes towards the consequences of their digital footprints are based on their joint attitudinal components. Both cognitive (PO, PSI, PC) and affective (enjoyment, SE and trust) attributes influence their adoption and adaptation as a composite process. Consumers may tend to exploit social media benefits and may be carefree towards the consequences of their digital footprints when they engage in exploitation to satisfice social media adaptation behaviour. This means that consumers may tend to reduce adaptation efforts, confine to the limited resources and ability that they have and resort to limited benefits satisficing adaptation efforts. They may aim to satisfice minimum social media benefits and be carefree towards the consequences of their digital footprints. This research postulates the following hypothesis.

H24– ESSMB has a negative effect on consumers' carefreeness towards their digital footprints on social media.

3.2.4.3 Exploration to Revert (ER)

As discussed above, social media adaptation and outcomes are not only influenced by cognitive appraisal of perceived control (Beaudry and Pinsonneault, 2005) but also by affective attributes of fear and trust. Consumers may tend to explore ways to revert from social media platforms if they have negative attitudes towards the consequences of their digital footprints such that they feel that their digital footprints are not secure (i.e. that they are exploited and unauthorised access is granted to third parties). Therefore, they would tend to be conscious towards the consequences of their digital footprints, and this research formulates the following hypothesis.

H25– ER has a positive effect on customers' consciousness towards their digital footprints on social media.

3.2.4.4 Avoidance of Social Media (ASM)

This research suggests that if consumers feel that their digital footprints are not secure and that social media providers may harm their well-being (exploit their digital footprints or provide unauthorised access to their personal information), they may tend to abandon social media and stop sharing digital footprints on these platforms. Unlike the CMUA and adoption literature, this research suggests that consumers may not only tend to cognitively remove themselves from the stressful situation but also tend to emotionally detach from these platforms. They would tend to both psychologically and emotionally disconnect from the platforms and engage in avoidance of social media adaptation behaviour. Thus, consumers' trust, fear and perceived control play a significant role: that is, customers' attitude towards social media would be negative if they perceive low control on these platforms, and if the feeling of fear is high and trust is low, they would tend to avoid social media altogether. They would tend to be cautious towards the consequences of their digital footprints on social media. The following research hypothesis is formulated.

H26– ASM has a positive effect on customers' cautiousness towards their digital footprints on social media.

3.2.5 Outcomes

The four behavioural outcomes – Carelessness, Carefree, Consciousness and Cautiousness (4C Matrix) – are presented in Figure 3.2 below and described in detail next.

		Digital Footprints Sharing	
		High	**Low**
Digital Footprints Concern	**High**	**Consciousness** (Mindfully aware, cognizant and fully considerate about digital footprints)	**Cautiousness** (Suspiciously alert and exercising caution about sharing digital footprints)
	Low	**Carelessness** (Inattentive and heedless about digital footprints)	**Carefreeness** (Indifferent and lighthearted about digital footprints)

Figure 3. 2 4C Matrix (Consumers' Behavioural Outcomes)

The following table 3.4 provides the details about outcomes, source and their contributions to hypothesis.

Outcomes	Themes	Source	Contribution to Relevant Hypothesis
Carelessness	Inattentive, negligent, lack of disciplined attitude	Lawson et al., 2013; Fu et al., 2017; White, 1961	Fail to pay attention to risks and fail to take precautions against harm, be negligent and inattentive of the risks, and do not pay attention to risks, lack of disciplined attitude and recognition to details.
Carefreeness	Indifferent, easy going, free from care, uninterested	Gladden et al., 2009; Leong et al., 2018; White, 1961	Indifferent to details with no anxious thoughts and anxiety, free from care, easy going, uninterested in things and the characteristic to be happy-go-lucky.
Consciousness	Awareness, attention and cognition	Dehaene and Naccache, 2001; Tolle, 1999	Awareness of the situation, require considerable attention towards social media digital footprints,

			systematic information processing to systematically distinguish, categorise and integrate information cognitively.
Cautiousness	Alert, exercising caution, suspiciously thoughtful	Fu et al., 2017; Rodríguez-Castro et al., 2017; White, 1961	Alert and exercising caution to something, suspiciously thoughtful about a situation, engage in social media with caution, make thoughtful efforts to identify risks and follow legitimate means to avoid them.

Table 3. 4 Outcomes' Contribution to Hypotheses

3.2.5.1 EMSMB and Carelessness

This research posits that if consumers' attitude towards social media is positive, they tend to explore ways to maximise technological benefits, taking full advantage of technology to maximise personal benefits. As a result, they would be careless towards social media and their digital footprints. Thus, exploration of ways to maximise social media benefits will have a positive influence on consumers' digital footprints and they will be careless in sharing digital footprints on social media platforms.

Carelessness refers to consumers' lack of attention to certain risks and failure to take precautions or care against harm (Lawson et al., 2013; White, 1961). Unlike carefreeness, careless individuals are negligent and inattentive towards harm. Similarly, Fu et al. (2017) argue that careless individuals neither make efforts to identify risks nor pay attention to them. A similar point was made by Lohiniva et al. (2016) and McKay et al. (2018), that careless individuals are inattentive towards harm and they lack a disciplined attitude and fail to give recognition to details (Kumar et al., 2017). Thus, this research hypothesises that carelessness is consumers' lack of attention towards the consequences of their social media digital footprints. Consumers become careless when they seek to maximise social media benefits and fail to attend to the risks involved in sharing digital footprints on social media platforms. This research suggests the following hypothesis.

H23– EMSMB has a positive effect on consumers' carelessness towards their digital footprints on social media.

3.2.5.2 ESSMB and Carefreeness

As discussed above, if consumers engage in exploration to satisfice limited social media benefits adaptation behaviour, they will tend to be carefree towards the consequences of their digital footprints. Carefreeness refers to an individual's indifference to details, with no anxious thoughts, being free from care (White, 1961). Leong et al. (2018) and Van Exel et al. (2006) describe carefree individuals as indifferent (easy-going and free from care), uninterested in things and happy-go-lucky in nature. A similar argument is made by Gladden et al. (2009) that carefreeness is the characteristic of having lack of forethought and planfulness. Similarly, Gerbing et al. (1987) noted that carefree individuals are not persistent in their behavioural mechanisms. Tapp and Cloves (2000) segmented such individuals as carefree casuals, and Chittaro et al. (2017) described them as those individuals who are relaxed and optimistic. Thus, this research hypothesises that when consumers seek to satisfice limited social media benefits, they tend to be carefree (indifferent, free of care) towards the consequences of their digital footprints, and formulates the following hypothesis.

H24– ESSMB has a positive effect on consumers' carefreeness towards their digital footprints on social media.

3.2.5.3 ER and Consciousness

As discussed above, consumers will tend to explore ways to revert from social media platforms if they have negative attitudes towards the consequences of their digital footprints such that they feel that their digital footprints are not secure (i.e. that they are exploited and unauthorised access is granted to third parties). They will tend to be conscious towards the consequences of their digital footprints.

Consciousness refers to awareness of a situation and being aware of one's own awareness (Tolle, 1999). Dehaene and Naccache (2001) describe that individuals requires considerable attention to be conscious towards a task. Their consciousness determines systematic information processing which make them systematically distinguish between mental states to make them conscious. They also posit that consciousness is required for a specific mental activity. Consciousness is both vigilance and conscious processing of information, and it is the ability to discriminate, categorise and integrate information rationally and focus attention (Chalmers, 1995; Dehaene and Changeux, 2011). Therefore, this research suggests that consumers will tend to be conscious towards the consequences of their digital footprints if they engage in exploration to revert from social media adaptation behaviour, and formulates the following hypothesis.

H25– ER has a positive effect on customers' consciousness towards their data digital footprints on social media.

3.2.5.4 ASM and Cautiousness

This research suggests that consumers will tend to both psychologically and emotionally disconnect from social media platforms if their attitude towards the consequences of their social media digital footprints is negative. They will tend to abandon social media platforms altogether and will tend to be cautious towards the consequences of their digital footprints.

Cautiousness refers to alertness, exercising caution over an activity and paying attention to certain risks (White, 1961; Rodríguez-Castro et al., 2017). Consumers will tend to be thoughtful and alert (undertake caution) towards the consequences of their digital footprints. Tseng and Teng (2016) describe that consumers' cautious and careful behaviour is how thoroughly and thoughtfully they determine the effectiveness of an activity. When consumers tend to engage in social media with caution, this strengthens their attitude towards informativeness. As a result, it leads them to consider the perceived effort more cautiously and carefully. Similarly, Fu et al. (2017) suggest that individuals make efforts to identify risks by being cautious, paying attention to risks and following legitimate means to avoid them and make no mistakes. Thus, this research postulates that if consumers' attitude towards the consequences of their social media digital footprints is negative, they will tend to abandon social media platforms altogether and will tend to be cautious towards the consequences of their digital footprints, and formulates the following hypothesis.

H26– ASM has a positive effect on customers' cautiousness towards their digital footprints on social media.

Table 3.5, below, provides a summary of the hypotheses developed and discussed in this chapter and shown in the conceptual framework (Figure 3.1).

No	Summary of the Hypothesised Relationships
H1	Perceived Opportunity (PO) has a positive effect on exploration to maximise social media benefits.
H2	Perceived Opportunity (PO) has a positive effect on exploitation to satisfice social media benefits.
H3	Perceived Social Influence (PSI) has a positive effect on exploration to maximise social media benefits.

H4	Perceived Social Influence (PSI) has a positive effect on exploitation to satisfice social media benefits.
H5	Perceived Control has a positive effect on exploration to maximise social media benefits.
H6	Perceived Control has a positive effect on exploitation to satisfice social media benefits.
H7	Perceived Control has a positive effect on exploration to revert from social media.
H8	Perceived Control has a positive effect on avoidance of social media.
H9	Enjoyment has a positive effect on exploration to maximise social media benefits.
H10	Enjoyment has a positive effect on exploitation to satisfice social media benefits.
H11	Self-enhancement has a positive effect on exploration to maximise social media benefits.
H12	Self-enhancement has a positive effect on exploitation to satisfice social media benefits.
H13	Fear has a direct positive effect on exploration to revert from social media.
H14	Fear has a positive effect on avoidance of social media.
H15	Fear has a negative effect on consumers' consciousness towards their digital footprints on social media.
H16	Fear has a positive effect on consumers' cautiousness towards their digital footprints on social media.
H17	Trust has a positive effect on exploration to maximise social media benefits.
H18	Trust has a positive effect on exploitation to satisfice social media benefits.
H19	Trust has a negative effect on exploration to revert from social media.
H20	Trust has a negative effect on avoidance of social media.
H21	Trust has a negative effect on consumers' carelessness towards their digital footprints on social media.
H22	Trust has a negative effect on consumers' carefreeness towards their digital footprints on social media.
H23	EMSMB has a positive effect on consumers' carelessness towards their digital footprints on social media.
H24	ESSMB has a negative effect on consumers' carefreeness towards their digital footprints on social media.
H25	ER has a positive effect on customers' consciousness towards their digital footprints on social media.
H26	ASM has a positive effect on customers' cautiousness towards their digital footprints on social media.

Table 3. 5 Summary of Hypothesised Relationships

3.3 Conclusion

This chapter addressed the theoretical framework and highlighted the base theories used to underpin this research to facilitate the development of the conceptual framework of the Technology Adoption and Adaptation Model (TAAM). In addition, it delineated the details of the causal relationships given in the model by setting hypothesis and dependent relationships for empirical testing. In addition, this chapter focused on the theories that are used to underpin this research and also how these theories are integrated to facilitate the development of the conceptual framework. The CMUA and the UTAUT are chosen as the base model theories to facilitate this research on consumers' social media adoption, adaptation and outcomes as a composite process.

Chapter 4. Methodology

4.1 Introduction

This chapter is divided into two parts, the first part provides details on the research paradigm, research approach, design, strategy, data collection and data analysis techniques along with the sampling strategy and justification of the choices for the current study. It provides details and discussion on data collection procedures; questionnaire design, pre-pilot test, pilot study and main survey.

The second part focusses on Structural Equation Modelling (SEM). It gives the details on statistical techniques for data analysis. It also focuses on the techniques used for analysis to test hypotheses. Finally, the ethical consideration for the present study are discussed.

Part I: Research Methodology

The aim of this study is to examine consumers' social media adoption, adaptation and behavioural outcome as a composite process. It is to understand (a) consumers' joint attitudinal components as antecedents to technology adoption and adaptation (b) post adoption behavioural outcomes (c) a composite model of adoption and adaptation with outcomes. This study drew specific hypothesised relationships in the previous chapter. Therefore, research methodology of this study provides the research perspective adopted for this research along with research method and design.

4.2 Philosophy

Research design is the plans and procedures for research which involves decisions wide assumptions to detailed methods of data collection and analysis (Creswell, 2009). Figure 4.1 illustrates the wide assumptions about research design. It is the interaction between philosophy, methods and methodology. It also provides reflection on ethics and reflexivity and other aspects of the research. It consists of the following elements.

- ontology
- epistemology
- research paradigm
- research strategy
- research methods

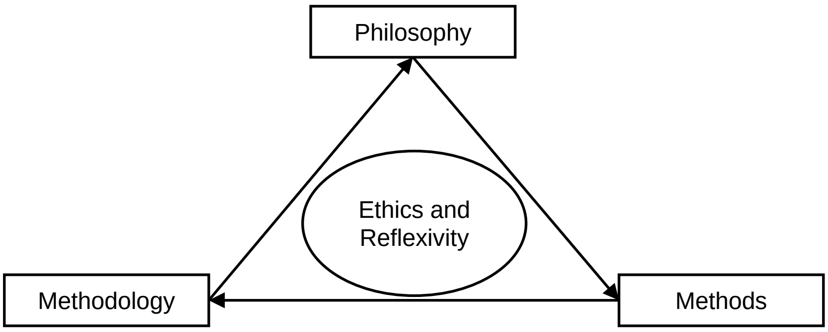

Figure 4. 1 Research Design Framework (Source: Cresswell, 2009)

Research Design consists of a series of linked decisions as illustrated in Figure 4.2 below.

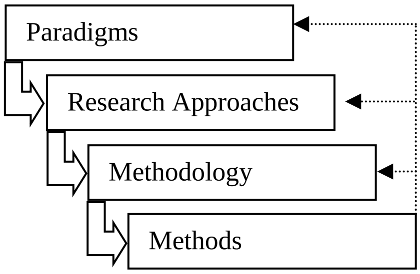

Figure 4. 2 Research Design Linked Decisions (Source: Trafford and Leshem, 2008)

4.2.1 Paradigm

Paradigm is how a researcher sees his/her research topic. It represents the ways of seeing or perceiving and knowing the world. The researcher needs to understand what philosophical approaches lead him/her to create knowledge. These paradigms and philosophical approaches enable the researcher to justify the knowledge he/she have created (William, 2007). This in turn influences how the researcher perceives the research topic and the research approach as a paradigm. Moreover, Saunders et al. (2009) describe that the rudimentary aspect in research design is to choose the most suitable paradigm as it mirrors the reasoning knowledge. It is the philosophical outline which determines the ways to undertake research reflecting how individuals view the world and information. In addition, Hussey and Hussey (1997) argue that research paradigm lays the foundation for the research framework that encompasses an acknowledged arrangement of the right approach and methods to describe data. Therefore, paradigm is a guide for the researcher as it reveals essential issues of a discipline and develops concepts and theories to find solutions for chosen issue (Filstead, 1979). In addition, it determines the criteria for methodology, instruments and data gathering etc. Thus, the researcher adopts a paradigm depending the assumptions the researcher holds for the following ontology and epistemology.

Ontology explains reality. It is described as to how one experiences and constructs a sense of self in the world (Wand and Weber, 1993). It is the basis for epistemological and methodological position in a research. Philosophy is described to be scientific and worldview as non-scientific. However, positivism, rationalism and realism make the efforts to make it scientific. Whereas, phenomenologists, empiricists and constructivists work in the non-scientific domain.

Epistemology identifies two main approaches of rationalism and empiricism (Heylighen, 1993). Rationalism, which has three sub schools (Realism, Idealism and Positivism), refers to innate knowledge gained through deduction and reason. It is superior to knowledge gained through experience. Whereas Proctor (1998) argue that positivism and post-positivism are the two extremes of research philosophies in the methodology literature. It is important for a researcher to explore research philosophies before making a choice for a specific research method.

It is important to highlight that researchers do not have consensus on the choice of a particular research philosophy as they cannot make a clear distinction amongst positivist and post-positivist philosophies due to their inherent strengths and weaknesses (Webb, 1989). However, Wood and Welch (2010) noted that such philosophies in the literature are associated to specific research approaches and methods for instance positivism is found to be associated to a deductive approach leading to a quantitative research method. Whereas post-positivism (interpretivism) to inductive research approach and qualitative research method.

Moreover, Oates (2005) suggests that positivism, interpretivism and critical research are the three research paradigms, which can be used by a researcher to seek direction for a specific research. Therefore, it is vital for this research to explore the orientation of the research aim of this study towards positivism or post-positivism before choosing a research method (qualitative or quantitative). Thus, a brief introduction is carried out for both positivism and interpretivism in the following section before the choice and justification of positivism for this study is laid out in detail.

4.2.2 Positivism

Positivism means knowledge acquisition can be done through sensory experiences or observation. The researcher remains completely objective so that facts and truth is absolute.

Positivism deals with the traditions of natural scientists. (Wand and Weber, 1993). Positivists see things as hard facts to explain a phenomenon wherein the fact and a researcher are distinct from each other and law like generalisation could be established from the relationship amongst these facts (Saunders et al., 2015). Similar point is made by Myers and Avison (2002) that reality is more objective independent of the researcher and can be measured objectively. Reality, which is objective, exists beyond the realm of the human mind (Ron, 2004). It requires quantifiable measures, hypothesis setting through the proposition of characteristics of a sample from a specified population (Orlikowski and Baroudi, 1991). Similar point was made by Smith (1998) that positivism is based on hard facts and scientific laws that can be derived from the relationships that exist amongst these facts. Therefore, positivism is governed by the laws of cause and effect relationship (Trochim, 2006). Positivism guides several research methods such as experiment, survey, structured interviews and observation which usually lead the research through hypothetical deductive research method to quantitatively test hypothesis through statistical analysis and generalise findings (Saunders et al., 2015).

However, positivism is not without criticisms and has been heavily criticised for its scientific process of specifying a priori the cause and effect relationships. Bryman (2004) describe that it is difficult to deal with social reality through the scientific process. Other scholars criticise positivism for its limitations such as Bond (1993) and Playle (1995) argue that positivism provides a rather superficial knowledge about a phenomenon and it does not delve deeper into it. In contrast, Cuskelly et al. (2006) posit that positivism is more appropriate paradigm to objectively study a phenomenon using existing theories including phenomena that entail human behaviour. The same line of argument was made by Saunders et al. (2015) that positivism is the most used research paradigm for surveys and experiment research strategies and more suitable for empirical data and quantitative statistical analysis.

4.2.3 Interpretivism

Interpretivism stands on the view that world is the creation of mind and world cannot be interpreted unless it is interpreted according to an individual views and interpretation. Unlike positivism, interpretivism veers towards subjectivity that is the interpretation of social reality as to how an individual sees, interprets and makes sense of the world (Sarantakos, 2005). Ron (2004) argues that things have no existence independent of human thought and are merely appearances. Things only become in existence as individuals perceive them to be in existence such as human experiences have no meaning unless they are interpreted by individuals to give them meaning. Interpretivism is an individual’s own frame of reference to understand a phenomenon (Hussey and Hussey, 1997). These scholars argue that facts can only be known through social developments on the complete human sense and meanings that individuals make of the fact. Individuals through interpretivist paradigm develop understating of thoughts of other social actors in the real life context and socially construct the meaning through such understanding (Myers, 1997). They further argue that reality does not exist in a vacuum but it is constructed in many different ways as it is influenced by context, which leads to a conclusion and further developments (Hughes and Sharrock, 2016). Similarly, interpretivism is not without criticisms and has been heavily criticised for its lack of rigour (Denscombe, 2002).

4.2.4 Rational for the choice of Positivism

The current research is focusing on the philosophical underpinning to develop clear links between ontology – epistemology – methodology and methods of this research. Although positivism has its limitation, considering the need to objectively study consumers' underlying attitudinal components using existing theories and survey strategy (Cuskelly et al., 2006), positivism is the most suitable paradigm for this research (Saunders et al., 2015). This study undertakes research to explain attitudinal attributes of adoption as hard facts from the relationships that exists with the adaptation behaviour and behavioural outcomes to establish a robust theoretical model (TAAM),which is governed by empirical data and laws of cause and effect relationships (Trochim, 2006). Moreover, positivism provides a logical premise to this research as Collis and Hussey (2014) posit that positivist approach enables a researcher to examine literature and develop a theoretical proposition and hypothesis.

This research based on such proposition is close to positivist paradigm because it has reviewed literature and chosen two existing models of technology adoption (UTAUT) and adaptation (CMUA) respectively and develops the proposed TAAM framework for social media adoption, adaptation and behavioural outcome as a composite process. Furthermore, this doctoral research specifies hypothesised relationships for empirical investigation by collecting data from a random sample of social media consumers to test these propositions and validate the proposed framework. Moreover, aligned with the positivist paradigm, this research is based on the existing theories, which Saunders et al. (2015) argue that existing theories are a good source of knowledge. Thus, in light of the above discussion, this research uses quantifiable measures by operationalising the constructs to test the testable hypotheses set through the proposition of characteristics of a random sample (Myers and Avison, 2002; Orlikowski and Baroudi, 1991) of social media consumers and tests the laws of cause and effect relationship based on the previously researched relationships (Meredith et al., 1989; Trochim, 2006). Therefore, positivist paradigm is more appropriate for this study as it is based on the existing theories (UTAUT and CMUA) and data is gathered systematically (questionnaire administered to a random sample of social media consumers) to empirically examine the cause and effect relationship amongst the antecedents of social media adoption, adaptation and behavioural outcomes.

4.3 Research Approach

Saunders et al. (2015) identify two types of research approaches namely, inductive and deductive. Inductive research starts from empirical observed reality and develops a theory, starting from observation leading to a theory. In contrast, deductive research approach starts from the development of a conceptual and theoretical structure. It starts from developing a theoretical proposition and testing the theory by empirical observation. Hussey and Hussey (1997) posit that deductive research approach is mainly associated with quantitative research method for data collection whereas inductive employ qualitative research approach. Moreover, Saunders et al. (2015) argue that instead of starting from data to theory or vice a versa, it is worth to use abduction that is both approaches (back and forth). Abduction is to build a theory through empirical observation and subsequently test the same theory through deductive reasoning approach.

In addition, both inductive and deductive research approaches have their limitations. Inductive research takes longer. It is described to be more protracted leading to risks that may affect the generalisability of the research (Saunders et al., 2015). In contrast deductive approach builds on existing theories and previous research outcomes and tests the existing theory. Moreover, deduction based on the above characteristics of setting the theoretical proposition from previous research outcomes puts a constraint on the richness in data collection, lacking depth due to the development of hypotheses and variable relationships from existing theory.

4.3.1 Rational for the Choice of Research Approach

To examine consumers' underlying factors affecting their social media adoption, adaptation and behavioural outcomes as a composite process, the existing theories of technology adoption and adaptation are needed to determine the underlying factors affecting the composite process of relationships. Therefore, based on deductive approach, this research has chosen UTAUT and CMUA models to examine the underlying factors and develops the TAAM model drawing concrete outcomes, which can be generalised both for the consumer world of social media and technology adoption and adaptation in general.

Through the explanatory positivist paradigm, based on a hypothetical deductive research approach, the theoretical framework is proposed to support and validate the dynamic relationships between key variables through quantitative analysis to test the theory (Sekaran and Bougie, 2013). Hence, the research approach chosen for this research is deductive followed by appropriate methodology and methods to test the proposed theoretical framework and seek empirical findings from the data. This approach is chosen to ensure empirical research is carried out to generate evidence and achieve the objectives set for this research. Therefore, deductive approach is considered to be more appropriate for this study to achieve the aim and arrive at generalisable conclusions with the following research design, method and strategy of enquiry.

4.4 Research Design

Research design refers to the master plan delineating procedures, data gathering method and analysis. It helps to set limits for the research, study settings and the unit of analysis and determines the types of examination (Burns and Bush, 2002). Trafford and Leshem (2008) argue that it is important for a researcher to match the conceptual and theoretical frameworks so that it establishes cohesion between theoretical perspectives and the practicalities of research design to investigate the research topic. Research design aligns research problem with the methodology (Hair et al., 2018). Similarly, research design is important for implementing methodology (Lundberg, 2003). It determines the type of data, sampling techniques, the choice of data collection method and time frame (Hair et al., 2018). Moreover, extant literature suggest that research design is the outline of research that supports the validity, reliability and generalisability of research findings and assists to achieve the aim and objectives of a research (Churchill and Iacobucci, 2006; Galliers and Land, 1987; Chen and Hirschheim, 2004). Saunders et al. (2015) identify three types of research exploratory, explanatory and descriptive respectively (Cooper and Schindler, 2001).

This research uses explanatory research based on hypothetical deductive approach. It has developed TAAM framework for social media adoption, adaptation and behavioural outcome as a composite process and the framework delineates the dynamic relationships between the key variables and generates hypotheses for testing through quantitative data analysis. Moreover, aligned with explanatory research design, this research is based on the existing theory and uses quantifiable measures by operationalising the constructs to test the testable hypothesis (Saunders et al., 2015). Hence, explanatory research design suits this research because it delineates the hypothetical cause and effect relationships based on the existing theory and gathers quantitative data systematically through a questionnaire administered to a random sample of consumers on social media to empirically examine the cause and effect relationship amongst the antecedents of social media adoption, adaptation and behavioural outcomes as a composite process.

Furthermore, aligned with the explanatory research design and aim of the study, this research uses cross sectional research technique so that data is gathered at a specific point in time. As discussed in the aforementioned chapters that technology adoption is not an end in itself and needs to be studied as a composite process of adoption, adaptation and behavioural outcomes. Therefore, this research conducts a cross sectional data from a random sample of consumers on social media. As Hair et al. (2018) suggest that cross sectional research is structured questions administered through a questionnaire to a sample survey to gauge their attitude (thinking, feeling and what they do), this research collected data in a cross sectional technique because, unlike longitudinal research technique, it suits to the aim of this research. It also suits the timeframe and the nature of study. Similar point was made by Zikmund et al. (2003) that the choice of a survey in a cross sectional data collection technique captures respondent's attitude and behaviour more specifically. It saves time, cost and is more effective when administered to a large representative sample of the given population.

4.4.1 Research Strategy (Appropriate Methodology)

Research methodology is required to balance the conflicting tensions of access to data, time, resources, ethical aspects and the suitability of different options for data collection techniques (Trafford and Leshem, 2008). Research strategy is identified as the planning on the type of data collection technique wherein the appropriate research strategy helps to determine generalisable findings for the study (Scandura and Williams, 2000). Saunders et al. (2015) and Crotty (1998) highlight several categories of a research strategy such as experiment, case study, archival research, ethnographic research, survey, grounded theory and action research etc. In order to achieve the aim, this doctoral study needed to collect data from social media consumers for representativeness. The section below provides more details on sampling. It is difficult to measure the exact population of social media consumers. Therefore, drawing a sample from social media consumers is needed to draw inferences about the population. Survey strategy is described to be the best suited research strategy for such a type of research as it allows the researcher to collect data from each sample case or element to represent the entire population (Hussey and Hussey, 1997). In addition, Dwivedi et al. (2006) argue that survey is the preferred method when conducting research with consumers and individual clients.

In line with the same argument, this research conducted an online survey based on the online-administered questionnaire. The survey strategy provides accessibility, speed, convenience, cost, availability and flexibility (Gilbert, 2001). Looking to the aim of this research, which is to examine consumers' attitudinal components as antecedents to adoption, adaptation and outcomes as a composite process with predictor variables to test hypotheses, survey is considered to be the most suitable method to collect data from social media consumers. Thus, survey method is chosen because the number of social media consumers could run into millions. Moreover, the choice of survey is made for this research by looking at other important aspects of research as well such as time, cost, population size, the type of study, rate of response and format of questions etc. (Aaker et al., 2001).

4.4.2 Research Method

Williams (2007) suggests that there are two types of research methods, namely quantitative and qualitative. Carter and Little (2007) argue that the choice of research method should be linked to the aim of a research as the research method is an important part of a research methodology. Similar point was made by Buchanan and Bryman (2007) that research method should be aligned with the research aim, paradigm and context of a research as it determines the type and nature of data that needs to be collected for a specific research.

In line with the above argument and looking to the aim of this research, quantitative research method is more appropriate for this study as it is based on predetermined instruments generating statistical data. Since this study has developed a framework which raises relational variables, quantitative research method will enable this research to quantify the information gathered through a questionnaire to explain the causal relationships and validate the model. Saunders et al. (2015) suggest that quantitative research is often associated with a questionnaire data collection and statistical data analysis. Whereas, qualitative research is used as a synonym for interviews and categorising qualitative data analysis using thematic analysis etc. Quantitative research deals with numeric data and qualitative with non-numeric data (Brown et al., 1999). Table 4.1 below illustrates the difference between a quantitative and qualitative research method. Based on the above discussion, quantitative research method is more appropriate for this study to approach data numerically and adopt a statistical approach because such a method provides a robust interpretation of the data to explain a phenomenon and separates the research and the researcher (Saunders et al; 2015; Williams, 2007).

However, quantitative research method is not without its limitations. Cloke et al. (1991) and Morris (1991) argue that it does not provide objectivity and lacks depth of understanding.

However, other research scholars disagree with these limitations and posit that it is the most suitable method to test relationships amongst variables in a scientific investigation because this method treats reality more objectively (Cohen et al. 2007; Saunders et al., 2015). Therefore, aligned with the above argument and details given in Table 4.1, quantitative research method is more appropriate for this study based on a survey strategy and structured questionnaire.

The domain of constructs are defined and items are generated for the instrument and most scales are adapted from earlier studies so that items measuring the constructs are adapted appropriately for the reliability and validity purposes. Instruments and scales from previous studies are modified to match the context of this research. Furthermore hypotheses are developed based on cause and effect relationship in the model. Thus data is collected through a mono method comprising online survey based on internet mediated questionnaire to a random sample of social media consumers.

	Qualitative	**Quantitative**
Purpose	Explain and gain understanding of phenomena through collection of narrative data and generate hypothesis.	Explain phenomena through collection of numerical data and test hypotheses
Approach to Inquiry	subjective, process- oriented, Inductive	Objective, outcome- oriented, Deductive
Hypotheses	Tentative, evolving	Specific, testable, stated prior to research
Research Setting	Controlled not as important	Controlled to the degree possible
Sampling	Purposive	Random, representative sample (results generalised to population)
Measurement	Narrative (written word), ongoing	Standardized, numerical
Design and Method	Flexible (Ethnography, Phenomenology, Grounded Theory, Case Study etc.)	Structured, specified in advance (Descriptive Correlation Causal testing)
Data Collection Strategies	Document and artefact (participant, non-participant). Interviews	Observations, questionnaires (close ended), structured interviews
Data Analysis	Data in words, observations/comments to come to a conclusion.	Data in numbers, statistical analysis, using numbers to derive conclusions

Table 4. 1 Qualitative and Quantitative Research Methods (Source: Diffencom, 2019)

4.4.3 Research Instrument

Instruments for data collection are highly structured questionnaire. They are developed from prior studies and most of the constructs are measured by adapting established scales from the literature. Items are developed and generated from established scales to measure: (1) Perceived Opportunity (2) Perceived Social Influence (3) Perceived Control (4) Enjoyment (5)

Self-enhancement (6) Trust (7) Fear (8) Exploration to Maximise Social Media Benefits (9) Exploitation to Satisfice Social Media Benefits (10) Exploration to Revert (11) Avoidance of Social Media (12) Carelessness (13) Carefreeness (14) Consciousness (15) Cautiousness. Items are given in Table 4.2 and the details of the instruments are given in Appendix 1. Most of these scales have been widely adopted in different studies and contexts. In order to measure these scales in the context of this study, a pre-pilot and a pilot study was conducted to check that the scales are applicable to the context of this research. Data for this research was collected from a random sample of consumers using social media platforms.

4.4.4 Operationalisation of Constructs

Hair et al. (2014) describe that operationalisation is deriving construct's meaning in measurement terms and each construct should be operationalised with the type and scale items (Hinkin, 1995). In line with the same argument this research operationalised each construct's meaning in measurement terms and items. Items are given in Table 4.2 below and scales in Appendix 2. These items are reflective as they have a common core (Petter et al., 2007) representing theoretically the construct.

Construct	Items	Source
Perceived Opportunity (PO)	• I am confident that social media will have positive outcome for the information I share on these platforms. • I believe social media will open new opportunities for me to share information, memories, interests, likes and dislikes etc. with others. • I believe social media platforms will provide me opportunities to share my likes, dislikes, interests and information etc. with others. • I believe social media will give me opportunities to share my memories, interests and information etc. with others to gain recognition and praise.	Bala and Venkatesh, (2016)
Perceived Social Influence (PSI)	• I think I interact well with others on social media for sharing my memories, likes, dislikes, interests and information etc. • I believe I fit well with others on social media that share the same interests as me. • I believe social media help me establish relationship with others to share information and interests. • I think I maintain close relationships with others on social media for sharing information and interests etc.	Cheung et al., (2015)

Perceived Control (PC)	• I think I have control over sharing information on social media platforms. • I believe I can control sharing information on social media platforms. • I believe I have control over what to share on social media platforms. • I believe I can control sharing my memories, likes, dislikes and information on social media platforms.	Dinev et al., (2013)
Enjoyment	• I feel I have a lot of enjoyment in sharing my memories, likes, dislikes, interests and information with others on social media. • Social media give me a lot of excitement in sharing my memories, likes, dislikes, interests and information with others. • I find social media quite entertaining in sharing my memories, likes, dislikes, interests and information with others. • I spend enjoyable and relaxing time on social media by sharing my memories, likes, dislikes, interests and information with others.	Cheung et al., (2015)
Self-Enhancement (SE)	• I feel social media improve my image by sharing my interests, likes and dislikes etc. with others. • I feel I can influence others on social media by sharing my memories, likes, dislikes, interests and information etc. • I feel I can make a good impression on others on social media through my interests, memories, likes, dislikes, and information etc. • Social media platforms help me present my best side to others by sharing my interests, likes and dislikes.	Al-Jabri et al., (2015)
Fear	• I am afraid of sharing information on social media. • I do not feel comfortable to share information on social media. • I feel social media gather my highly personal information, likes, dislikes interests and memories etc. • I feel social media share my digital footprints with third parties without my consent.	Dinev et al (2013)
Trust	• I feel social media providers are honest and caring about my digital footprints which I share on their platforms. • I feel social media platforms are reliable as they do not share my digital footprints with others. • I feel social media providers are interested in my well-being and they do not share my digital footprints with third parties. • I feel social media do not give access to third parties to have access to my personal information etc. •	Dowell et al., 2015; Morrow, et al., 2004
Exploration to Maximise Social Media Benefits (EMSMB)	• I explore social media to find new ways of sharing information, interests and memories with others. • I explore social media for potential new applications to share information etc. • I discover new ways of using social media to share my likes, dislikes, interests and information etc. with others.	Bala and Venkatesh, (2016)

	• I experiment with social media to find new features to share information, interests and memories etc.	
Exploitation to Satisfice Social Media Benefits (ESSMB)	• I use the same social media features that I learnt from others to share information on social media platforms. • I use common social media features to share my memories, likes, dislikes and interests etc. with others. • I use the same social media features suggested to me by others to share my memories and interests etc. on social media platforms. • I use social media features that I learnt from others on these platforms to share my likes, dislikes, interests and information etc.	Bala and Venkatesh, (2016)
Exploration to Revert (ER)	• Due to my privacy and security I now search for old ways of sharing information with others rather than social media. • Due to my privacy and security, I now look for old ways of sharing information with others when social media was not here. • I now use those methods, which were used before social media was introduced to share information with others due to my privacy and security. • Due to privacy and security, I have changed the use of social media now so that I can use old ways of sharing information with others.	Bala and Venkatesh, (2016)
Avoidance of Social Media (ASM)	• I try to avoid sharing information on social media due to my privacy and security. • I find other ways of sharing information without using social media due to my privacy and security. • I try to perform most of my information sharing without social media due to my privacy and security. • I stay away from sharing my memories, interests and information etc. on social media as much as I can because of my privacy and security.	Bala and Venkatesh, (2016)
Carelessness	• I do not care about my privacy and security when I share information on social media. • I do not take any precautions about my privacy and security when I share information on social media platforms. • I am inattentive to my privacy and security of my digital footprints on social media. • I do not pay attention to my privacy and security when I share information on social media.	White, (1961)
Carefreeness	• All things considered, there are no privacy and security concerns in sharing information on social media. • Information sharing is a normal part of social media due to which I am not worried about my privacy and security. • I am indifferent to my privacy and security when I share my digital footprints on social media platforms. • Information sharing is a regular part of social media due to which I have no issues with my privacy and security on these platforms.	Castro et al., (2017); White, (1961)
Consciousness	• I am aware that I will have privacy and security issues if I share information on social media platforms.	Dehaene and Naccache,

	• I am aware that there are privacy and security issues in sharing information on social media. • I am aware of the fact that sharing digital footprints on social media has privacy and security risks. • I am aware that sharing digital footprints on social media will have negative outcome for my privacy and security.	(2001); Tolle, (1999)
Cautiousness	• Sharing information on social media may cause me privacy and security issues in the future. • Sharing information on social media is a big issue for my privacy and security. • Sharing information, interests, memories, likes and dislikes on social media makes my privacy and security vulnerable. • I am alert about sharing information on social media as it may cause me privacy and security issues.	Rodríguez-Castro et al., 2017; White, (1961)

Table 4. 2 Questionnaire Items

4.4.5 Research Population and Sampling

In conducting research, it is vital to know whom and what to study for the feasibility of the study. Saunders et al. (2015) suggest that it is possible in some cases to collect data from the entire population. However, collection of data from the entire population does not necessarily provide useful information. In contrast, a representative sample provides a valid alternative to data from the entire population. Moreover, it is impractical in most cases to gather data from the entire population for several reasons, such as time, resources and the nature of research. It is usually impossible to determine the entire population due to several factors such as cost, time, resources and complexity of data (Saunders et al., 2015; Singleton and Straits, 2005). In line with the above argument, it is difficult to reach all social media consumers in this doctoral study and difficult to determine the total population of social media consumers at a specific point in time. Social media consumers are described to be in millions and it is difficult to determine the exact total number. Around 2.5 million British consumers, driven by social connection, alone are noted to buy on social media using smart phones and other smart devices (Criteo, 2016; Statista, 2019). Thus, it is difficult to determine and measure the total population of social media consumers.

Therefore, this research chose a random sample of social media consumers (over 18 years of age). Saunders et al. (2015) also provides a similar view. They posit that to examine the entire population, a researcher needs to gather components from a population to draw conclusions for the entire population and generalise the results. Similarly, Sarantakos (2012) suggests that a sample requirement, which reflects population attributes, is a very important characteristic for a quantitative research so that the conclusion derived can be attributed to the entire population called as a representativeness. Such attributes are considered to be valid and can be generalised. Moreover, the higher the representativeness is in sampling the higher the generalisability of the findings (Czaja and Blair, 2005).

4.4.5.1 Sampling Technique

De Vaus (2002) describe sample frame as the list or resources that contains the population elements. Saunders et al. (2015) identified two types of sampling techniques, namely probability and non-probability. Each element in the population has equal chance to be selected in probability sampling. Whereas in non-probability sampling, there is no equal chance for each element in the population to be selected from the population. The following Figure 4.3 illustrates the different types of sampling techniques.

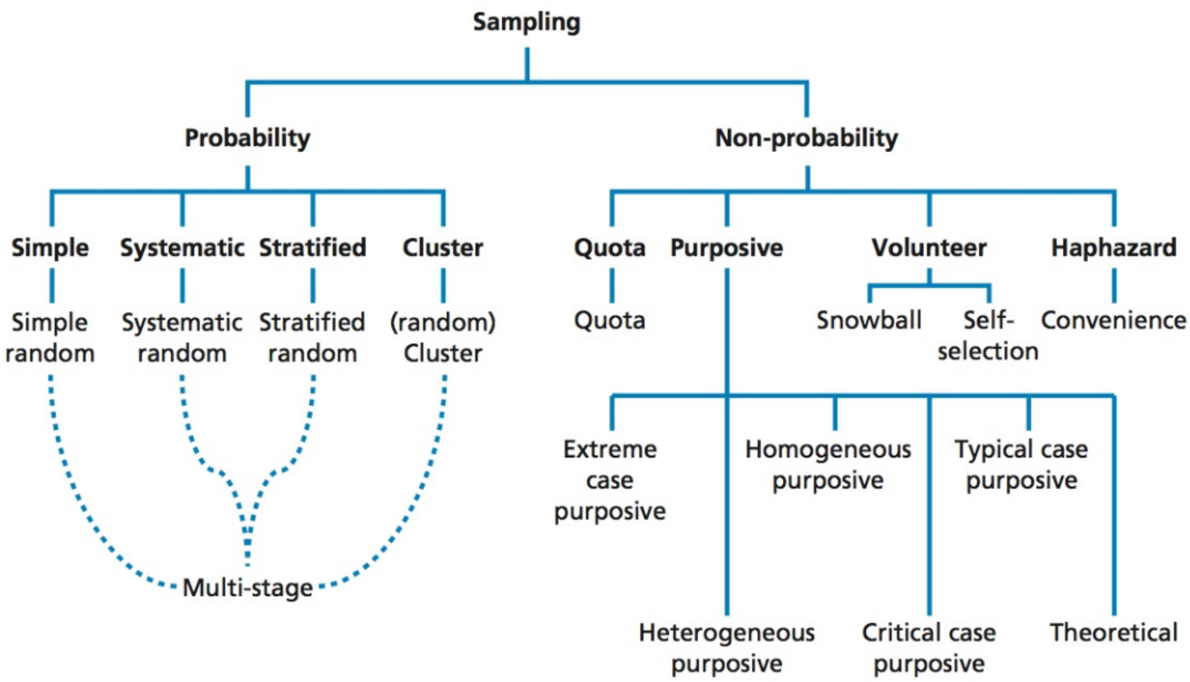

Figure 4. 3 Sampling Techniques (Source : Saunders et al., 2015)

Looking to the research aim and objectives of this research, simple random sampling technique is more suitable for this study. This technique enables the researcher to make inferences from a sample about a population to answer the research objectives. Simple random sampling eliminates a sampling bias. Moreover, it gives equal chance to every element in the population and provides a fair way to select an element from a population (Saunders et al., 2009). Therefore, this research uses a simple random sampling technique so that social media consumers have equal chance to be considered in the research. In this way the sampling bias is eliminated and the research derives generalisable inferences.

4.4.6 Data analysis

For the research design, to validate the relationships between key variables through quantitative analysis to test the theory, this research uses statistical procedures to analyse quantitative data which includes inferential advanced statistical analysis using Structure Equation Modelling (SEM).

4.4.7 Reliability and Validity

Cuskelly et al. (2006) suggest that the research instruments developed for the study needs to be validated. In line with the same argument, this research used Cronbach's Alpha to provide reliability measure and SEM for the validity of the instruments.

4.4.8 Time Horizon

To examine the underlying attitudinal components that determine social media adoption, adaptation and behavioural outcomes as a composite process, this research requires to collect data at a specific point in time (cross sectional data) as this doctoral research propose that consumers' social media adoption and adaptation is a composite process. Therefore, it needs to be examined as a composite process rather than separately. Thus, this research conducted a cross sectional data collection from a random sample of social media consumers. Questions are structured in a cross sectional research and they are administered through a questionnaire to a random sample in a survey to gauge respondents' (consumers') attitude (thinking and feeling) (Hair et al., 2018). In addition, cross sectional data collection provides several advantages such as save time, cost and is more effective when administered to a large representative sample of a population. Thus, this research collected data in a cross sectional technique to examine consumers' social media adoption, adaptation and behavioural outcome as a composite process.

4.5 Data Collection

This research chose online survey method to collect data due to the nature of data needed. As discussed above, it is considered to be the best suited method for consumer and client data collection. It allows to collect data from each sample case or element to represent the entire population (Hussey and Hussey 1997). This doctoral research developed an online survey which generated a URL. The URL was shared on social media platforms (Facebook, Twitter, Instagram and WhatsApp etc.) and consumers were requested to participate in the survey as per the research protocols. Respondents were also requested to forward the link to other social media consumers in their network. Matute et al. (2016) argue that social media platforms are very useful in sharing research questionnaire as they provide flexibility of communication amongst users. It provides ease and effectiveness to reach to the relevant participants. They also suggest that they are more appropriate for a random sampling technique and covers the demographic details well. Hence, looking at each aspect of this research such as time, cost, population size, rate of response, format of questions etc. (Aaker et al., 2001) and aim of the study online survey was the most suitable and appropriate choice for this research. It is the preferred method to conduct research with consumers and individual clients (Dwivedi et al, 2006). It provides accessibility, speed, convenience, availability and flexibility as suggested by extant literature (Cheung and Lee, 2012; Evans and Mathur, 2005; Gilbert, 2001). The online survey is given in Appendix 2. A covering letter was included in the questionnaire providing important details about this research and research ethics protocol. Before administering the questionnaire, approval was sought from the research ethics committee of Brunel University London.

4.5.1 Questionnaire Design

This research developed a questionnaire by following three important data collection variables, namely attribute, opinion and behaviour along with the appropriate scales, codes and categories (Dillman, 2006). Likert scale is chosen for the questions (Saunders et al., 2015). Questionnaire items are adapted from previous studies for construct retention and to the current research context (Cuskelly et al., 2006). Sekaran and Bougie (2013) describe that a questionnaire is pre-formulated set of questions for all respondents. They are more common in a survey, experiment and field studies and most efficient data collection mechanism for explanatory research. This research adhered to the rudimentary aspects of questionnaire design prescribed by Saunders et al. (2015) such as choice of words (simple words, avoided long and double barrelled questions), types of variable, the length of questionnaire and reliability etc. The questionnaire has three sections. The first section is the covering letter, which provides details about the research aim and objectives and other necessary details. The second section of the questionnaire covers important demographic details such as gender, age, and qualification etc. and screening (filter) questions about social media such as use of social media platforms, social media platform preferences and type of digital footprints they share on these platforms. The final section delineates the measures for antecedents, adoption, adaptation and behavioural outcomes using Likert scale. Most of the items of the constructs are adapted from the previous scholarly works of Al-Jabri et al., 2015; Bala and Venkatesh, 2016; Castro et al., 2017; Cheung et al., 2015; Dehaene and Naccache, 2001; Dinev et al., 2013; DeVellis 2016; Dowell et al., 2015; Morrow, et al., 2004; Rodríguez-Castro et al., 2017; Tolle, 1999; and White, 1961 respectively. Since most of these items had already been used and tested by other studies, it provides validity and reliability to this study. Moreover, prior literature and the base theories helped in the construction of the questionnaire items and its sequential development to pre-pilot, pilot test and full scale online administration of the questionnaire. Final questionnaire used in the survey is given in Appendix 2.

4.5.2 Likert Scale

This research used Likert scale as it is more suitable to for scale questions to measure consumers' degree of agreement to constructs (Sekaran and Bougie, 2013). It is considered to be more suitable scale for an online survey and easy to measure respondents agreement or disagreements, mental and behavioural beliefs (Hair et al., 2014). Prior studies used 7 point Likert scale for higher reliability (Oaster, 1989) but Matell and Jacoby (1971) highlight that reliability is independent of the choice made on the number of points in the Likert scale. However, 5 point Likert scale is identified to be both simpler and quicker for respondents to choose from. Thus, 5 point Likert scale is used in this study for the questionnaire.

4.5.3 Pre-Pilot test

Pre-testing of a questionnaire evaluates questionnaire items and is good for a trial run to know the problems with questionnaire at an early stage (Hair et al., 2018). Sekaran and Bougie, (2013) suggest that a trial run with those that need to take part in the questionnaire is good so that the researchers gets feedback, spot early problems and improve on the weaknesses in the questionnaire. Sheatsley (1983) suggests that the number of cases needed for a pre-pilot test is between 12 to 25 cases. In line with the above argument, this research conducted a pre-pilot test with academics and PhD students of social media consumers. From the feedback of the pre-pilot test the wording and structure of some of the questions were revised such as unnecessary and words difficult to understand (e.g. considerate, cognisant etc.) were dropped.

4.5.4 Pilot Study

Pilot study tests the questionnaire on a small scale so that the possibility of any problems faced by the respondents is minimised (Saunders et al., 2015). Ticehurst and Veal (2000) suggest that all aspects of the survey can be tested by the pilot study. In addition, pilot study provides an opportunity to look at the validity of the constructs and improve questions before administering the questionnaire in full (Creswell et al., 2003). In line with the same argument, this research conducted a pilot study by sharing the survey link with 50 respondents on social media platforms in the network circle of the researcher. 40 responses were received and the required statistical analysis reliability and validity tests were done. The details are given in section 4.8 and 4.9 respectively. Based on the outcome of the pilot study, the wordings and structure in some questions were revised. This process is in line with the guidelines prescribed by Nisbet and Entwistle (1970) that questions need to be refined so that respondents do not encounter any problems responding to the questionnaire as pilot study helps in assessing the feasibility of the final survey. It tests the instruments and identifies any logistical issues that may hinder the full launch of the survey.

4.6 Reliability Test (Pilot Study)

Reliability determines the goodness of a measure and its accuracy. It means if a researcher repeats the same research from a different or same sample, it should derive similar results or findings and should be without bias or error (Sekaran and Bougie, (2013). Cronbach's Alpha is the most widely used and helpful tool in measuring reliability of a scale (Hayes and Pritchard, 2013). It is good for measuring reliability of inter-item consistency if the questionnaire items are correlated (Sekaran and Bougie, 2013). Generally 0.7 and above value of reliability is considered to be acceptable whereas the value of 0.6 and below are considered to be low. Hinton et al. (2014), suggest that the reliability values from 0.7 to 0.9 are high, 0.5 to 0.7 are moderate and values above 0.9 are excellent whereas values below 0.5 are a poor reliability.

This research used the Statistical tool package of SPSS (Statistical Package for the Social Sciences) version 25 to measure Cronbach's Alpha values for pilot study. Alpha value of each construct is given in Table 4.3 below. The reliability of most of the constructs are in the acceptable range with the highest value ranging from 0.842 to 0.671. Thus, the empirical evidence shown in Table 4.3, confirms that most construct items measuring the same construct dimension had an acceptable internal reliability and were satisfactory. However, for Consciousness and ESSMB the alpha values were less than 0.7, yet both were close to the moderate threshold of 0.7. None of the items were deleted but the wordings and sentence constructions for these items were simplified which improved reliability and item to item correlation in the final survey. Thus, research instruments overall were found to be reliable for a full launch of the survey.

Construct	Cronbach's Alpha
Perceived Opportunity (PO)	0.776
Perceived Social Influence (PSI)	0.700
Perceived Control (PC)	0.825
Enjoyment	0.842
Self-Enhancement (SE)	0.780
Fear	0.800
Trust	0.803
Exploration to Maximise Social Media Benefits (EMSMB)	0.755
Exploitation to Satisfice Social Media Benefits (ESSMB)	0.671
Exploration to Revert (ER)	0.796
Avoidance of Social Media (ASM)	0.757
Carelessness	0.830
Carefreeness	0.783
Consciousness	0.693
Cautiousness	0.748

Table 4. 3 Cronbach's Alpha (Pilot Study)

4.7 Instrument Validity

When data truly represents an event or a happening, the validity of that data would be high. As a result, the data would be accurately representing the event and the research would be called as a valid research. Validity assesses the ability of the construct to measure what it aims to measure (Burns and Bush, 2002; Cohen et al. 2007). Similar argument was made by Hair et al. (2014) that measurement of validity gives guarantees for content and construct validity. Ticehurst and Veal (2000) argue that if the true meanings of the responses are not obtained from the survey, it will create validity issues. Sekaran and Bougie (2013) identifies three types of validity tests, namely construct, criteria and content validity. Therefore, it can be argued that validity plays an important role and this research undertakes the following three types of validity tests in this study.

Content validity is a face validity that determines the relationship between items and the phenomenon that taps the concept with adequate set of items (Hair et al., 2006; Sekaran and Bougie, 2013). Content validity depicts a phenomenon or objectives set for a research. In other words, content validity as a scale of measurement shows the real meaning of the construct for which it is developed. This research, in line with the above argument, have chosen the constructs that have been used in previous research (Churchill and Iacobucci, 2006). The constructs are adapted from technology adoption and adaptation literature. Similarly, constructs used in behavioural outcomes are derived from consumer psychology studies and research that studied individuals' attitude.

Sekaran and Bougie (2013) argue that construct validity testifies the results derived from the use of the measure that fits the theories. The same line of argument is made by Zikmund (2000) that construct validity measures the extent to which measures link with each other to gauge the concept aligned with the theory. Construct validity, as described by Rowley (2002), is an important measure to study a concept as it deals with subjectivity of the measurement by linking instrument from data collection to the research aim. Similarly, validity results are vital for the research because they need to be of good value to the supporting theory. Johari et al. (2011) suggest that construct validity could be obtained by Exploratory Factor Analysis (EFA) or Confirmatory Factor Analysis.

Construct validity for this research is assessed through convergent and discriminant/criterion validity. When two different instruments, through their measured scores, measuring the same construct are highly correlated, convergent validity is established (Sekaran and Bougie, 2013). It is the correlation between the item and other items measuring the construct. Convergent validity will be high if the item correctly represents the measured construct (Holton et al. 2007). This research performed convergent validity to check for shared variance amongst different variables and deployed factor loading for each construct and Average Variance Extracted (AVE). To review convergent validity, Hair et al. (2014) suggest that a researchers needs to deploy factor loading for each construct and AVE such that AVE is >0.5, reliability >0.7 and standardised loading of the model is greater than or equal to 0.7. Similarly, Robinson et al. (1991) argue that convergent validity can be obtained by correlation of two measures, that is item to item and item to total correlation. This research deployed factor loading and AVE for each construct besides Construct Reliability (CR) and the results for all constructs have high convergent validity. The detailed results for convergent validity are given in the next chapter.

Discriminant validity for this research is assessed by AVE obtained from the squared inter-construct correlation of different constructs. Hair et al. (2014) described discriminant validity as the measure of distinction between latent construct and other constructs. It can be obtained by AVE obtained from the squared inter-construct correlation of different constructs. Similarly, Sekaran and Bougie (2013) argue that discriminant validity is obtained when two variables are predicted to be uncorrelated and their results from the empirical findings confirm such uncorrelated relationship. The results of discriminant validity obtained for this research are given in the next chapter.

4.8 Main Survey

Fink (2003) defines a survey as a system to collect information from people to describe their attitude, behaviour and knowledge etc. After the pilot study, the main survey was launched. Matute et al. (2016) argue that social media platforms provide flexibility of communication amongst users and provides flexibility for research scholars to share their research questionnaire with respondents. It provides ease and effectiveness to reach to the relevant participants. Looking to these and other aspects of time, cost, population size, the type of study etc. an online survey was more appropriate for this study. The link of the survey was shared on major social media platforms (Facebook, Twitter, Instagram, LinkedIn, WhatsApp etc.). As the population size of social media consumers is huge, a survey based on a random sampling technique was used to collect data. Initially, the response rate was low but repeated reminders and sharing of URL on these platforms helped in a better response rate.

As mentioned above, the total population of social media consumers could not exactly be determined. However, they are in millions (Criteo, 2016). Krejecie and Morgan (1970) provided guidelines for a sample size, given in Table 4.4, when the population size is in millions.

N	*n*	*N*	*n*	*N*	*n*	*N*	*n*	*N*	*n*
10	10	110	86	300	169	950	274	4,500	354
15	14	120	92	320	175	1,000	278	5,000	357
20	19	130	97	340	181	1,100	285	6,000	361
25	24	140	103	360	186	1,200	291	7,000	364
30	28	150	108	380	191	1,300	297	8,000	367
35	32	160	113	400	196	1,400	302	9,000	368
40	36	170	118	420	201	1,500	306	10,000	370
45	40	180	123	440	205	1,600	310	15,000	375
50	44	190	127	460	210	1,700	313	20,000	377
55	48	200	132	480	214	1,800	317	30,000	379
60	52	210	136	500	217	1,900	320	40,000	380
65	56	220	140	550	226	2,000	322	50,000	381
70	59	230	144	600	234	2,200	327	75,000	382
75	63	240	148	650	242	2,400	331	100,000	384
80	66	250	152	700	248	2,600	335	250,000	384
85	70	260	155	750	254	2,800	338	500,000	384
90	73	270	159	800	260	3,000	341	1,000,000	384
95	76	280	162	850	265	3,500	346	10,000,000	384
100	80	290	165	900	269	4,000	351	500,000,000	384

Table 4. 4 Sample Size Guide (Source: Krejecie and Morgan, 1970)

Similarly, Saunders et al. (2015) provide sample size guidelines for different population size with their respective confidence interval. The Table 4.5 below delineates the guidelines of sample size for certain margin of errors.

Target population	5%	3%	2%	1%
50	44	48	49	50
100	79	91	96	99
150	108	132	141	148
200	132	168	185	196
250	151	203	226	244
300	168	234	267	291
400	196	291	343	384
500	217	340	414	475
750	254	440	571	696
1 000	278	516	706	906
2 000	322	696	1091	1655
5 000	357	879	1622	3288
10 000	370	964	1936	4899
100 000	383	1056	2345	8762
1 000 000	384	1066	2395	9513
10 000 000	384	1067	2400	9595

Table 4. 5 Sample Size Guide (Source : Saunders et al., 2015)

Thus, this research followed guidelines provided by Krejecie and Morgan (1970) and Saunders et al. (2015) wherein they confirmed that when the total population size runs in millions, it is possible to have a sample size in hundreds to make meaningful predictions and inferences about the population. In addition, this research followed guidelines provided by Hair et al. (2018) for the sample size required for Structural Equation Modelling. As result of the final survey a total of 733 responses were achieved. However, some of the responses had to be discarded due to missing and unengaged responses.

4.9 Data Analysis

Saunders et al. (2015) suggest that it is vital for researchers to prepare, enter and check data for quantitative data analysis. Data needs to be checked for accuracy, completeness and suitability before analysis (Sekaran and Bougie, 2016). This research used coding under the

Likert Scale of 1 to 5 with 1 being Strongly Disagree, 2 Disagree, 3 Neutral, 4 Agree and 5 Strongly Agree respectively. Data was in the spreadsheet format, the row represented a case and each column represented a variable (Sekaran and Bougie, 2016). Coding of questionnaire items are provided in Appendix 3. Moreover, this research followed guidelines suggested by Gaskin (2016) for data screening. Missing data was removed along with inconsistent and unengaged responses. After cleaning the data, the final number of cases from the random sample arrived at 692. The cases that could have made the analysis biased were removed from the data (Sekaran and Bougie, 2016).

In addition, data was checked for normality which along with missing data are considered as important aspects for Confirmatory Factor Analysis (CFA). Standard deviation and measured Skewness and Kurtosis were carried to check for outliers because such tests are important for the normality of the data (Wilcox, 2011). Similarly, for multivariate normality of data Skewness and Kurtosis measures can be undertaken. Skewness determines the asymmetrical relation to a normal curve and Kurtosis detects to what extent the data is peaked or flat to the normal curve (Cohen et al. 2007). This research tested for outliers, Skewness and Kurtosis for multivariate normality. The data was found to be both normal and no multivariate issues were found in the data. Data for Skewness and Kurtosis fell within the normal range of ±2.0. The details are given in the next chapter.

Software package of SPSS and AMOS were used for overall data management. These packages were found extremely useful for data analysis as Arbuckle (2010) suggests that SPSS and AMOS can be used for structural equation modelling, covariance structure analysis and general linear modelling.

This research undertook data analysis in two steps by using SEM as suggested by Anderson and Gerbing (1988). In the first step, this study undertook factor loading followed by reliability and validity measurement through Confirmatory Factor Analysis of the latent constructs for the measurement model. In the second stage, this research undertook Structural Equation Modelling process to test for hypothesis connections amongst the latent constructs of the model.

4.10 Descriptive Statistics

Descriptive statistics means to present raw data in a format that can give meaning to factors such that they can be interpreted and understood (Zikmund, 2000). Similarly, it means to check for a mean, standard deviation, Skewness and Kurtosis etc. which are the necessary assumptions made for the research before data analysis (Pallant, 2007). Based on univariate analysis, descriptive statistics provides the details of the central tendencies, tabulated frequencies and graphical presentation and enables the researcher to describe and compare variables numerically (Saunders et al., 2015). In this research descriptive statistics is used to provide demographic details, which are given in the next chapter. In addition, it provides details about consumers' use of social media platforms and the type of digital traces they share on these platforms. Thus, descriptive statistic for this research summarises and organises the key characteristics from the survey.

Part II: Structure Equation Modelling and Justification

4.11 Structure Equation Modelling

This part discusses Structural Equation Modelling (SEM) and its justification for this study. As causal relationships and hypothesised relationships were specified in the previous chapter, this chapter provides details on how they are tested and what techniques have been used. Therefore this research uses multivariate analysis comprising Exploratory Factor Analysis (EFA) and the two step approach recommended by Anderson and Gerbing (1988) for Structural Equation Modelling (SEM). Hair et al. (2018) describe that SEM explains relationships among multiple variables. It examines all relationships amongst constructs involved in the analysis and it determines the structure of interrelationships expressed in equations. SEM is a unique combination of both factor analysis and multiple regression analysis. Mostly empirical research use SEM for statistical analysis (Hox and Bechger, 1998). Multivariate type of data can be analysed using SEM and it can analyse multiple dependent and independent variables. SEM is prevalent in many research areas especially it is found more common in IS and Marketing research. Both latent and observed variables can be analysed using SEM along with theory and model assessments. SEM is a very useful statistical tool for model analysis and assessment. It provides flexibility to deal with non-standard models, time series, longitudinal data, incomplete data and not normally distributed variables (Hair et al., 2018).

In this research, the measurement of technology adoption, adaptation and behavioural outcomes are developed from prior established scholarly works. EFA is used to test the items and check for dimensionality of the constructs and factor cross loadings to refine research instruments, retain or delete any research items. EFA is followed by a Confirmatory Factor Analysis (CFA) to test for reliability and validity of the model in SEM. EFA followed by a CFA in the same study is criticised by some researchers e.g. Chin, (1998); Hurley et al., (1997). They argue that EFA does not lead to replicate results but capitalise more on the possibility of chance. However, many researchers support EFA and CFA in the same study e.g. Parasuraman et al., (2005) and Wolfinbarger and Gilly, (2003). They argue that when a theoretical model has been specified a priori, EFA provides a better first step for CFA.

Factor analysis comprises of EFA and CFA. Coakes and Steed (2003) argue that factor analysis is a technique used to reduce large variables into a smaller factors containing essential underlying information. In EFA, the analysis is exploratory in nature which means a researcher has no prior knowledge that the items measure specific measures. The link between observed and latent variables in EFA is therefore not known to the researcher. In contrast, Byrne (2001) argue that in CFA a researcher based on the knowledge of the theory specifies the relationship between the observed and latent variables a priori. It means the researcher in CFA knows that the postulated relationship between the observed and latent variables exists and tests these propositions statistically.

EFA helps researchers in identifying which items constitute the constructs, whereas CFA is a more rigorous test of unidimensionality. CFA provides stricter interpretation of unidimensionality. It provides different conclusions as compare to EFA about the acceptability of scales (Gerbing and Anderson, 1988). Nonetheless, both EFA and CFA have their own unique utilities, strengths and weaknesses (Kelloway, 1995). Thus, the above discussion justifies the use of EFA in this research prior to CFA.

As discussed above, a two-step approach as recommended by Anderson and Gerbing (1988) is used in SEM, the first step is a measurement model dealing with the Confirmatory Factor Analysis, which determines a connection between a series of observed variables and latent variables. The measurement model comprising of CFA evaluates convergent and discriminant validity of the measurement model. Both convergent and discriminant validity are discussed at length above under data analysis.

CFA is followed by step two, the full Structural Model. This step deals with testing the full theoretical model and hypotheses. This step deals with multivariate regression equations. It tests the existing relationships among factors, observed variables and between the observed variables and the factors that are not among the factor indicators. Such relationships are called multinomial logistic regression equations (MacCallum and Austin, 2000). The second step approach of SEM deals with nomological or predictive validity in this research. Hair et al. (2018) suggest five steps for SEM, namely model specification, model identification, measure selection and data preparation, model estimation and model fit. This research carried out the above steps for structural model to test for the hypothesised relationships, In model identification under SEM, this research checked for any offending estimates such as negative variance or Haywood cases. From the results of this research given in chapter 5, the model did not indicate any non-positive definite situation or Haywood case. Secondly, this research checked for model fit indices which are classified into goodness and badness of fit indices. However, the recommended or ideal fitness indices reported in prior research are Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Residual (RMSEA) (Gaskin, 2016). In addition to these, this study also report CMIN/DF ($\chi 2$/df), Incremental Fit Index (IFI) and Normed Fit Index (NFI) etc.

After model fit indices, statistical significance of all parameter estimates are checked for convergent validity in SEM. It is checked through standardised factor loadings with values >0.5 and parameter estimates which must be significant with values of at least <0.05 or less. This study as mentioned above used AMOS version 25 both for factor analysis and SEM.

Thus, based on the above discussion this research uses SEM because it is considered to be a confirmatory tool, which can lead to identify a model that can make a theoretical sense (Byrne, 2016; Kline, 2015). Furthermore, SEM is used because it helps the researcher to model the direction of the relationship in multiple regression equation and uncover how independent variables explain the dependent variables (Abramson et al., 2005). As this research uses interrelated dependence relationships in adoption, adaptation and behavioural outcomes as a composite process, SEM allows to test the theoretical model in addition to cause related hypothesis. Moreover, SEM supports multiple regression equations (Kline, 2015). It integrates factor analysis tools with regression analysis to assess connections in different constructs. Therefore, this research uses SEM as it combines the rationality of multiple regression and path analysis and it considers relationships amongst the constructs and latent variables (Hair et al., 2014).

4.12 Ethical Considerations

For any research ethics is the most critical part (Saunders et al., 2015). Stutchbury and Fox (2009) summarised that research undertaken in situations which involve people interacting with others will have ethical dimension and the current research is no exception. Similarly, ethical concerns will be massive if research involves human participants (Saunders et al., 2015). Researchers need to take into account while collecting data such as confidentiality, respondents should not be forced to respond and distortion of the data (Sekaran and Bougie, 2016). This doctoral research, aligned with the above argument, took into account all the ethical issues that generally arrive at any stage of the research. Before administering the questionnaire including pre-pilot and pilot tests, both questionnaire and the covering letters were approved by the research ethics committee of Brunel University London. In addition, this research adhered to the research ethics standards and followed the necessary steps for ethics approval from the Brunel Research Ethics Committee. It also complied with the PhD research ethics guide of Brunel Business School and followed the due process for ethics approval. This study provided a covering letter to respondents delineating the details about the research, aim and objectives of the research along with the necessary research protocol guidelines, which gave the option to participants to withdraw from the survey at any time they wished. In addition they were given contact details of the researcher if they had any ethics related query. This research took into account the research ethics code of the university and maintained anonymity, confidentiality and respect for others including beneficence, justice, respect for communities and informed consent etc.

4.13 Conclusion

This chapter focused on the research methodology explaining the research framework and design along with the research analysis used to test hypothesis. It analysed several research philosophies and chose the positivist research paradigm for this research along with the choice of research approach, strategy, design and research methods with justification for this research. Furthermore, this chapter delineated data collection and data analysis techniques used in this research along with the sampling techniques chosen for data collection with details of pre-pilot, pilot and main survey. It discussed in detail the research methodology in depth with each section separately and highlighted the ethical consideration for this research.

Chapter 5. Results and Analysis

5.1 Introduction

This chapter provides the results and analysis of this study. A two-step approach, as recommended by Anderson and Gerbing (1988), is used to test the model. In the first step, Confirmatory Factor Analysis (CFA) is carried out to test the validity and reliability of the Measurement Model. In the second step, a full structural model is carried out to assess the nomological validity of all the constructs in the proposed model and to test the research propositions and hypothesis. This chapter is structured as follows. First, data management and descriptive statistics with demographic details of the respondents are presented. Second, Exploratory Factor Analysis (EFA), KMO and reliability tests are given. Finally, the two-step approach of CFA and the structural model are delineated, followed by a brief summary of the chapter.

5.2 Data Management (Normality)

Data need to be prepared before SEM analysis can be carried out (Dwivedi et al., 2017a). Sekaran and Bougie (2013) suggest that data should be edited to check for missing data, unengaged responses, inconsistencies, omissions and outliers. For data management, this research cleaned the data, covering the above aspects, following the data cleaning process specified by Gaskin (2016). Missing data were removed, along with inconsistent and unengaged responses. The final number of cases in the data was 692 and 41 cases were removed, which could have made the analysis biased (Sekaran and Bougie, 2013).

This research carried out standard deviation and measured Skewness and Kurtosis to check for outliers, because such tests are important in assessing the normality of the data (Wilcox, 2011). Skewness and Kurtosis for multivariate normality and data were both found to be normal, and no normality issues were found. Data given in Table 5.1 for Skewness and Kurtosis fell within the normal range of ±2.0. Researchers argue that for multivariate normality of the data, Skewness and Kurtosis measures can be used (Cohen et al. 2007; Sposito et al., 1983). Skewness determines the asymmetrical relation to a normal curve and Kurtosis detects the extent to which the data is peaked or flat relative to the normal curve (Cohen et al. 2007). Kurtosis will not be different from the normal distribution if its value is less than three times the standard error (Sposito et al., 1983). A similar point was made by Kline (2015), who stated that if Skewness and Kurtosis of the variable deviate by more than ±3.0, it will not have a normal distribution.

Skewness and Kurtosis				
	Skewness	**Std. Error of Skewness**	**Kurtosis**	**Std. Error of Kurtosis**
Cautious	-0.15	0.09	-1.23	0.19
Conscious	-0.20	0.09	-1.14	0.19
ASM	0.13	0.09	-0.99	0.19
ER	0.59	0.09	-0.10	0.19
Trust	0.03	0.09	-0.98	0.19
Fear	-0.02	0.09	-1.05	0.19
Carefree	0.27	0.09	-1.04	0.19
Careless	1.01	0.09	0.41	0.19
ESSMB	-1.14	0.09	0.75	0.19
EMSMB	-0.85	0.09	0.36	0.19
SE	-0.89	0.09	0.20	0.19
Enjoyment	-0.80	0.09	0.21	0.19
PC	-0.76	0.09	-0.61	0.19
PSI	-0.80	0.09	0.28	0.19
PO	-0.52	0.09	-0.34	0.19

Table 5. 1 Skewness and Kurtosis

5.3 Descriptive Statistics

Descriptive statistics provide demographic information with details about the respondents' use of social media platforms and the types of digital traces they share on these platforms. Similarly, descriptive statistics for this research summarised and organised the key characteristics from the survey.

5.3.1 Demographic data

5.3.1.1 Gender

The online survey questionnaire was designed with the demographic details in the first section. Important demographic details were included to capture the key details, such as age, gender, education level and whether the respondents are UK residents. Having run the survey for more than six months, the response rate initially was low. However, as the survey was facilitated online on social media platforms, it provided both flexibility and agility to send frequent reminders and sharing of links with the respondents. Having received the responses, Figure 5.1 shows that the questionnaire was undertaken by both the genders. However, it was found that more males undertook the survey than females. As shown in the figure below, around 67% of respondents were male and 33% were female.

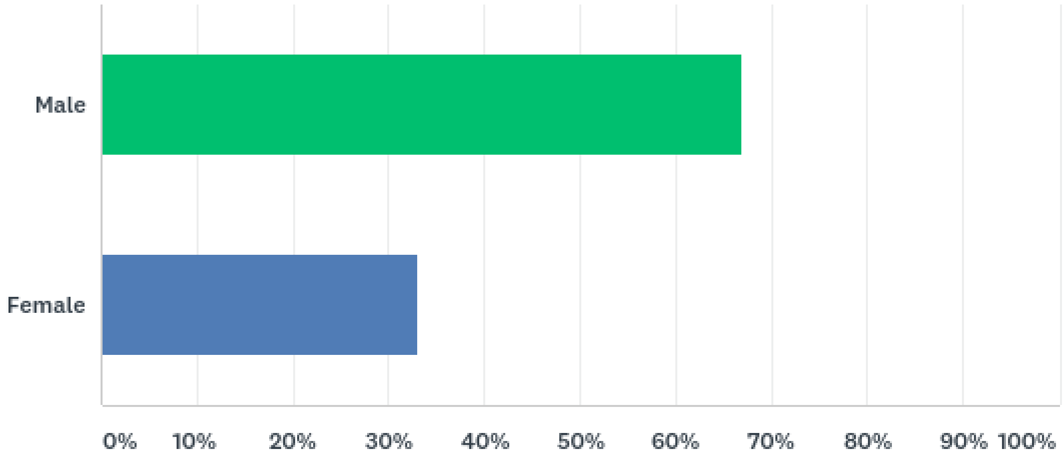

Figure 5. 1 Gender

5.3.1.2 Age

This research investigates social media consumers. Social media platforms are expanding very rapidly and their adoption and adaptation span the different ages. The questionnaire in the demographic section included a question about respondents' age. It is interesting to see the outcome, as shown in Figure 5.2. Social media adoption spans the age spectrum, ranging from 18 years to over 65. As per the research ethics protocol, only respondents aged 18 and above were included in the questionnaire. It can be seen from Figure 5.2 below that the highest age group accepting and using social media comprises respondents aged 30 to 49. Moreover, respondents over 50 have also adopted social media platforms. In the survey, around 52.39% were in the 30-49 year age group, which was the highest, followed by 40.77% aged 18-29 and 6.29% aged 50-65. No respondent in the over-65 age group attempted the survey. However, they may have adopted social media platforms.

A filter questions was given in the survey for non-social media users, with the option to provide the reasons for not using/accepting social media. Only 13 respondents mentioned that they did not use social media. Two respondents mentioned that they used to use social media but do not do so any more, while the reasons for other respondents are quoted in Figure 5.3. It is also interesting to note that these respondents selected the option of not using social media but provided details suggesting that they were using social media. For instance, some respondents selected the option of not using social media but mentioned that they used social media platforms in different contexts, such as for work, or for different purposes such as sharing information or gaining knowledge. Moreover, the majority of the respondents highlighted time, risk and control factors as the key reasons for not using social media.

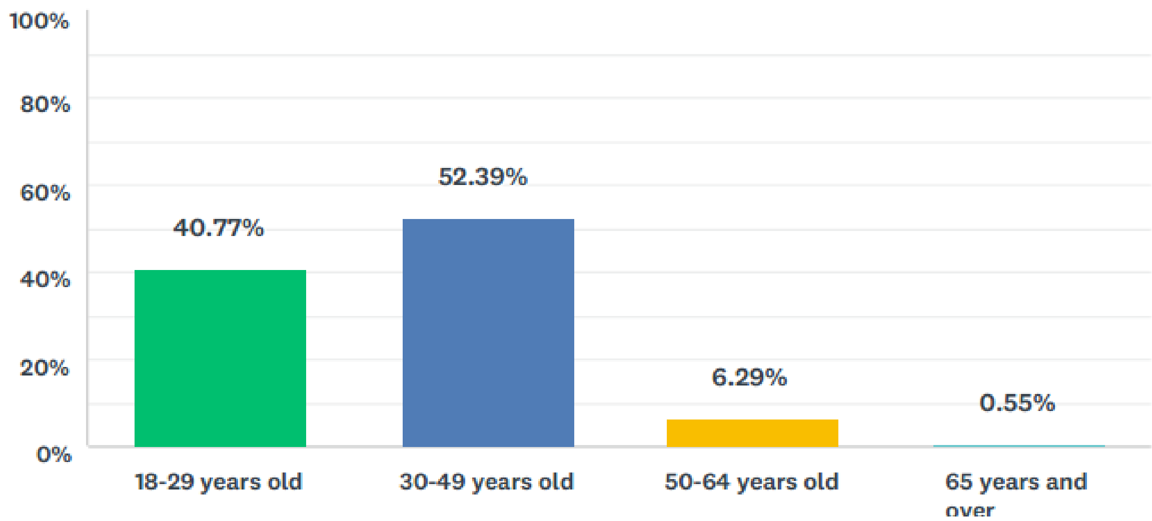

Figure 5. 2 Age

	REASONS:
1	Once I have used Facebook and Twitter. Then I realized that most of social media tools a major trap of today's individuals and time consuming.
2	WhatsApp
3	Waste of time
4	Too much risk by exposing the personal information to many and unspecified people
5	Knowledge
6	because it wastes the time.
7	It's just a weast of time
8	I have never felt the need or that I was disadvantaged in anyway by not doing so.also I think it will be a distraction.and I'm time poor.
9	I am using social media
10	facebook
11	Information
12	Because they take a control and check everything
13	Being a working mum I don't have much time to spend on social media- although I could use twitter only at work to tweet for important events

Figure 5. 3 Reasons for Avoiding Social Media

5.3.1.3 Qualifications

Figure 5.4 delineates the details about the qualifications of respondents. Qualification does not have a significant contribution to the participants' information. However, it does provide respondents' level of education. As shown in Figure 5.4, around 49.04% of the respondents had postgraduate qualifications. Similarly, 33.06% had graduate qualifications and 17.90% reported high school as their highest qualification. Therefore, it can be argued that most of the respondents were educated to undergraduate or postgraduate level.

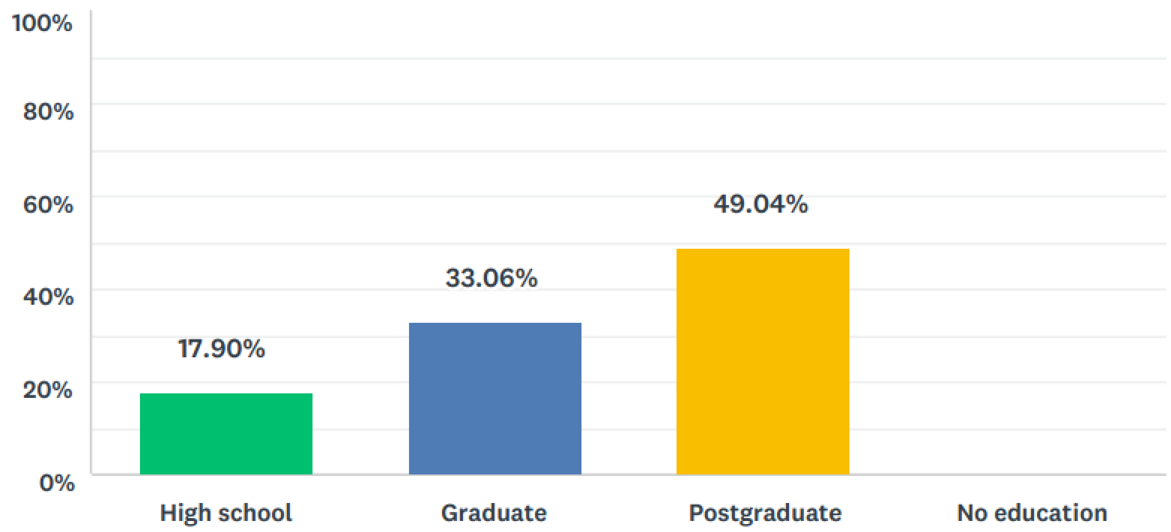

Figure 5. 4 Respondents' Qualifications

5.3.1.4 UK Residents

Respondents were also asked about their status in the UK (residents). Social media is borderless, and therefore this research aimed to gather a random sample of consumers on social media platforms. Figure 5.5 shows that the majority of the respondents (54.17%) were UK residents, while 45.83% were from other geographic regions. Therefore, this research has social media consumers both from the UK and other geographic regions.

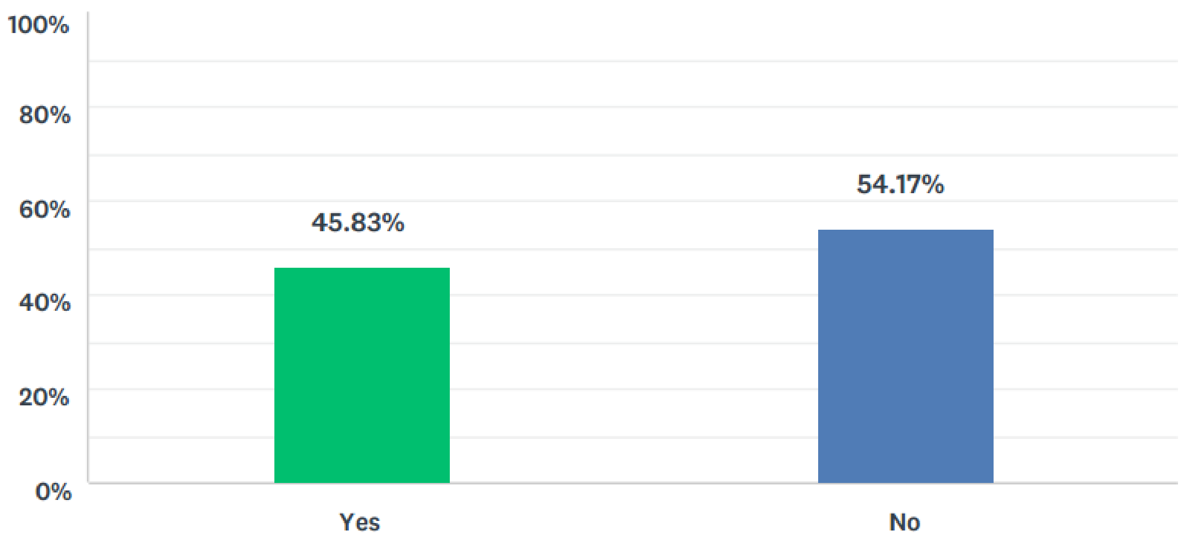

Figure 5. 5 UK Residents

5.3.1.5 Use of Social Media

Adoption and adaptation of social media is the main focus of this research. Along with the demographic information, respondents in the survey were asked if they use and have adopted social media. It was very interesting to note that almost every respondent had used and accepted social media. Figure 5.6 shows that around 99.05% respondents were social media users and fewer than 1% were non-social media users. Those respondents who did not use social media were asked to provide reasons for not adopting and using social media. Respondents provided some interesting responses for not using social media; for example, one respondent provided the following note:

> "*Being a working mum, I don't have much time to spend on social media-although I could use twitter only at work to tweet for important events*".

This shows that they still use social media, even though they think that they don't use or accept social media.

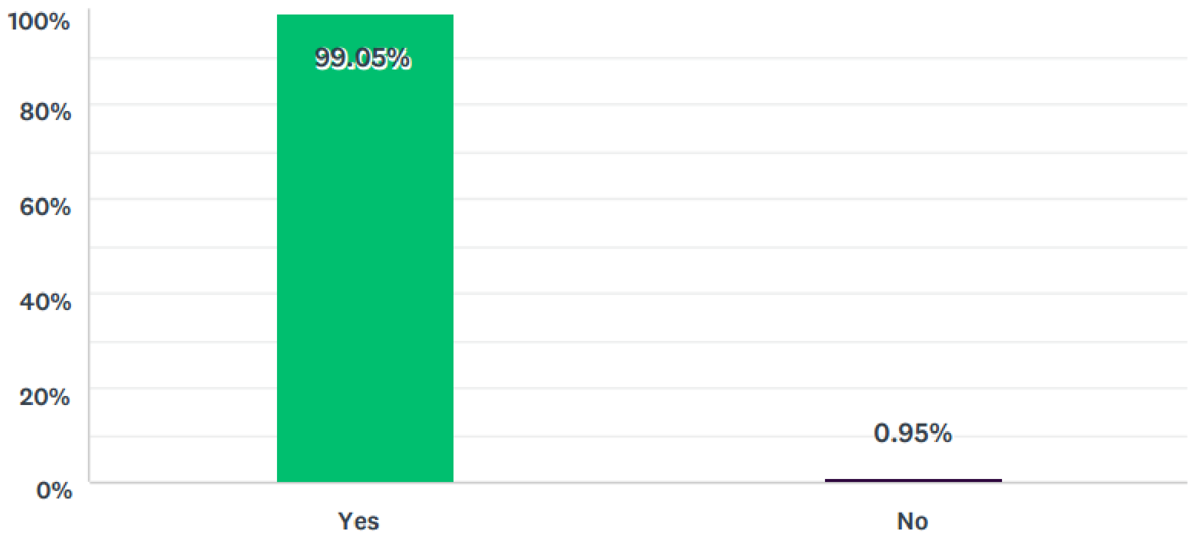

Figure 5. 6 Social Media Users

5.3.1.6 Social Media Platforms

Consumers use many different social media platforms. The details of the social media platforms adopted and used by consumers are given in Figure 5.7. The main platforms used by consumers are Facebook, Instagram, WhatsApp, YouTube, Twitter, and LinkedIn. It can be noted that Facebook users, as mentioned in Chapter 1, number in the billions, but respondents in the present study are found to be inclined more towards WhatsApp and YouTube. In addition, respondents mentioned many other platforms that they use, such as Viber, IMO (In My Opinion), Research Gate and Skype.

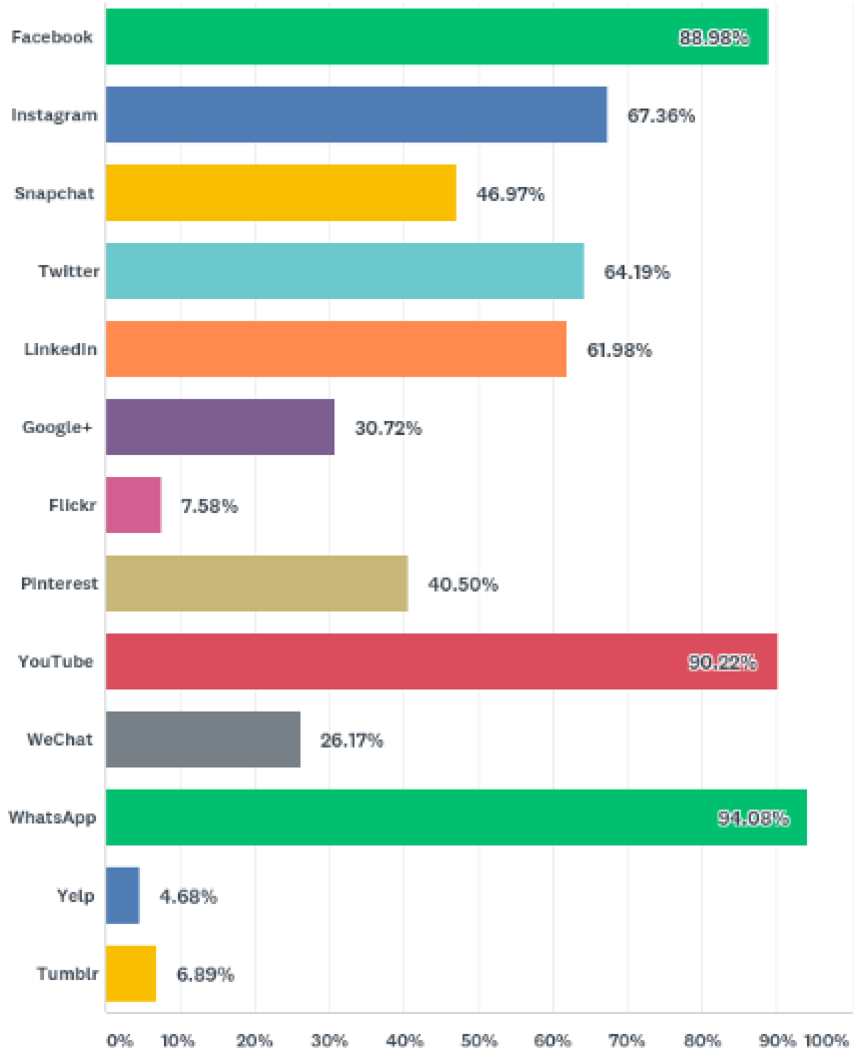

Figure 5. 7 Social Media Platforms Used by Consumers

5.3.1.7 Digital Footprints Consumers Share on Social Media

It is important for this research to know what digital traces consumers share on these platforms. Therefore, the survey provided a list of digital traces that consumers might share. Figure 5.8 shows the type of digital footprint that consumers share on social media platforms. The key digital traces shared are shopping, networking, downloading movies/music, sharing information, interests, likes and dislikes. Figure 5.8 shows that the highest digital traces shared on these platforms are shopping-related. In addition, respondents mentioned that they share digital footprints such as lectures, notes, current issues, stories, study materials, cooking recipes, advertising, running campaigns, business-related material, marketing products, learning resources, job searches and adverts, foreign language learning materials, sports information, browsing the web and commenting on the information received. It can be argued that consumers share different types of digital footprints in many shapes and forms.

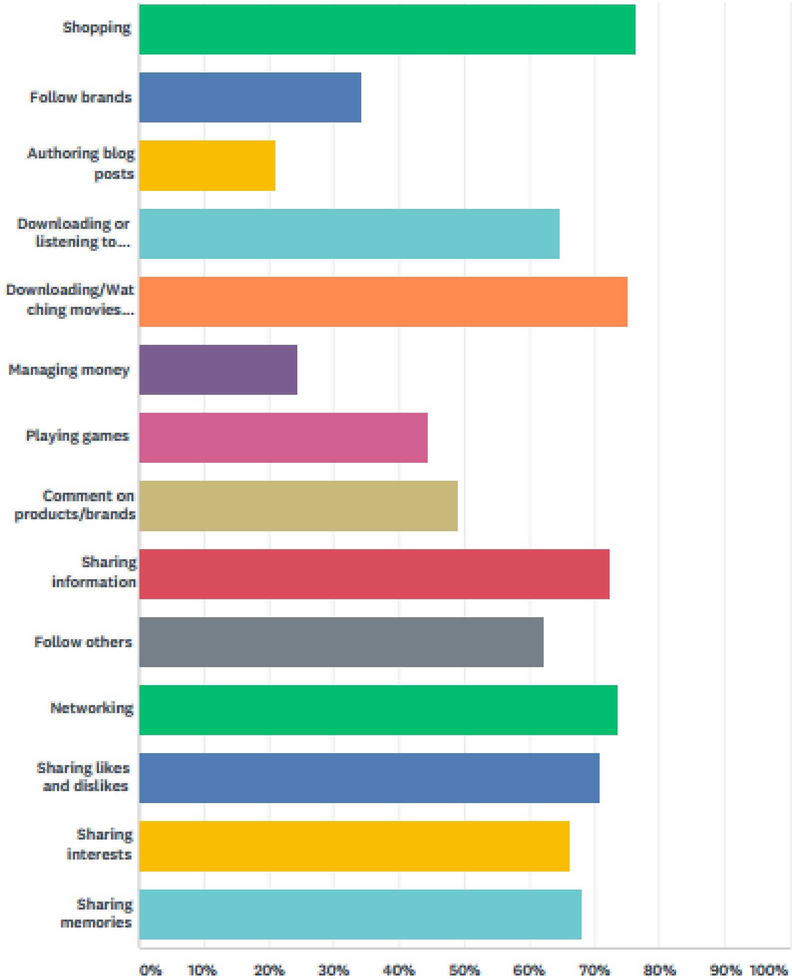

Figure 5. 8 Digital Traces Consumers Share on Social Media

Further to the descriptive statistics, this study proceeded to evaluate the reliability and validity of the data collected to assess its internal consistency.

5.4 Reliability

As mentioned in Chapter 4, Cronbach's Alpha is the most helpful and widely used tool in measuring the reliability of a scale (Hayes & Pritchard, 2013). Moreover, it is good for measuring the reliability of inter-item consistency (Sekaran and Bougie, 2013). Generally, reliability values of 0.7 and above are considered to be acceptable, whereas values of 0.6 and below are considered to be low. Hinton et al. (2014) suggest that reliability values from 0.7 to 0.9 are high and 0.5 to 0.7 are moderate, whereas values below 0.5 indicate poor reliability. Values above 0.9 are considered to indicate excellent reliability.

In line with the above, all constructs in this research were tested for reliability using Cronbach's Alpha test. Table 5.2 provides the Alpha values of the final data for each construct, along with the Item-Total Correlation Range. Reliability values of all the constructs are in the acceptable range, as they are above 0.7. In addition, item-item correlation values are also in the acceptable range for internal consistency measurement. All constructs have scores above the reference value and thus achieve acceptable internal item consistency.

Construct	Cronbach's Alpha	Item-Total Correlation Range	Reliability Result
Perceived Opportunity (PO)	0.946	0.761-0.884	Good
Perceived Social Influence (PSI)	0.936	0.758-0.821	Good
Perceived Control (PC)	0.930	0.741-0.806	Good
Enjoyment	0.937	0.760-0.817	Good
Self-Enhancement (SE)	0.939	0.743-0.901	Good
Fear	0.928	0.725-0.862	Good
Trust	0.891	0.625-0.786	Good
Exploration to Maximise Social Media Benefits (EMSMB)	0.922	0.676-0.817	Good
Exploitation to Satisfice Social Media Benefits (ESSMB)	0.926	0.705-0.851	Good
Exploration to Revert (ER)	0.932	0.727-0.875	Good
Avoidance of Social Media (ASM)	0.932	0.752-0.824	Good
Carelessness	0.913	0.667-0.865	Good
Carefreeness	0.915	0.660-0.871	Good
Consciousness	0.825	0.194-0.878	Good
Cautiousness	0.950	0.774-0.876	Good

Table 5. 2 Alpha Values (Main Survey)

5.5 Validity

As highlighted in Chapter 4, validity assesses the ability of the construct to measure what it aims to measure (Burns and Bush, 2002; Cohen et al. 2007). Hair et al. (2014) argue that measurement of validity gives guarantees for content and construct validity. Content validity was tested in a pilot study and this research chose constructs that have been used in previous research (Churchill and Iacobucci, 2006). In addition, the language, format and scales were tested in consultation with experts to ensure that the contents measure the constructs they are developed to measure. The final set of items used in the questionnaire after checking for content validity is given in Table 5.3 below.

Question Code	Description	Measure	Value
	Perceived Opportunity (PO)		
PO1	I am confident that social media will have positive outcome for the information I share on these platforms.	Ordinal	5-Points Likert Scale
PO2	I believe social media will open new opportunities for me to share information, memories, interests, likes and dislikes etc. with others.	Ordinal	5-Points Likert Scale
PO3	I believe social media platforms will provide me opportunities to share my likes, dislikes, interests and information etc. with others.	Ordinal	5-Points Likert Scale
PO4	I believe social media will give me opportunities to share my memories, interests and information etc. with others to gain recognition and praise.	Ordinal	5-Points Likert Scale
	Perceived Social Influence (PSI)		
PSI1	I think I interact well with others on social media for sharing my memories, likes, dislikes, interests and information etc.	Ordinal	5-Points Likert Scale
PSI2	I believe I fit well with others on social media that share the same interests as me.	Ordinal	5-Points Likert Scale
PSI3	I believe social media help me establish relationship with others to share information and interests.	Ordinal	5-Points Likert Scale
PSI4	I think I maintain close relationships with others on social media for sharing information and interests etc.	Ordinal	5-Points Likert Scale
	Perceived Control (PC)		
PC1	I think I have control over sharing information on social media platforms.	Ordinal	5-Points Likert Scale
PC2	I believe I can control sharing information on social media platforms.	Ordinal	5-Points Likert Scale
PC3	I believe I have control over what to share on social media platforms.	Ordinal	5-Points Likert Scale
PC4	I believe I can control sharing my memories, likes, dislikes and information on social media platforms.	Ordinal	5-Points Likert Scale
	Enjoyment		
Enj1	I feel I have a lot of enjoyment in sharing my memories, likes, dislikes, interests and information with others on social media.	Ordinal	5-Points Likert Scale
Enj2	Social media give me a lot of excitement in sharing my memories, likes, dislikes, interests and information with others.	Ordinal	5-Points Likert Scale
Enj3	I find social media quite entertaining in sharing my memories, likes, dislikes, interests and information with others.	Ordinal	5-Points Likert Scale
Enj4	I spend enjoyable and relaxing time on social media by sharing my memories, likes, dislikes, interests and information with others.	Ordinal	5-Points Likert Scale
	Self-Enhancement (SE)		
SE1	I feel social media improve my image by sharing my interests, likes and dislikes etc. with others.	Ordinal	5-Points Likert Scale

SE2	I feel I can influence others on social media by sharing my memories, likes, dislikes, interests and information etc.	Ordinal	5-Points Likert Scale
SE3	I feel I can make a good impression on others on social media through my interests, memories, likes, dislikes, and information etc.	Ordinal	5-Points Likert Scale
SE4	Social media platforms help me present my best side to others by sharing my interests, likes and dislikes.	Ordinal	5-Points Likert Scale
	Fear		
Fear1	I am afraid of sharing information on social media.	Ordinal	5-Points Likert Scale
Fear2	I do not feel comfortable to share information on social media.	Ordinal	5-Points Likert Scale
Fear3	I feel social media gather my highly personal information, likes, dislikes interests and memories etc.	Ordinal	5-Points Likert Scale
Fear4	I feel social media share my digital footprints with third parties without my consent.	Ordinal	5-Points Likert Scale
	Trust		
Trust1	I feel social media providers are honest and caring about my digital footprints which I share on their platforms.	Ordinal	5-Points Likert Scale
Trust2	I feel social media platforms are reliable as they do not share my digital footprints with others.	Ordinal	5-Points Likert Scale
Trust3	I feel social media providers are interested in my well-being and they do not share my digital footprints with third parties.	Ordinal	5-Points Likert Scale
Trust4	I feel social media do not give access to third parties to have access to my personal information etc.	Ordinal	5-Points Likert Scale
	Exploration to Maximise Social Media Benefits (EMSMB)		
EMSMB1	I explore social media to find new ways of sharing information, interests and memories with others.	Ordinal	5-Points Likert Scale
EMSMB2	I explore social media for potential new applications to share information etc.	Ordinal	5-Points Likert Scale
EMSMB3	I discover new ways of using social media to share my likes, dislikes, interests and information etc. with others.	Ordinal	5-Points Likert Scale
EMSMB4	I experiment with social media to find new features to share information, interests and memories etc.	Ordinal	5-Points Likert Scale
	Exploitation to Satisfice Social Media Benefits (ESSMB)		
ESSMB1	I use the same social media features that I learnt from others to share information on social media platforms.	Ordinal	5-Points Likert Scale
ESSMB2	I use common social media features to share my memories, likes, dislikes and interests etc. with others.	Ordinal	5-Points Likert Scale
ESSMB3	I use the same social media features suggested to me by others to share my memories and interests etc. on social media platforms.	Ordinal	5-Points Likert Scale
ESSMB4	I use social media features that I learnt from others on these platforms to share my likes, dislikes, interests and information etc.	Ordinal	5-Points Likert Scale
	Exploration to Revert (ER)		
ER1	Due to my privacy and security I now search for old ways of sharing information with others rather than social media.	Ordinal	5-Points Likert Scale
ER2	Due to my privacy and security, I now look for old ways of sharing information with others when social media was not here.	Ordinal	5-Points Likert Scale

ER3	I now use those methods, which were used before social media was introduced to share information with others due to my privacy and security.	Ordinal	5-Points Likert Scale
ER4	Due to privacy and security, I have changed the use of social media now so that I can use old ways of sharing information with others.	Ordinal	5-Points Likert Scale
	Avoidance of Social Media (ASM)		
ASM1	I try to avoid sharing information on social media due to my privacy and security.	Ordinal	5-Points Likert Scale
ASM2	I find other ways of sharing information without using social media due to my privacy and security.	Ordinal	5-Points Likert Scale
ASM3	I try to perform most of my information sharing without social media due to my privacy and security.	Ordinal	5-Points Likert Scale
ASM4	I stay away from sharing my memories, interests and information etc. on social media as much as I can because of my privacy and security.	Ordinal	5-Points Likert Scale
	Carelessness		
Careless1	I do not care about my privacy and security when I share information on social media.	Ordinal	5-Points Likert Scale
Careless2	I do not take any precautions about my privacy and security when I share information on social media platforms.	Ordinal	5-Points Likert Scale
Careless3	I am inattentive to my privacy and security of my digital footprints on social media.	Ordinal	5-Points Likert Scale
Careless4	I do not pay attention to my privacy and security when I share information on social media.	Ordinal	5-Points Likert Scale
	Carefreeness		
Carefree1	All things considered, there are no privacy and security concerns in sharing information on social media.	Ordinal	5-Points Likert Scale
Carefree2	Information sharing is a normal part of social media due to which I am not worried about my privacy and security.	Ordinal	5-Points Likert Scale
Carefree3	I am indifferent to my privacy and security when I share my digital footprints on social media platforms.	Ordinal	5-Points Likert Scale
Carefree4	Information sharing is a regular part of social media due to which I have no issues with my privacy and security on these platforms.	Ordinal	5-Points Likert Scale
	Consciousness		
Conscious1	I am aware that I will have privacy and security issues if I share information on social media platforms.	Ordinal	5-Points Likert Scale
Conscious3	I am aware of the fact that sharing digital footprints on social media has privacy and security risks.	Ordinal	5-Points Likert Scale
Conscious4	I am aware that sharing digital footprints on social media will have negative outcome for my privacy and security.	Ordinal	5-Points Likert Scale
	Cautiousness		
Cautious1	Sharing information on social media may cause me privacy and security issues in the future.	Ordinal	5-Points Likert Scale
Cautious2	Sharing information on social media is a big issue for my privacy and security.	Ordinal	5-Points Likert Scale
Cautious3	Sharing information, interests, memories, likes and dislikes on social media makes my privacy and security vulnerable.	Ordinal	5-Points Likert Scale
Cautious4	I am alert about sharing information on social media as it may cause me privacy and security issues.	Ordinal	5-Points Likert Scale

Table 5. 3 Questionnaire Items

As discussed in Chapter 4, this doctoral study used two types of factor analysis, namely Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). EFA is used to check for the dimensionality of the constructs, refine research instruments, retain or delete any research items and check for any factors cross-loadings.

5.6 Exploratory Factor Analysis (EFA)

First, this research used EFA to determine the dimensionality of the constructs. EFA is necessary because most items are generated from previous studies and EFA is used to check the nature of the constructs influencing a set of responses and the dimensionality of these constructs. The results are given below and further details are provided in Appendix 4. In addition, it is important to carry out EFA because it determines how various constructs operate with one another, and explores the nature of the variables and how they influence a set of responses. DeCoster (2000) argues that EFA is used for justification of scales and sub-scales. However, this research does not use EFA for theoretical predictions (DeCoster, 2000; Gaskin, 2016).

5.6.1 Adequacy

Sampling Adequacy can be measured using the Kaiser-Meyer-Olkin (KMO) test, which determines the appropriateness of EFA for the data. This research conducted both KMO and Bartlett's test, as shown in Table 5.4. KMO is described to be satisfactory if it is >0.60, whereas a p-value <0.05 is required for Bartlett's test (Hair et al., 2018). Both KMO and Bartlett's test results are given in Table 5.4: the KMO statistic is 0.856 and the p-value for Bartlett's test is >0.05. Both results are satisfactory. Based on the results of the KMO and Bartlett's tests, it can be argued that the data is suitable for Confirmatory Factor Analysis (Hinton et al., 2014). Hair et al. (2018) argue that KMO determines the suitability and accuracy of the factors for correlation purposes, whereas Bartlett's test is for the presence of correlation among variables. It is a statistical test for the overall significance of correlation in a correlation matrix.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.856
Bartlett's Test of Sphericity	**Approx. Chi-Square**	37983.530
	df	1770
	Sig.	0.000

Table 5. 4 KMO and Bartlett's Test

In addition, under the Communalities given in Appendix 4, which is another adequacy measure, it can be seen from the extraction column that all the communalities are >0.3 except for one item of Conscious 2, with a value of 0.264, which was suppressed as recommended by Tabachnick et al. (2007). Moreover, a fifteen-factor model explains 77.3% of the variance and the non-redundant residuals are 0.0%, which is less than the recommended value of 0.3% (Gaskin, 2016).

The evidence of convergent validity from EFA is given in the pattern matrix (Table 5.5): all loadings are above 0.5. As shown in Table 5.4, the final set of items was retained, as they had loadings above 0.5 and there were no cross-loadings of 0.5 on two factors. Similarly, the evidence of discriminant validity from EFA is given in the pattern matrix (Table 5.5), which shows that there are no cross-loadings. The final set of items is given in Table 5.3. Hair et al. (2014) argue that measurement of validity gives guarantees for content and construct validity.

Pattern Matrix

	Factor														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
PO1		.918													
PO2		.861													
PO3		.959													
PO4		.877													
PSI1				.908											
PSI2				.877											
PSI3				.870											
PSI4				.899											
PC1								.860							
PC2								.870							
PC3								.883							
PC4								.906							
Enj1					.902										
Enj2					.878										
Enj3					.880										
Enj4					.896										
SE1			.778												
SE2			.847												
SE3			.954												
SE4			.968												
Fear1										.785					
Fear2										.898					
Fear3										.857					

Fear4										.956					
Trust1														.785	
Trust2														.748	
Trust3														.865	
Trust4														.905	
EMSMB1												.871			
EMSMB2												.810			
EMSMB3												.900			
EMSMB4												.891			
ESSMB1									.871						
ESSMB2									.865						
ESSMB3									.854						
ESSMB4									.899						
ER1						.850									
ER2						.817									
ER3						.927									
ER4						.924									
ASM1							.847								
ASM2							.873								
ASM3							.914								
ASM4							.898								
Careless1													.780		
Careless2													.791		
Careless3													.923		
Careless4													.907		
Carefree1											.808				
Carefree2											.777				
Carefree3											.932				
Carefree4											.921				
Conscious1															.906
Conscious3															.953
Conscious4															.914
Cautious1	.919														
Cautious2	.917														
Cautious3	.931														
Cautious4	.881														
Cronbach Alpha	**.95**	**.94**	**.93**	**.93**	**.93**	**.93**	**.93**	**.93**	**.92**	**.92**	**.91**	**.92**	**.91**	**.89**	**.82**

Extraction Method: Maximum Likelihood.

Total Variance Extracted by the Factors=77.3%, KMO=.856, Bartlett’s Test <.000

Table 5. 5 Pattern Matrix

These 15 factors accounted for 77.3% of the variance in items explaining social media adoption, adaptation and behavioural outcomes as a composite process. As mentioned above, the results show that all items have loadings >.5 and reliability ranging from .8 to .9, indicating acceptable internal consistency.

5.7 Confirmatory Factor Analysis (CFA)

This section delineates the Confirmatory Factor Analysis (CFA), followed by Structural Equation Modelling. As suggested by Anderson and Gerbing (1988), this study followed a measure validation procedure with CFA and tested the convergent and discriminant validity of the scales using CFA for measurement model justification. It is essential to examine construct validity through Convergent and Discriminant validity for CFA and check for the Model Fit (Goodness and Badness) Indices (Gaskin, 2016; Hair et al., 2018). For acceptable fit, the model must have its chosen fit indices within the acceptable threshold and must not have substantial misfit. If there are large standardised residual values >2.58 and >5% in the overall data, there will be misspecifications and cross-loadings among the variables in the data, and therefore unacceptable fit, which means that the model could only be evaluated if it is within the acceptable threshold values (e.g. CFI and TLI >.9). Similarly, parameter estimates need to be significant, with values <.05 (Hair et al., 2018).

In line with the above arguments, this research tested both convergent and discriminant validity in CFA along with the Model Fit Indices. In the measurement model given in Figure 5.9 (step one), as proposed by Anderson and Gerbing (1988), all items were subjected to CFA in order to establish their construct validity and reliability. The initial result of CFA showed statistics of $\chi 2$ = 3904; p 0.000; $\chi 2/df$ = 2.36; TLI = 0.936; CFI = 0.942; and RMSEA = 0.044, indicating a good fit. However, the CFI value was slightly less than 0.95 and some items had high Modification Indices (MI). Items with high modification indices were co-varied (Figure 5.10) for further analysis, measuring the same constructs as suggested by researchers such as Kenny (2011) and Gaskin (2016). A total of 24 items were co-varied (Figure 5.10). The final measurement model had a total of 59 items for 15 constructs of the TAAM model with all the model fit indices within the acceptable range given in Table 5.7. Convergent and discriminant validity and model fit indices are discussed below.

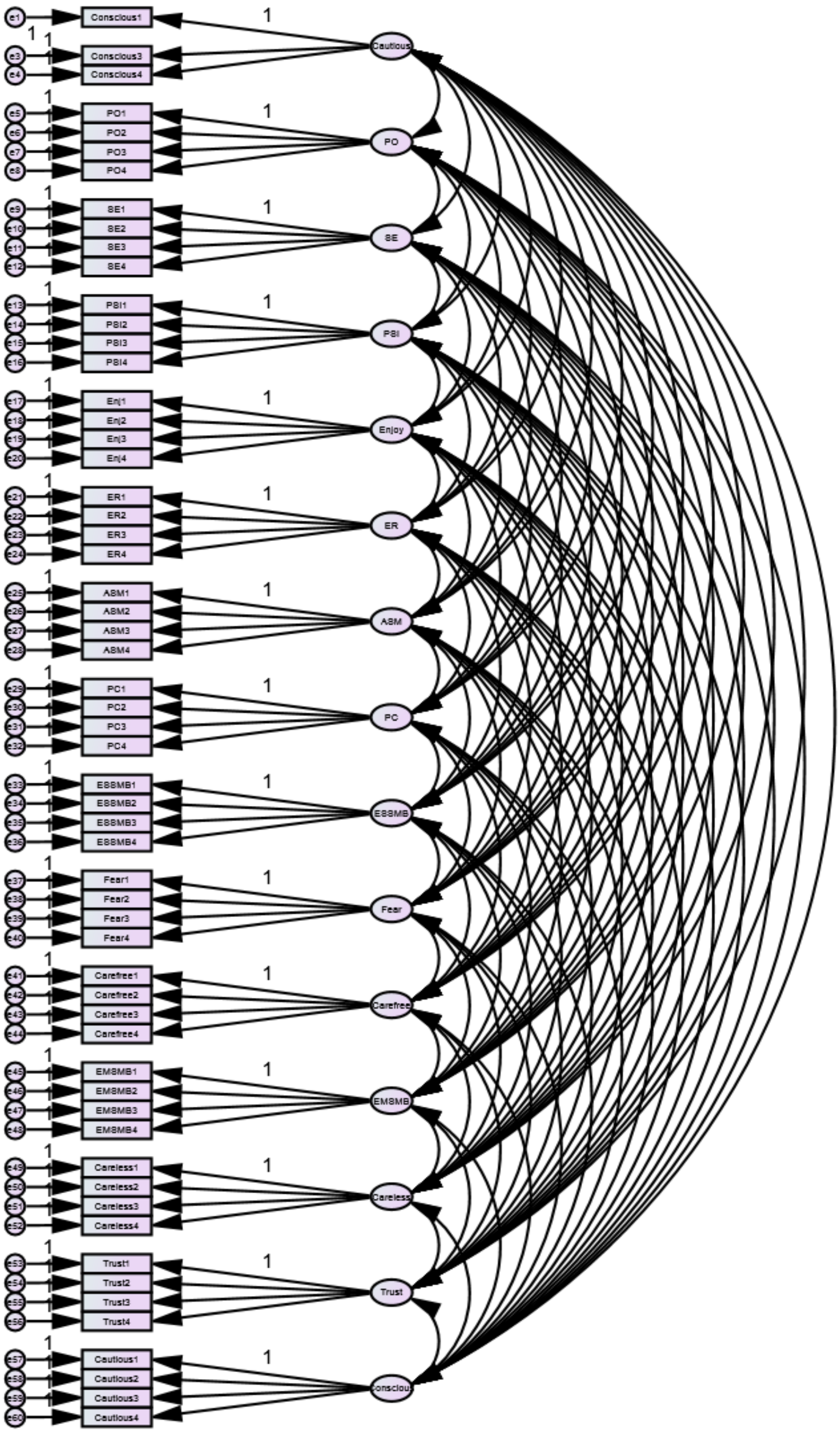

Figure 5. 9 Measurement Model CFA (Step One)

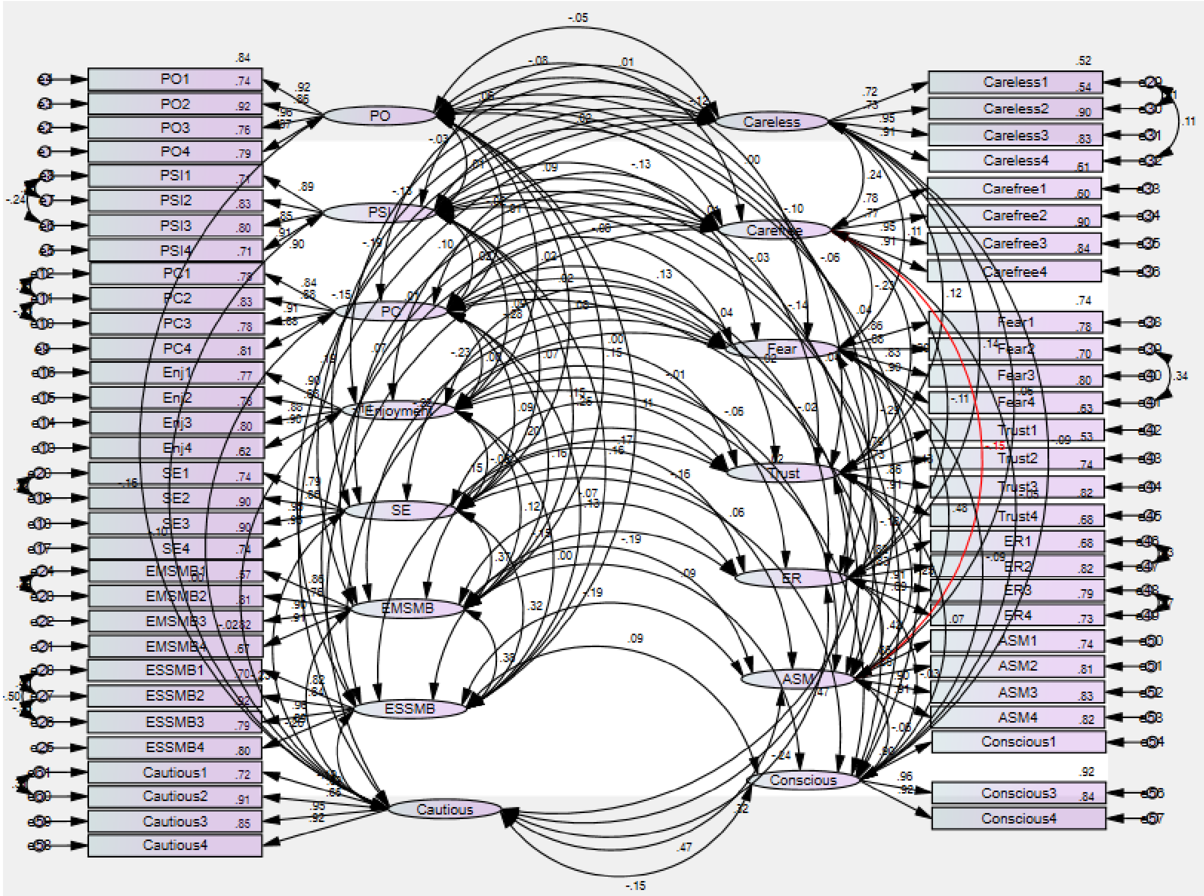

Figure 5. 10 Items with High MI Co-Varied

Hair et al., (2014) posit that the validity of CFA can be determined through the validated item constructs. Validity measures the extent to which measures link with each other to measure the concept aligned with the theory and support it (Zikmund, 2000). Convergent validity and discriminant validity results are discussed below.

5.7.1 Convergent Validity

Sekaran and Bougie (2013) describe that convergent validity will be high if two instruments measuring the concept are highly correlated, such that the correlation between the item and other items measuring the construct is high if the item correctly represents the measured construct (Holton et al. 2007).

Hair et al. (2014) describe that to review convergent validity, researchers needs to deploy factor loading for each construct such that AVE is greater than 0.5, reliability is greater than 0.7 and standardised loading of the model is equal to or greater than 0.7. Factor loadings or regression weights should be greater than 0.5. Similarly, Composite Reliability (CR) is described to measure the reliability and validity of the model and its value needs to be greater than 0.7. Robinson et al. (1991) argue that convergent validity can be obtained by correlation of two measures: that is, item-to-item and item-to-total correlation.

In light of the above arguments, this research deployed three tests for convergent validity, as recommended by Anderson and Gerbing (1988), namely factor loadings, composite reliability and average variance extracted. The results are given in Table 5.6. For convergent validity, this research deployed factor loadings and AVE for each construct besides Construct Reliability (CR) and the outcomes for all constructs have high convergent validity. Factor loadings represent the link between the latent variables and the scale items. It can be seen that standardised factor loadings are highly significant in all cases. Similarly, the results for Composite Reliability are well beyond the minimum threshold limit of 0.7 in each case. The results for AVE are the measures for variations explained by latent variable to random measurement error. The range of AVE is 0.679 to 0.859 for all constructs, which are well beyond the threshold limit of 0.5. Thus, convergent validity with regards to the scales in all constructs is supported.

From CFA, convergent validity is evidenced in Table 5.6 with parameter estimates all above 0.5 (Kline, 2015) and AVE all above 0.5 for all the constructs and CR greater than 0.7. Thus, these results support the research propositions specified in the TAAM model. Both CR and AVE are above the required thresholds, as shown in Table 5.6. Therefore, it can be inferred that convergent validity in this research demonstrates high variance, as the indicators are measuring the selected constructs (Hair et al., 2018).

Construct	**Item**	**Factor Loading**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
Perceived Opportunity (PO)	PO1	0.916	0.946	0.815
	PO2	0.86		
	PO3	0.96		
	PO4	0.872		
Perceived Social Influence (PSI)	PSI1	0.891	0.936	0.784
	PSI2	0.845		
	PSI3	0.909		
	PSI4	0.896		
Perceived Control (PC)	PC1	0.843	0.932	0.775
	PC2	0.884		
	PC3	0.911		
	PC4	0.882		
Enjoyment	Enj1	0.898	0.937	0.789
	Enj2	0.877		
	Enj3	0.882		
	Enj4	0.895		
Self-Enhancement (SE)	SE1	0.786	0.937	0.789
	SE2	0.859		

	SE3	0.947		
	SE4	0.95		
Fear	Fear1	0.861	0.925	0.755
	Fear2	0.884		
	Fear3	0.834		
	Fear4	0.896		
Trust	Trust1	0.792	0.894	0.679
	Trust2	0.73		
	Trust3	0.857		
	Trust4	0.906		
Exploration to Maximise Social Media Benefits (EMSMB)	EMSMB1	0.86	0.917	0.735
	EMSMB2	0.757		
	EMSMB3	0.899		
	EMSMB4	0.906		
Exploitation to Satisfice Social Media Benefits (ESSMB)	ESSMB1	0.819	0.930	0.769
	ESSMB2	0.836		
	ESSMB3	0.959		
	ESSMB4	0.888		
Exploration to Revert (ER)	ER1	0.824	0.920	0.743
	ER2	0.827		
	ER3	0.905		
	ER4	0.888		
Avoidance of Social Media (ASM)	ASM1	0.852	0.933	0.776
	ASM2	0.863		
	ASM3	0.898		
	ASM4	0.909		
Carelessness	Careless1	0.724	0.901	0.698
	Careless2	0.733		
	Careless3	0.947		
	Careless4	0.913		
Carefreeness	Carefree1	0.784	0.917	0.737
	Carefree2	0.773		
	Carefree3	0.949		
	Carefree4	0.914		
Consciousness	Conscious1	0.905	0.948	0.859
	Conscious3	0.957		
	Conscious4	0.918		
Cautiousness	Cautious1	0.893	0.947	0.817
	Cautious2	0.846		
	Cautious3	0.953		
	Cautious4	0.92		

Table 5. 6 Convergent Validity

5.7.2 Discriminant validity

Discriminant validity was measured by deploying the tests recommended by Anderson and Gerbing (1988). The results for discriminant validity are given Table 5.7. The factor correlation between a pair of latent variables should be less than the square root of AVE of each variable. The results show that discriminant validity based on the square root of AVE is greater than any inter-factor correlation highlighted in bold in Table 5.7. The results show that the square root of the AVE is greater than the correlation value of any pair of variables. Therefore, there are no substantial cross-loadings between the measured and error terms. Thus, discriminant validity is satisfied and supported for every variable of the proposed model. Hair et al. (2014)

explain that discriminant validity is the measure of distinction between the latent construct and other constructs. It is derived by AVE obtained from the squared inter-construct correlation of different constructs. Discriminant validity is significant, as the average variance extracted from the two constructs is greater than their squared correlation estimates. Sekaran and Bougie (2013) argue that discriminant validity can be checked if the square root of AVE is greater than any inter-factor correlation of the other constructs in the model.

Therefore, the results for Confirmatory Factor Analysis provide strong evidence of the construct validity of both convergent and discriminant validity. It can be argued that both convergent and discriminant validity are supported. The results show that factor loadings for all the constructs are greater than 0.7 and cross-loadings are lower than the loadings. Similarly, the square roots of the shared variance between the constructs and their measures are higher than the correlations across the constructs (Fornell and Larcker, 1981). Thus, the measurement model based on the above results can be argued to have significant convergent and discriminant validity.

	CR	AVE	MSV	MaxR(H)	Conscious	PO	PSI	PC	Enjoy	SE	EMSMB	ESSMB	Careless	Carefree	Fear	Trust	ER	ASM	Cautious
Conscious	0.948	0.859	0.023	0.954	**0.927**														
PO	0.946	0.815	0.026	0.958	0.036	**0.903**													
PSI	0.936	0.784	0.062	0.938	0.035	0.011	**0.886**												
PC	0.932	0.775	0.026	0.935	-0.018	0.014	0.024	**0.880**											
Enjoy	0.937	0.789	0.013	0.938	0.022	0.015	0.088	0.005	**0.888**										
SE	0.937	0.789	0.134	0.957	0.061	0.082	0.069	0.091	-0.077	**0.888**									
EMSMB	0.917	0.735	0.147	0.928	0.088	0.149	0.249	0.162	0.115	0.366	**0.858**								
ESSMB	0.930	0.769	0.147	0.951	0.092	0.107	0.160	0.130	0.004	0.317	0.384	**0.877**							
Careless	0.901	0.698	0.060	0.941	-0.094	-0.047	-0.083	0.062	-0.030	-0.127	-0.190	-0.147	**0.835**						
Carefree	0.917	0.737	0.088	0.945	-0.046	0.006	0.020	0.087	-0.017	0.101	0.013	0.066	0.244	**0.859**					
Fear	0.925	0.755	0.235	0.928	-0.093	-0.122	-0.129	-0.080	0.021	-0.276	-0.232	-0.220	0.111	-0.227	**0.869**				
Trust	0.894	0.679	0.088	0.910	0.066	0.002	0.006	0.129	-0.003	0.150	0.203	0.153	0.116	0.297	-0.293	**0.824**			
ER	0.920	0.743	0.185	0.926	-0.027	-0.100	-0.029	0.044	-0.006	-0.173	-0.069	-0.151	0.137	-0.113	0.430	-0.178	**0.862**		
ASM	0.933	0.776	0.235	0.935	-0.061	-0.059	-0.136	0.021	-0.060	-0.161	-0.194	-0.187	0.061	-0.146	0.485	-0.252	0.422	**0.881**	
Cautious	0.947	0.817	0.224	0.956	-0.151	-0.162	-0.102	-0.003	-0.023	-0.234	-0.262	-0.192	0.185	-0.140	0.470	-0.244	0.322	0.473	**0.904**

Table 5. 7 Discriminant Validity

5.7.3 Model Fit Indices of CFA

Byrne (2016) highlight different model fit indices for both goodness and badness of fit, such as the Comparative Fit Index (CFI), Goodness-of-Fit-Index (GFI), Incremental Fit Index (IFI), Normed Fit Index (NFI), Tucker-Lewis Index (TLI), Root Mean Square Residual (RMR) and Chi-square. These indices determine the goodness and badness of the model's fit with the observed data. Hayduk (1996) argues that there is no consensus on a single model fit index. Therefore, it is good to report different model fit indices. Generally, scholars argue that there should be at least one goodness-of-fit and one badness-of-fit index reported in the research (Gaskin, 2016). However, Schreiber et al. (2006) posit that the widely used indices should be included to report the goodness and badness of the model's fit, such as CFI, IFI, TLI, RMR and RMSEA.

In line with the above argument, the model fit indices of the measurement model of this research are given in Table 5.8. As model fit indices provide different information, this research has chosen both goodness and badness of fit indices, as set out in Table 5.8.

Model Fit Indices of CFA							
Model	**CMIN/DF**	**IFI**	**TLI**	**CFI**	**RMR**	**RMSEA**	**PCLOSE**
Default model	1.748	0.969	0.966	0.969	0.043	0.033	1

Table 5. 8 Model Fit Indices

The threshold values for model fit indices are given in Table 5.9. Looking to the acceptable threshold level for each of the model fit indices chosen (Table 5.8) in this research for the measurement model, all the values are well above the recommended minimum threshold. The goodness of fit indices should be more than 0.9 and badness of fit should be less than 0.05 (Byrne, 2016; Kline, 2015). Hu and Bentler (1999) suggest that an acceptable value for CMIN (minimum discrepancy)/DF (degrees of freedom) of less than 3 is good and less than 5 is also permissible. Similarly, they explained that threshold values for Incremental Index of Fit (IFI) and Tucker–Lewis Index (TLI) of close to 0.95, Standardized Root Mean Square Residual (SRMR) value of less than 0.09 and Root Mean Square Error of Approximation (RMSEA) value of less than 0.05 are good and the values between 0.05 and 0.10 are moderate. Browne and Cudeck (1993) suggest that the threshold value of the Comparative Fit Index (CFI) should be greater than 0.90. Based on the above thresholds and thresholds given in Table 5.9, it can be argued that the results of Model Fit Indices of CFA for this research are well above the recommended minimum threshold.

Measure	Threshold
CMIN/DF	< 3 good ; < 5 sometimes permissible (Hu and Bentler, 1999)
IFI	Close to 0.95 good fit (Hu and Bentler, 1999)
TLI	Close to 0.95 good fit (Hu and Bentler, 1999)
CFI	> 0.90 (Browne and Cudeck, 1993)
SRMR	<.09 (Hu and Bentler, 1999)
RMSEA	< 0.05 good; 0.05-0.10 moderate (Hu and Bentler, 1999)
PCLOSE	> .05 (Hu and Bentler, 1999)

Table 5. 9 Threshold Values

5.8 Common Method Bias Test (CMB)

CMB is a bias in the dataset that is due to something external to the measure which influences the response. This means that if the research has a Common Method Bias, the majority of the variance will be explained by a single factor (Podsakoff et al., 2003). It checks for any bias that the instrument presents, which occurs when the instrument itself uncovers variations in responses but not the actual predispositions of the respondents, resulting in noise caused by the biased instrument (Bagozzi and Yi, 1991). Moreover, CMB occurs when the measures try to represent a variance that is attributable to the measurement method rather than the construct (Podsakoff et al., 2003). Common Latent Factor (CLF) is considered to be a widely accepted method to check CMB. In this method, a new common latent factor is introduced to capture the common variance amongst the observed variables. A latent factor is added to the CFA model and it is connected to the observed variables of the measurement model. As a result, the standardised regression weights are compared with and without the common CLF factor in the model. If the differences are greater than 0.2, then the common factor CLF needs to be maintained before moving to step 2 of the structural model and composites need to be imputed from the factor score (Gaskin, 2016).

In line with the above process, this research used CLF analysis to test for common method bias in Figure 5.11. The specific bias test was carried out and the results are given in Table 5.10, which shows that measurable bias exists, as the chi-square test for the zero constrained model is significant. Similarly, a bias distribution test of equal constraints was conducted, revealing unevenly distributed bias, as the chi-square test was significant as well (see Table 5.10). Therefore, a CMB test was carried out, and as a result, “A test of equal specific bias demonstrated unevenly distributed bias" (Gaskin, 2016). Thus, this research retained the Specific Bias CLF construct for structural model and causal analyses and imputed the composites from the factor scores with CLF retained.

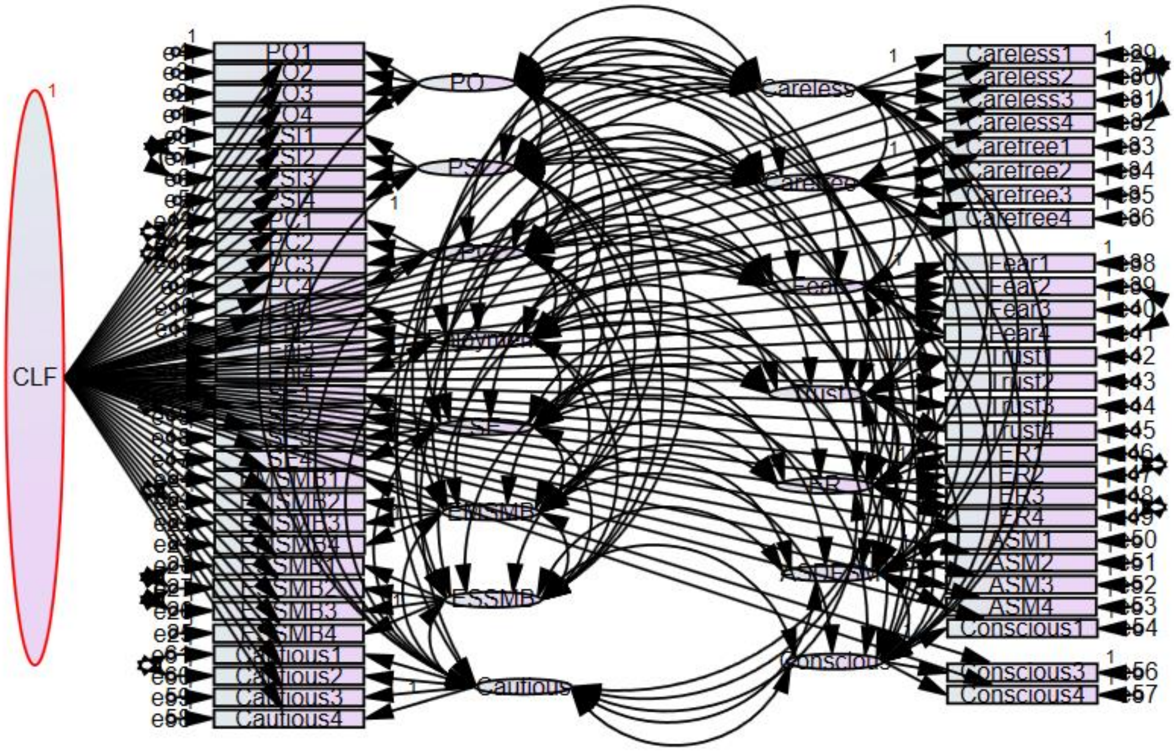

Figure 5. 11 Common Method Bias Test

Zero Constraints Test (Is there specific bias?)				
	X^2	DF	Delta	p-value
Unconstrained Model	2405.106	1473	X^2=272.118	0.000
Zero Constrained Model	2677.224	1532	DF=59	
Equal Constraints Test (Is bias evenly distributed?)				
	X^2	DF	Delta	p-value
Unconstrained Model	2405.106	1473	X^2=268.511	0.000
Equal Constrained Model	2673.617	1531	DF=58	

Table 5. 10 Specific Bias Tests

As discussed above, this research undertook a two-step approach to test the model. In the first step, CFA was carried out through factor loading followed by reliability and validity measurement and the CMB test. By using the co-variance based approach in CFA, the evidence given in the above sections provides strong support for the measurement model. The following section focuses on the second step of the Structural Model to test for hypothesised relationships amongst the latent constructs of the proposed model.

5.9 Structural Equation Modelling (Direct Effects)

After the measurement model is validated, the second step of the structural model, as recommended by Anderson and Gerbing (1988), needs to commence to test the theoretical model of this research and the hypothesised relationships. The role of the measurement model was to determine acceptable model fit indices or misfit in the model along with the statistically significant parameters. Step two of the structural model deals with the full model, predictive nomological validity and testing of hypotheses. The initial structural model is given in Figure 5.12. The following steps, as recommended by Byrne (2016), Hair et al. (2018) and Kline (2015), are used for the second step of the structural model to test for the hypothesised relationships.

- Model specification
- Model identification
- Measure selection and data preparation
- Model estimation
- Model fit

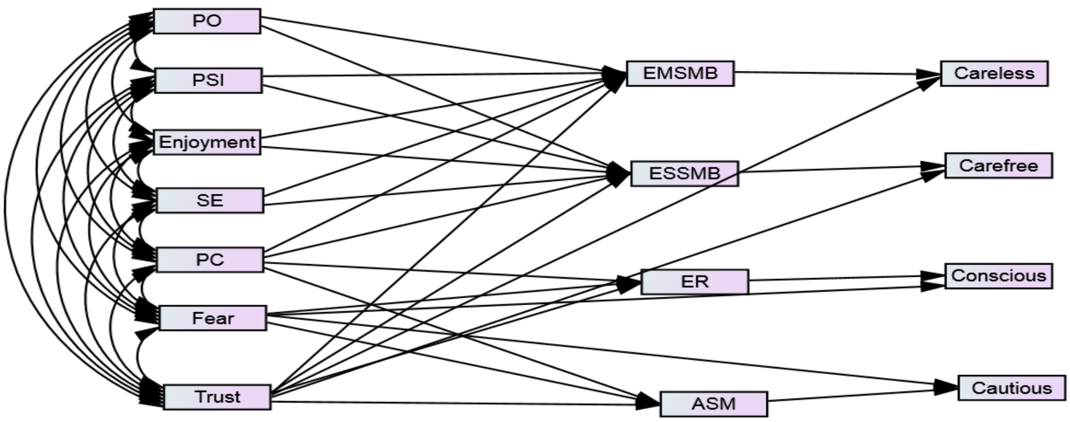

Figure 5. 12 Structural Model

5.9.1 Model Specification

After the Confirmatory Factor Analysis (CFA), the structural model (step 2) for nomological validity of all the constructs in the proposed model was carried out using the above five steps. Firstly, model specification was performed, which involves diagrammatic representation of the variables to show relationships amongst the exogenous and endogenous variables, as shown in Figure 5.12. Model specification is an important step for the structural model, as it provides a diagrammatic representation of the relationships amongst the variables. There are seven exogenous (PO, PSI, PC, Enjoyment, SE, Trust and Fear) and eight endogenous constructs (EMSMB, ESSMB, ER, ASM, Carelessness, Carefreeness, Consciousness and Cautiousness) in the proposed TAAM model of this study.

5.9.2 Model Identification

Model identification involves the determination of systematic relationships amongst the variables (Model Definition), and formation and representation of a theory. In this process, the causal and theoretical relationships are identified, determining the recursive nature of the model, which implies unidirectional causal relationships amongst the constructs (Kline, 2015). The results given in Table 5.11 and Figure 5.12 show that the model is recursive and theoretically identified.

Notes for Group (Structural Model)
The model is recursive.
Sample size = 692

Table 5. 11 Structural Model Notes

5.9.3 Measure Selection

This step involves both measure selection (that is, manifest variables measuring latent variables) and data preparation (quality of data and the adequacy of sample size). As shown in Figure 5.12, the number of manifest variables in the proposed model to test the latent variables exceeds two (fulfilling the minimum requirement), which satisfies the measure selection criteria for the model. For data preparation, as discussed in Chapter 4, the quality of data was good and the sample size was sufficient to test the model. Furthermore, reliability (section 5.4), convergent (Section 5.7.1) and discriminant validity (Section 5.7.2) were also checked. Convergent (as shown in Table 5.6, AVE >0.5 for all the constructs along with composite reliability >0.7) and discriminant validity (as shown in Table 5.7, square root of AVE greater than any inter-factor correlation highlighted in bold) are satisfactory and are within the acceptable range, which satisfies the minimum measure selection conditions (Kline, 2015).

5.9.4 Model Estimation and Model Fit

After the measure selection, the model was analysed using Maximum Likelihood Estimation (MLE) to estimate the parameters in the model. MLE is the most widely used method for parameter estimation in structural equation modelling using AMOS (Gaskin, 2016; Hair et al., 2018). AMOS gives both standardised and unstandardised outputs of parameters for the model. For the initial structural model of this research, the standardised outputs are given in Figure 5.13.

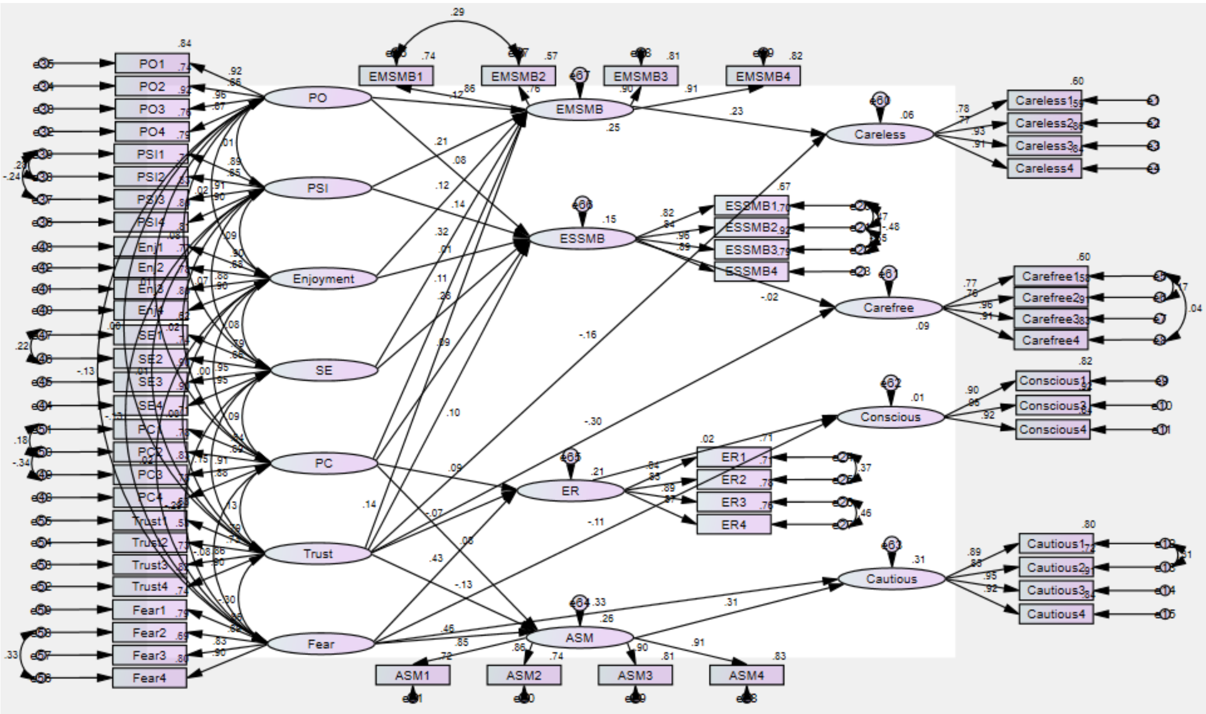

Figure 5. 13 Standardised Output of Parameters for SEM

For the validity of the initial structural model, sample correlation, covariance and fitness indices of the model were examined. AMOS outcomes for correlation and covariance for the structural model are given in Appendix 6. The correlation values given in the table are less than 0.8 and standardised residual covariance is less than ±2.0. Both are within the acceptable threshold (Eom, 2008). The model fitness measures are given below. Direct effect was tested via AMOS, with the full structural model showing a good fit. The details of tests for direct effects are given in Table 5.13. For goodness-of-fit measures, IFI, TLI, and CFI were used, and for badness-of-fit indices, RMR and RMSEA were chosen. All fitness measures for the model are given in Table 5.12 and all values are well within the acceptable threshold.

As shown in Table 5.12, the structural model suggests that the hypothesised model is a satisfactory fit to the sample data. The CMIN/DF value is 1.843 (< 3 good), IFI is 0.964 (Close to 0.95 is a good fit), TLI is 0.961 (Close to 0.95 is a good fit), and CFI is 0.964 (> 0.90): all are well within the acceptable thresholds. Similarly, the RMSEA value is 0.035 (< 0.05 good) and PCLOSE is 1.000 (> .05): both all are well within the acceptable threshold. Thus, step 2 of the full structural model provides evidence that all values for model fit indices are well within the acceptable range. Therefore, it can be argued that the model (TAAM) is a well-fitting model.

Model Fit Indices of Structural Model						
Model	**CMIN/DF**	**IFI**	**TLI**	**CFI**	**RMSEA**	**PCLOSE**
Default model	1.843	0.964	0.961	0.964	.035	1.000

Table 5. 12 Model Fitness Measure

In addition, all hypothesised paths are analysed through the significance of p-values. The structural model showing paths for each hypothesis is given in Figure 5.14, along with paths shown in the AMOS graphic in Figure 5.15. Albright and Park (2009) suggest that a p-value of <0.05 supports a hypothesis and a value > 0.05 leads to rejection of the hypothesis. In line with the same argument, all hypotheses with direct effects in the model are tested and discussed below. Table 5.13 provides estimated path coefficients for each hypothesised path and their level of significance. In addition to model fit indices, Modification Indices were also examined for any mis-specification in the model. The results shown in Table 5.12 demonstrate that the final structural model did not have any mis-specification issues and all the standardised residuals are well within the acceptable range.

As noted in Chapter 3, this study examines the direct effect relationships, as social media adoption is not an end in itself but a composite process of adoption, adaptation and behavioural outcomes giving consumers the impetus to share digital footprints on social media platforms. The composite process is based on consumers' joint attitudinal components towards the consequences of their digital footprints. These antecedents have a direct effect on the composite patterns and behavioural outcomes in the hypothesised relationships of the proposed TAAM model. Thus, the direct effects are examined in the proposed TAAM model, as they represent the direct effect of a variable on another variable. Kline (1998) argues that it is vital to examine the decomposition of structural effects in the model through SEM. The estimation of direct effects can be examined in such a way as to decompose observed correlations into constituent parts, and if these decompositions reproduce the observed correlations, the path model would be called to fit the data (Kline, 1998). The direct effects between the hypothesised relationships shown in Figure 5.14 were performed into a full structural model. The results are given in Table 5.13, which shows that all directions have significant direct effects except for four hypothesised propositions. In addition, the evidence from this research provides empirical support that the R^2 for the dependent variables (EMSMB .25, ESSMB .15, ER .21 and ASM .26) account for 87% of the variance in adoption and adaptation behaviour, showing the predictive power of the model. TAAM accounts for 87% of the variance in adoption and adaptation behaviour. The results for each of the hypotheses are discussed below.

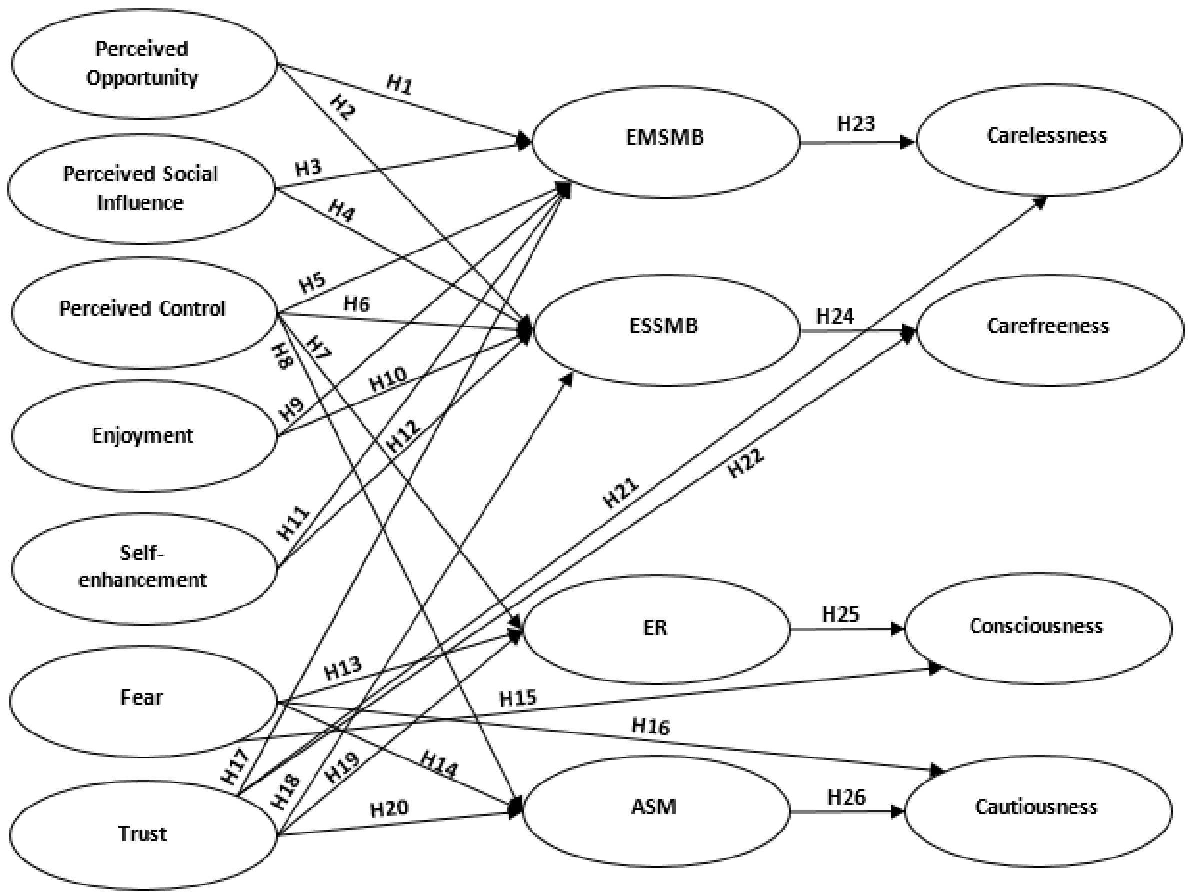

Figure 5. 14 Structural Model Hypotheses Paths

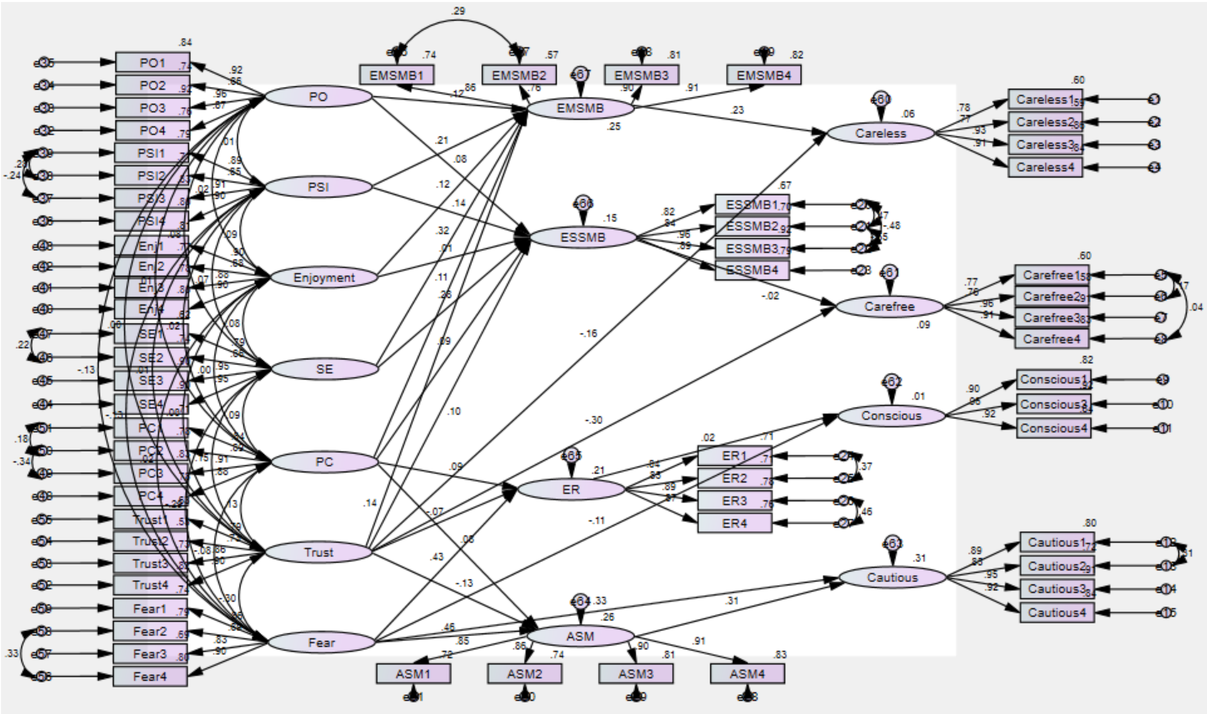

Figure 5. 15 Structural Model Hypotheses Path (AMOS Output)

No	Hypotheses			Estimate	S.E.	C.R.	P	Result
H1	PO	→	EMSMB	0.112	0.034	3.274	0.001	Supported
H2	PO	→	ESSMB	0.065	0.029	2.239	0.025	Supported
H3	PSI	→	EMSMB	0.21	0.036	5.832	***	Supported
H4	PSI	→	ESSMB	0.113	0.03	3.728	***	Supported
H5	PC	→	EMSMB	0.099	0.034	2.914	0.004	Supported
H6	PC	→	ESSMB	0.067	0.029	2.339	0.019	Supported
H7	PC	→	ER	0.073	0.031	2.399	0.016	Supported
H8	PC	→	ASM	0.079	0.038	2.109	0.035	Supported
H9	Enjoyment	→	EMSMB	0.117	0.036	3.274	0.001	Supported
H10	Enjoyment	→	ESSMB	0.011	0.03	0.373	0.709	Not supported
H11	SE	→	EMSMB	0.287	0.033	8.67	***	Supported
H12	SE	→	ESSMB	0.205	0.028	7.322	***	Supported
H13	Fear	→	ER	0.334	0.034	9.727	***	Supported
H14	Fear	→	ASM	0.471	0.041	11.618	***	Supported
H15	Fear	→	Conscious	-0.117	0.049	-2.378	0.017	Supported
H16	Fear	→	Cautious	0.35	0.045	7.82	***	Supported
H17	Trust	→	EMSMB	0.12	0.032	3.767	***	Supported
H18	Trust	→	ESSMB	0.073	0.027	2.718	0.007	Supported
H19	Trust	→	ER	-0.053	0.03	-1.782	0.075	Not supported
H20	Trust	→	ASM	-0.124	0.037	-3.354	***	Supported
H21	Trust	→	Careless	0-.090	0.023	-3.954	***	Supported
H22	Trust	→	Carefree	-0.224	0.031	-7.283	***	Supported
H23	EMSMB	→	Careless	0.146	0.027	5.437	***	Supported
H24	ESSMB	→	Carefree	-0.017	0.041	-0.415	0.616	Not supported

H25	**ER**	→	**Conscious**	0.031	0.064	0.486	0.627	Not supported
H26	**ASM**	→	**Cautious**	0.329	0.043	7.594	***	Supported

Table 5. 13 Hypotheses Paths Coefficient and P Values

H1– Perceived Opportunity (PO) has a positive effect on exploration to maximise social media benefits.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.001 (at a regression coefficient estimate value of 0.112) given in Table 5.12 is less than 0.05, which means that hypothesis H1 is supported.

H2– Perceived Opportunity (PO) has a positive effect on exploitation to satisfice social media benefits.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.025 (at a regression coefficient estimate value of 0.065) given in Table 5.12 is less than 0.05, which means that hypothesis H2 is supported.

H3– Perceived Social Influence (PSI) has a positive effect on exploration to maximise social media benefits.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at a regression coefficient estimate value of 0.21) given in Table 5.12 is less than 0.05, which means that research hypothesis H3 is supported.

H4– Perceived Social Influence (PSI) has a positive effect on exploitation to satisfice social media benefits.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at a regression coefficient estimate value of 0.113) given in Table 5.12 is less than 0.05, which means that hypothesis H4 is supported.

H5– Perceived Control has a positive effect on exploration to maximise social media benefits.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.004 (at a regression coefficient estimate value of 0.099) given in Table 5.12 is less than 0.05, which means that research hypothesis H5 is supported.

H6– Perceived Control has a positive effect on exploitation to satisfice social media benefits.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.019 (at a regression coefficient estimate value of 0.067) given in Table 5.12 is less than 0.05, which means that research hypothesis H6 is supported.

H7– Perceived Control has a positive effect on exploration to revert from social media.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.016 (at a regression coefficient estimate value of 0.073) given in Table 5.12 is less than 0.05, which means that research hypothesis H7 is supported.

H8– Perceived Control has a positive effect on avoidance of social media.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.035 (at regression coefficient estimate value of 0.079) given in Table 5.12 is less than 0.05, which means that research hypothesis H8 is supported.

H9– Enjoyment has a positive effect on exploration to maximise social media benefits.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.001 (at a regression coefficient estimate value of 0.117) given in Table 5.12 is less than 0.05, which means that research hypothesis H9 is supported.

H10– Enjoyment has a positive effect on exploitation to satisfice social media benefits.

The t-test result indicates that the null hypothesis cannot be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.709 (at a regression coefficient estimate value of 0.011) given in Table 5.12 is more than 0.05, which means that research hypothesis H10 is not supported.

H11– Self-enhancement has a positive effect on exploration to maximise social media benefits.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at a regression coefficient estimate value of 0.287) given in Table 5.12 is less than 0.05, which means that research hypothesis H11 is supported.

H12– Self-enhancement has a positive effect on exploitation to satisfice social media benefits.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the P value of 0.000 (at a regression coefficient estimate value of 0.205) given in Table 5.12 is less than 0.05, which means that research hypothesis H12 is supported.

H13– Fear has a direct positive effect on exploration to revert from social media.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at a regression coefficient estimate value of 0.334) given in Table 5.12 is less than 0.05, which means that research hypothesis H13 is supported.

H14– Fear has a positive effect on avoidance of social media.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at regression coefficient estimate value of 0.471) given in Table 5.12 is less than 0.05, which means that research hypothesis H14 is supported.

H15– Fear has a negative effect on consumers' consciousness towards their data digital footprints on social media.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.017 (at a regression coefficient estimate value of -0.117) given in Table 5.12 is less than 0.05, which means that research hypothesis H15 is supported.

H16– Fear has a positive effect on consumers' cautiousness towards their digital footprints on social media.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at a regression coefficient estimate value of 0.35) given in Table 5.12 is less than 0.05, which means that research hypothesis H16 is supported.

H17– Trust has a positive effect on exploration to maximise social media benefits.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at a regression coefficient estimate value of 0.12) given in Table 5.12 is less than 0.05, which means that research hypothesis H17 is supported.

H18– Trust has a positive effect on exploitation to satisfice social media benefits.

Trust has a direct positive effect on exploitation to satisfice social media benefits. The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.007 (at a regression coefficient estimate value of 0.073) given in Table 5.12 is less than 0.05, which means that research hypothesis H18 is supported.

H19– Trust has a negative effect on exploration to revert from social media.

The t-test result indicates that the null hypothesis cannot be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.075 (at a regression coefficient estimate value of -0.053) given in Table 5.12 is more than 0.05, which means that research hypothesis H19 is not supported.

H20– Trust has a negative effect on avoidance of social media.

The t-test result indicates that the null hypothesis of no direct negative significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at a regression coefficient estimate value of -0.124) given in Table 5.12 is less than 0.05, which means that research hypothesis H20 is supported.

H21– Trust has a negative effect on consumers' carelessness towards their digital footprints on social media.

The t-test result indicates that the null hypothesis of no direct negative significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at a regression coefficient estimate value of 0.083) given in Table 5.12 is less than 0.05, which means that research hypothesis H21 is supported.

H22– Trust has a negative effect on consumers' carefreeness towards their digital footprints on social media.

The t-test result indicates that the null hypothesis of no direct negative significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at a regression coefficient estimate value of 0.227) given in Table 5.12 is less than 0.05, which means that research hypothesis H22 is supported.

H23– EMSMB has a positive effect on consumers' carelessness towards their digital footprints on social media.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.000 (at a regression coefficient estimate value of -0.136) given in Table 5.12 is less than 0.05, which means that research hypothesis H23 is supported.

H24– ESSMB has a negative effect on consumers' carefreeness towards their digital footprints on social media.

The t-test result indicates that the null hypothesis cannot be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.616 (at a regression coefficient estimate value of 0.021) given in Table 5.12 is more than 0.05, which means that research hypothesis H24 is not supported.

H25– ER has a positive effect on customers' consciousness towards their digital footprints on social media.

The t-test result indicates that the null hypothesis cannot be rejected for the regression coefficient estimate at a 0.05 level of significance, as the p-value of 0.627 (at a regression coefficient estimate value of 0.031) given in Table 5.12 is more than 0.05, which means that research hypothesis H25 is not supported.

H26– ASM has a positive effect on customers' cautiousness towards their digital footprints on social media.

The t-test result indicates that the null hypothesis of no direct positive significant effect needs to be rejected for the regression coefficient estimate at 0.05 level of significance, as the p-value of 0.007 (at a regression coefficient estimate value of 0.073) given in Table 5.12 is less than 0.05, which means that research hypothesis H26 is supported.

5.10 Conclusion

This chapter discussed the findings and hypothesised relationships given in the proposed TAAM model by examining the joint attitudinal components of attitude as antecedents of adoption and adaptation to understand consumers' social media joint attitudinal response towards the consequences of their digital footprints. It highlighted the findings and discussed in detail the two-step process of Confirmatory Factor Analysis and Structural Modelling, along with hypothesis testing. It identified three cognitive (PO, PSI and PC) and four affective attitudinal components (SE, enjoyment, trust and fear) as antecedent to social media adoption and adaptation behavioural strategies (EMSMB, ESSMB, ER and ASM), which are hypothesised to result in outcomes (Carelessness, Carefreeness, Consciousness and Cautiousness) of consumers' responses to their digital footprints. This chapter also presented the sample's demographic details and descriptive statistics.

Chapter 6. Discussion

6.1 Introduction

This doctoral research developed a framework of the Technology Adoption and Adaptation Model (TAAM) as a composite process. Chapter 3 of this thesis formulates and hypothesises this model (TAAM) in light of existing literature. Chapter 5 delineates the findings and the outcome of the hypothesised relationships amongst various constructs of the TAAM. By using structural equation modelling (AMOS version 25) in path analysis in the previous chapter, 26 hypotheses were tested to determine the interrelationships amongst the joint attitudinal components (cognitive and affective) as antecedents of social media adoption, adaptation and outcomes as a composite process. This chapter provides discussion, analysis, and interpretation of the results of the hypothesised relationships and relevant literature to address the research questions and establish the causal links in the proposed model.

6.2 Research Questions RQ1 and RQ2

RQ1. What are the underlying attitudinal factors that drive consumers' social media adoption, adaptation and behavioural outcomes as a composite process?
RQ2. How do the joint attitudinal components impact consumers' social media adoption, adaptation and behavioural outcomes as a composite process?

The findings and results of this research indicate that attitude plays a central and significant role in social media adoption and adaptation as a composite process. Consumers' adoption of social media is not an end in itself but involves various adaptation strategies leading to outcomes. Both adoption and adaptation are components of the composite process, and the results of this research, given in Chapter 5, confirm that consumers' joint attitudinal components are the determinants of the composite patterns and behavioural outcomes towards the consequences of their digital footprints.

The TAAM framework was developed with 26 causal relationships (hypotheses, Figure 6.1), as given in Table 6.1. Of the 26 hypotheses, 22 causal relationships are significant (Table 6.2). The hypothesised relationships are discussed and analysed below.

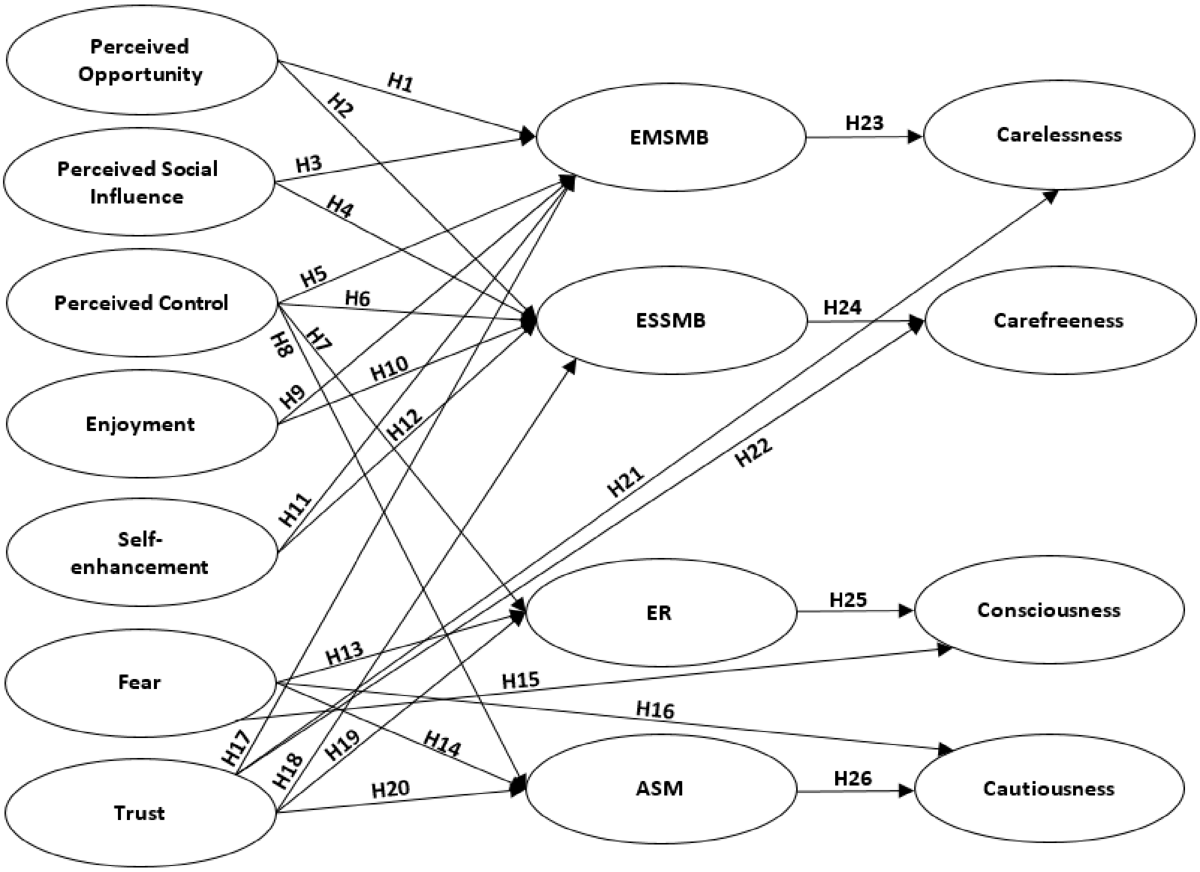

Figure 6. 1 Hypotheses Paths (TAAM Model)

No	Hypotheses	Result
H1	Perceived Opportunity (PO) has a positive effect on exploration to maximise social media benefits.	Supported
H2	Perceived Opportunity (PO) has a positive effect on exploitation to satisfice social media benefits.	Supported
H3	Perceived Social Influence (PSI) has a positive effect on exploration to maximise social media benefits.	Supported
H4	Perceived Social Influence (PSI) has a positive effect on exploitation to satisfice social media benefits.	Supported
H5	Perceived Control has a positive effect on exploration to maximise social media benefits.	Supported
H6	Perceived Control has a positive effect on exploitation to satisfice social media benefits.	Supported
H7	Perceived Control has a positive effect on exploration to revert from social media.	Supported
H8	Perceived Control has a positive effect on avoidance of social media.	Supported
H9	Enjoyment has a positive effect on exploration to maximise social media benefits.	Supported
H10	Enjoyment has a positive effect on exploitation to satisfice social media benefits.	Not supported
H11	Self-enhancement has a positive effect on exploration to maximise social media benefits.	Supported
H12	Self-enhancement has a positive effect on exploitation to satisfice social media benefits.	Supported
H13	Fear has a direct positive effect on exploration to revert from social media.	Supported
H14	Fear has a positive effect on avoidance of social media.	Supported

H15	Fear has a negative effect on consumers' consciousness towards their digital footprints on social media.	Supported
H16	Fear has a positive effect on consumers' cautiousness towards their digital footprints on social media.	Supported
H17	Trust has a positive effect on exploration to maximise social media benefits.	Supported
H18	Trust has a positive effect on exploitation to satisfice social media benefits.	Supported
H19	Trust has a negative effect on exploration to revert from social media.	Not supported
H20	Trust has a negative effect on avoidance of social media.	Supported
H21	Trust has a negative effect on consumers' carelessness towards their digital footprints on social media.	Supported
H22	Trust has a negative effect on consumers' carefreeness towards their digital footprints on social media.	Supported
H23	EMSMB has a positive effect on consumers' carelessness towards their digital footprints on social media.	Supported
H24	ESSMB has a negative effect on consumers' carefreeness towards their digital footprints on social media.	Not supported
H25	ER has a positive effect on customers' consciousness towards their digital footprints on social media.	Not supported
H26	ASM has a positive effect on customers' cautiousness towards their digital footprints on social media.	Supported

Table 6. 1 Hypothesis

No	Hypothesis			Estimate	P
H1	EMSMB	<---	PO	.112	.001
H2	ESSMB	<---	PO	.065	.025
H3	EMSMB	<---	PSI	.210	***
H4	ESSMB	<---	PSI	.113	***
H5	EMSMB	<---	PC	.099	.004
H6	ESSMB	<---	PC	.067	.019
H7	ER	<---	PC	.073	.016
H8	ASM	<---	PC	.079	.035
H9	EMSMB	<---	Enjoyment	.117	.001
H10	ESSMB	<---	Enjoyment	.011	.709
H11	EMSMB	<---	SE	.287	***
H12	ESSMB	<---	SE	.205	***
H13	ER	<---	Fear	.334	***
H14	ASM	<---	Fear	.471	***
H15	Conscious	<---	Fear	-.117	.017
H16	Cautious	<---	Fear	.350	***
H17	EMSMB	<---	Trust	.120	***
H18	ESSMB	<---	Trust	.073	.007
H19	ER	<---	Trust	-.053	.075
H20	ASM	<---	Trust	-.124	***
H21	Careless	<---	Trust	-.090	***
H22	Carefree	<---	Trust	-.224	***
H23	Careless	<---	EMSMB	.146	***
H24	Carefree	<---	ESSMB	-.017	.616
H25	Conscious	<---	ER	.031	.627
H26	Cautious	<---	ASM	.329	***

Table 6. 2 Coefficient Estimate and P Value

6.2.1 Joint Attitudinal Components

As discussed in the above chapters, CMUA and UTAUT do not focus on the joint attitudinal components. The results of this research confirm that consumers' social media adoption and adaptation as a composite process are driven by both cognitive and affective attitudinal components. This point is consistent with prior literature which argues that combining both attitudinal components provides more useful and comprehensive meaning to understand consumers' attitudes in a particular context (Alwi and Kitchen, 2014). Unlike the UTAUT and the CMUA, based on the results of this research, it can be argued that cognitive utilitarian (perceived opportunity, perceived social influence and perceived control) and affective (enjoyment, self-enhancement, fear and trust) attitudinal components are the antecedents of adoption and adaptation as a composite process of consumers' engagement with digital footprints.

The results of this research show that both cognitive and affective components (positive or negative) (Chiu, 2002; Eagly and Chaiken 1993; Lazarus, 1982) constitute beliefs and affect about the composite process linking with certain outcomes. The empirical evidence from this doctoral research confirms that attitude comprises both cognitive beliefs (positive or negative) and emotions (positive or negative) that consumers hold in their interactions with social media, such that a positive attitude is favourable (EMSMB and ESSMB) and a negative attitude is unfavourable (ER or ASM) towards social media digital footprints. It can be argued that in their adoption, adaptation and behavioural outcomes, they tend to make adjustments to social media features based on their beliefs and emotions. They embrace different adaptation behaviours to cope with the consequences of their digital footprints. Thus, based on the empirical findings and results of this research, the following attitudinal factors tend to drive consumers' social media adoption, adaptation and behavioural outcomes as a composite process.

6.2.1.1 Cognitive Attitudinal Components

The results in Chapter 5 indicate that consumers' social media adoption is influenced by positive or negative attitudes towards the consequences of their social media digital footprints. Their cognitive beliefs of perceived opportunity, perceived social influence and perceived control are the constituents of cognitive utilitarian attitude, which are analysed and discussed below in the light of the results of this research.

6.2.1.1.1 Perceived Opportunity (PO)

The results of this research indicate that PO has a significant direct effect on exploration to maximise social media and exploitation to satisfice social media benefits. As shown in Table 6.2, H1 and H2 are supported, with regression coefficient estimate values of 0.112 and 0.21 and p-values < 0.001 and < 0.000 respectively. The results confirm that consumers regard social media as a perceived opportunity due to its functional attributes of performance, relative advantage, ease of use and convenience, which affect their cognitive utilitarian attitude. Consistent with prior research, consumers perceive that social media has compatibility with their needs and provides them with convenience, success and improved performance (Bala and Venkatesh, 2016; Venkatesh et al., 2012). As a result, consumers seek to maximise and satisfice social media benefits.

6.2.1.1.2 Perceived Social Influence (PSI)

The findings of this doctoral research indicate that consumers perceive social media as a cognitive social pressure for social interaction, social ties and social support, having an impact on their cognitive attitude. The results show that PSI has a significant direct effect on exploration to maximise social media and exploitation to satisfice social media benefits. As shown in Table 6.2, H3 and H4 are both supported, with regression coefficient estimate values of 0.21 and 0.113 and p-values of < 0.000 and < 0.000 respectively. The results confirm that consumers seek to maximise as well as satisfice social media benefits due to perceived social pressure. This gives them psychological pressure to adopt, maximise and satisfice social media benefits. Prior literature has similarly argued that social influence enhances the acceptance and adoption of social media (Hsu and Wu, 2011; Wei et al., 2009). Consumers believe that they are socially supported on social media platforms as a social aspect of exchange to share information with others within communication networks and to provide solutions, advice and recommendations (Ali, 2011). Thus, it can be inferred that PSI is consumers' cognitive psychological pressure from others to maintain social relations, interactions and support (Grace et al., 2015; Trivedi et al., 2018).

6.2.1.1.3 Perceived Control (PC)

The results given in Chapter 5 confirm that perceived control is consumers' cognitive attitude, which enhances their positive attitude towards exploration to maximise and satisfice social media benefits. The result shows that PC has a significant direct effect on exploration to maximise and exploitation to satisfice social media benefits. As shown in Table 6.2, H5 and H6 are supported, with regression coefficient estimate values of .099 and .067 and p-values of < 0.004 and < 0.019 respectively. The results confirm that consumers seek to maximise and satisfice social media benefits if social media providers give them more control. Consistent with previous studies, consumers have more positive attitudes towards technology if it provides them with more control (Cheung et al., 2015; Tucker, 2014). This further reinforces other classic models of technology adoption such as the TPB, in which perceived behavioural control is an antecedent of behavioural intention. This means that the growing autonomy sought by consumers in technology use and decision-making in general further concurs with the empirical findings of this doctoral study.

Similarly, the hypotheses regarding the effect of perceived control on exploration to revert to older technologies and avoid social media were tested. The results confirm that PC has a significant direct effect on exploration to revert and avoid social media. As shown in Table 6.2, H7 and H8 are both supported, with regression coefficient estimate values of 0.073 and .079 and p-values of < 0.016 and < 0.035 respectively. The results indicate that if consumers are given more control on social media platforms, they will neither revert from these platforms nor avoid them.

6.2.1.2 Affective Attitudinal Components

The evidence from this research provides empirical support that attitude is composed of affective components of enjoyment, self-enhancement and fear. As discussed in the above chapter, cognitive attitudinal attributes are not the sole determinants of social media adoption and adaptation, as affective components, which can be either positive or negative affective attributes, also play a role. Consumers may have positive or negative emotions towards the consequences of their social media digital footprints. Positive emotions (e.g. enjoyment, pleasure and self-enhancement) may result in positive social media experiences (Diffley et al., 2011; Park and Kim, 2014), which may make consumers' attitude to social media digital footprints more favourable. Negative emotions (fear and lack of trust) may arise from negative social media experiences, which may make consumers' attitudes to social media digital footprints more unfavourable.

6.2.1.2.1 Enjoyment

The results of this research confirm that enjoyment has a significant direct effect on exploration to maximise social media benefits but not on exploitation to satisfice such benefits. As shown in Table 6.2, H9 is supported, with a regression coefficient estimate value of 0.0117 and $p < 0.001$, indicating that enjoyment has a direct positive effect on exploration to maximise social media benefits. However, H10 is not supported, which means that enjoyment does not have a direct effect on exploitation to satisfice social media benefits, with a regression coefficient estimate value of 0.011 and $p < 0.709$. The results indicate that consumers are driven by enjoyment (hedonic and emotional), which drives their attitude to maximise social media benefits. However, they may not exploit to satisfice social media benefits. The empirical findings of this research for exploitation to satisfice social media benefits indicate that consumers may make the least use of social media functions and features. However, in the case of EMSMB, the affective attitudinal component of enjoyment induces consumers' attitude and they adopt social media to maximise its benefits.

According Bala and Venkatesh (2016), exploitation refers to more routine use of technology, while exploration to maximise refers to seeking optimum benefits. When it comes to enjoyment, the findings of this research suggest that consumers tend to go beyond the regular features of a technological application such as social media and maximise its benefits rather than satisfice the minimum social media offers. In other words, it can be argued that consumer enjoyment of social media use relates to finding new features. This also underpins consumers' desire for innovation and characterises their desire for freedom and liberty, which has a bearing on the success of Web2.0 and smart technologies. Hence, consistent with prior research, it appears that consumers' affective needs lead to pleasant hedonic motivation, which drives their elements of enjoyment (Chiang, 2013; Kim et al., 2011). The results of this research confirm that enjoyment drives consumers' sharing of information, participation in discussions and engaging in sensations (Lin et al., 2008; Nov et al., 2010) on social media platforms.

6.2.1.2.2 Self-Enhancement (SE)

The empirical findings of this research confirm that self-enhancement is a component of consumers' affective attitude and is the antecedent of exploration to maximise and satisfice social media benefits. Self-enhancement enhances consumers' positive attitude towards maximising and satisficing social media benefits. The results show that SE has a significant direct effect on exploration to maximise and exploitation to satisfice social media benefits. As shown in Table 6.2, H11 and H12 are supported, with regression coefficient estimate values of .287 and .205 and p-values of < 0.000 and < 0.000 respectively. This indicates that consumers seek to maximise as well as satisfice social media benefits when their hedonic self-enhancement increases. They share digital footprints on social media platforms due to self-fulfilment of status, image and attention from others. Their self-enhancement gives them high self-esteem and they present more of their self-focused status on social media. They tend to be more emotionally engaged with social media platforms, as confirmed by the empirical results reported in Chapter 5. This result is consistent with previous scholarly works which indicate that self-status and self-esteem gratify social media consumers' self-fulfilling hedonic needs of self-esteem to portray the desired impression on social media platforms (Ali and Lee, 2010; Sas et al., 2009; Hepper et al., 2011; Terry et al., 2007). Thus, the evidence from this research provides empirical support that consumers' self-enhancement is increased when they interact with social media and share information for status, image and to attract attention. They tend to reveal desirable information to formulate the impression they wish to produce on others for self-fulfilment. Therefore, this research confirms that self-enhancement enhances consumers' self-esteem, self-presentation and self-image, which drive social media adoption to maximise or satisfice social media benefits.

6.2.1.2.3 Fear

The results of this research confirm that fear is a component of consumers' affective attitude and is the antecedent of exploration to revert and avoid social media. In addition, the findings indicate that fear has a direct significant effect on behavioural outcomes. The evidence from the results of this research supports the notion that fear of digital footprints enhances consumers' negative attitude towards exploration to revert and avoid social media. The results confirm that fear has a significant direct effect on exploration to revert and avoid social media. As shown in Table 6.2, H13 and H14 are supported, with regression coefficient estimate values of 0.334 and 0.471 and p-values of < 0.000 and < 0.000, respectively. Similarly, this research confirms that fear also has a direct significant effect on the behavioural outcomes of consciousness and cautiousness. As shown in Table 6.2, H15 and H16 are supported, with regression coefficient estimate values of -0.117 and 0.350 and p-values of < 0.017 and < 0.000 respectively. The above results suggest that consumers' affective attitude of fear towards the consequences of their social media digital footprints has a negative impact on their attitude and they feel threatened, which in turn influences their adoption and adaptation behaviour. Thus, it can be inferred from the above results that consumers feel threatened towards the consequences of their social media digital footprints, which may make them conscious towards their digital footprints. They tend to give more attention and enhance their awareness of sharing digital footprints on social media. The results confirm that as consumers pay more attention towards their digital footprints, they feel less fearful toward their digital footprints. They tend to be vigilant towards their digital footprints due to fear of privacy and security. They tend to consciously interact with social media platforms with focus attention.

Similarly, the results confirm that when consumers feel that their digital footprints are at stake of privacy and security risks, they tend to be more cautions towards sharing digital footprints on social media. They tend to be suspiciously alert towards sharing digital footprints on social media platforms. Therefore, the evidence from this research provides empirical support that as consumers' fear of digital footprints increases, they tend to either revert from social media or abandon them completely. As a result, they may cease to share digital footprints on social media platforms.

This finding is consistent with prior research which contends that individuals develop overall feelings of anxiety towards a specific technological situation or technological disruption and that this anxiety may lead to incompatibility with a technology (Bala and Venkatesh, 2016; Cheung et al., 2015; Karyda et al., 2009). Consumers may develop fear of the consequences of disclosure of personal information, fear of identity theft, cyber-harassment and scrutiny of personal records by others. Fear of digital footprints (privacy and security risks) generates fear amongst consumers towards the consequences of their digital footprints, which may give rise to negative attitudes towards sharing digital footprints. The results of this research confirm that fear about the consequences of the accumulation, use and sharing (collection, processing, purpose, storage, unauthorised access etc.) of their digital footprints by social media providers influences consumers' adoption and adaptation of social media.

6.2.1.2.4 Trust

The findings and results discussed in Chapter 5 confirm that consumers' feelings of trust influence their attitude towards social media adoption and adaptation. Social media providers' lack of reliability and honesty may make them emotionally sensitive to the privacy and security of their digital footprints and reluctant to adopt and adapt social media.

As shown in Table 6.2, H17 and H18 are supported, with regression coefficient estimate values of 0.120 and 0.073 and p-values of < 0.000 and < 0.007, respectively. The above results suggest that consumers' affective attitude of trust is the antecedent to social media adoption and exploration to maximise or satisfice social media benefits. This means that consumers tend to seek to maximise or satisfice social media benefits when their affective-based trust increases. They may share digital footprints on social media platforms if their feelings of trust in social media platforms increase.

Moreover, this research hypothesised that lack of trust may make consumers reluctant to adopt social media and they may revert or abandon its use completely. As shown in Table 6.2, H19 is not supported, with a regression coefficient estimate value of -0.053 and a p-value of < 0.075. However, H20 is supported, with a regression coefficient estimate value of -0.124 and a p-value of < 0.000. These results confirm that trust has a direct negative effect on avoidance of social media but no direct negative effect on exploration to revert from social media platforms. The latter result confirms that consumers may not tend to revert to older technologies if they have little feeling of trust in these platforms. However, they may avoid social media altogether if they have no trust at all in these platforms. A similar point was made by Beaudry and Pinsonneault (2005), who argued that when individuals assess a technology as a threat, they will opt to avoid it altogether.

In addition, this research hypothesised that trust has a direct effect on behavioural outcomes such that consumers may become careless or carefree when their feeling of trust towards the consequences of their digital footprints is enhanced. The results of this research confirm that the feeling of trust has a direct significant effect on the behavioural outcomes of carelessness and carefreeness towards the consequences of their digital footprints. As shown in Table 6.2, H21 and H22 are supported, with regression coefficient estimate values of -0.090 and -0.227 and p-values of < 0.000 and < 0.000, respectively. Therefore, the evidence from this research provides empirical support that as consumers' feelings of trust in social media platforms increase, their carelessness towards their digital footprints decreases. The results confirm that consumers would tend to have careless engagement with their digital footprints.

Similarly, as consumers feeling of trust in social media providers increases, their carefreeness towards digital footprints decreases. The evidence from this research provides empirical support that consumers would tend to have carefree engagement with their digital footprints and they would be indifferent and easy going about their social media digital footprints.

These findings are consistent with prior research which argues that consumers' trust is influenced by their emotions of trust in service providers' respect, reliability and credibility. Trust enhances their loyalty and influences their acceptance of social media (Gamboa and Gonçalves, 2014; Terres et al., 2015). The results of this research confirm that consumers' trust towards their digital footprints does not undergo a careful and methodical thought process (Rousseau et al., 1998); rather, it is based on their emotions and feelings. The evidence from this research provides empirical support for the contention that consumers' privacy and security paradox is due to their emotions rather than cognition, as they may not require awareness of the consequences of their digital footprints. Thus, they may rely more on their feelings of trust and less on cognitive evaluation or awareness of the consequences of their digital footprints.

It can be inferred from the results of this research that the R^2 for the dependent variables (EMSMB .25, ESSMB .15, ER .21 and ASM .26) account for 87% of the variance in adoption and adaptation behaviour, showing the predictive power of the model. TAAM was able to account for 87% of the variance in adoption and adaptation behaviour.

6.3 Research Questions RQ3 and RQ4

RQ3. What adaptation behavioural efforts do consumers undertake to cope with the consequences of their social media digital footprints?
RQ4. What are the behavioural outcomes of the adaptation behaviour based on consumers' attitudes towards the consequences of their digital footprints?

6.3.1 Adaptation Behaviour and Outcome

6.3.1.1 Exploration to Maximise Social Media Benefits (EMSMB) and Carelessness

Consumers' adaptation behaviour for social media use entails their actions, which they adjust to social media functions such as exploration to maximise, exploitation to satisfice social media benefits or exploration to revert or avoid social media. As discussed above, consumers develop attitudes towards the consequences of their social media digital footprints and undertake certain adaptation efforts. They may have favourable or unfavourable attitudes towards the consequences of their digital footprints. If their attitudes are favourable, they may explore to maximise or exploit to satisfice social media benefits; whereas if their attitude is unfavourable, they may abandon social media platforms altogether. As shown in Table 6.2, H23 is supported, with a regression coefficient estimate value of 0.146 and a p-value of < 0.000. This result confirms that consumers may become careless towards the consequences of their digital footprints if they have a positive attitude towards social media adoption and explore ways to maximise social media benefits. Thus, the evidence from the findings of this research provides empirical support that consumers' positive cognitive (PO, PSI and PC) and affective (enjoyment, SE and trust) attitudinal components shape their positive attitudes towards social media adoption and exploration to maximise social media benefits. As a result, they tend to be careless towards the consequences of their digital footprints. This research confirms the outcome for Carelessness, highlighted in Figure 6.2, which is that consumers may become inattentive and negligent towards their social media digital footprints if their attitude towards these platforms is positive.

		Digital Footprints Sharing	
		High	**Low**
Digital Footprints Concern	**High**	**Consciousness** (Mindfully aware, cognizant and fully considerate towards digital footprints)	**Cautiousness** (Suspiciously alert and exercising caution towards digital footprints)
	Low	**Carelessness** (Inattentive and heedless towards digital footprints)	**Carefreeness** (Indifferent and lighthearted towards digital footprints)

Figure 6. 2 4C Matrix (Consumers' Behavioural Outcome)

6.3.1.2 Exploitation to Satisfice Social Media Benefits (ESSMB) and Carefreeness

As discussed above, social media consumers' adaptation behaviour is about consumers' actions based on their favourable or unfavourable attitude towards the consequences of their social media digital footprints. However, if this attitude is unfavourable, they may exploit to satisfice limited social media benefits. As consumers opt for adaptation acts of exploitation to satisfice social media benefits, they tend to make the least use of social media functions and features and they may be carefree towards the consequences of their digital footprints.

It can be argued that consumers adopt a technology due to its various positive features, social/occupational reasons and/or hedonic pleasure. But they simultaneously feel anxiety or tension due to negative aspects such as fear of privacy and security risks. If the latter has more influence, or if their fear and anxiety become stronger, they will make minimum to moderate use of the technology. Furthermore, they may tend to feel less trust towards these platforms. The results of this research confirm that exploitation to satisfice social media benefits does not have a direct significant effect on carefreeness. As shown in Table 6.2, H24 is not supported, with a regression coefficient estimate value of -0.017 and a p-value of < 0.616. As discussed above, it can be argued that when consumers opt for the adaptation behaviour of exploitation to satisfice social media, they may make the least use of social media functions and features, as they may be carefree towards the consequences of their digital footprints. Thus, this research confirms the outcome for Carefreeness, highlighted in Figure 6.3, which is that consumers may be free from care and may not be anxious towards the consequences of their digital footprints on social media platforms.

		Digital Footprints Sharing	
		High	**Low**
Digital Footprints Concern	**High**	**Consciousness** (Mindfully aware, cognizant and fully considerate towards digital footprints)	**Cautiousness** (Suspiciously alert and exercising caution towards digital footprints)
	Low	**Carelessness** (Inattentive and heedless towards digital footprints)	**Carefreeness** (Indifferent and lighthearted towards digital footprints)

Figure 6. 3 4C Matrix (Consumers' Behavioural Outcome)

6.3.1.3 Exploration to Revert and Consciousness

The evidence from the findings of this research provides empirical support that consumers' attitude towards the consequences of their digital footprints comprise their joint attitudinal components. It is not only the cognitive appraisal of perceived control but also affective components of fear and trust in social media providers that influence their adaptation efforts in the form of exploration to revert. As discussed above, the results for Perceived Control (section 6.2.1.1.3) and Fear (section 6.2.1.2.3) confirmed that these aspects have direct significant effects on exploration to revert from social media. However, the result for Trust (section 6.2.1.2.4) show that trust has no direct negative effect on exploration to revert from social media, which confirms that consumers may not want to revert to old technologies if they have little feeling of trust in social media platforms. Although trust has a negative direct effect on Avoidance of Social Media, it does not have a direct negative effect on Exploration to revert from social media. It means consumers may abandon social media altogether if they have no feeling of trust at all, but may not revert from social media platforms to old technologies if they have little feeling of trust in these platforms.

Thus, this research infers that exploration to revert from social media does not have a direct significant effect on consciousness. As shown in Table 6.2, H25 is not supported, with a regression coefficient estimate value of 0.031 and a p-value of < 0.627. This result confirms that when consumers opt for the adaptation behaviour of exploration to revert from social media, they may not be conscious towards their digital footprints. Thus, this research confirms the outcome for Consciousness, highlighted in Figure 6.4, which is that consumers may not pay considerable attention to their digital footprints on social media when engaged in the adaptation behaviour of exploration to revert from social media.

		Digital Footprints Sharing	
		High	**Low**
Digital Footprints Concern	**High**	**Consciousness** (Mindfully aware, cognizant and fully considerate towards digital footprints)	**Cautiousness** (Suspiciously alert and exercising caution towards digital footprints)
	Low	**Carelessness** (Inattentive and heedless towards digital footprints)	**Carefreeness** (Indifferent and lighthearted towards digital footprints)

Figure 6. 4 4C Matrix (Consumers' Behavioural Outcome)

6.3.1.4 Avoidance of Social Media and Cautiousness

As discussed in the above sections, both Perceived Control (section 6.2.1.1.3) and Fear (section 6.2.1.2.3) have a direct significant effect on avoidance of social media. Similarly, Trust has a significant direct negative effect on Avoidance of Social Media (section 6.2.1.2.4). The results in the above sections provide empirical evidence that the joint attitudinal components (Perceived Control, Fear and Trust) have a direct impact on Avoidance of Social Media. These results confirm that consumers may engage in social media avoidance adaptation behaviour if they perceive low control, high feelings of fear and low trust in social media platforms and they may be cautious towards the consequences of their digital footprints. Thus, the results of this research confirm the hypothesis that ASM has a direct significant effect on consumers' cautiousness towards social media digital footprints. As shown in Table 6.2, H26 is supported, with a regression coefficient estimate value of 0.329 and a p-value of < 0.000.

Therefore, this research concludes that consumers may be suspiciously alert and exercising caution over sharing digital footprints on social media platforms. They may undertake caution by thoroughly and thoughtfully avoiding sharing digital footprints on these platforms if they perceive low control, high feelings of fear and low trust in social media platforms. Thus, this research confirms the outcome for Cautiousness, as highlighted in Figure 6.5.

		Digital Footprints Sharing	
		High	**Low**
Digital Footprints Concern	**High**	**Consciousness** (Mindfully aware, cognizant and fully considerate towards digital footprints)	**Cautiousness** (Suspiciously alert and exercising caution towards digital footprints)
	Low	**Carelessness** (Inattentive and heedless towards digital footprints)	**Carefreeness** (Indifferent and lighthearted towards digital footprints)

Figure 6. 5 4C Matrix (Consumers' Behavioural Outcome)

6.4 Conclusion

This chapter discussed the findings of this research and analysed the results in light of the research aim and objectives. It provided in-depth analysis, interpretation and discussion of the findings in the context of the relevant literature to make inferences for the TAAM model and establish the causal links in the model. The discussion in this chapter was mainly based on the findings discussed in Chapter 5. This chapter tested all 26 hypotheses and confirmed that 22 of these hypotheses were supported, and provided an in-depth discussion and analysis of these hypotheses and the validation of the TAAM model.

Chapter 7. Conclusion

7.1 Introduction

The aim of this research was to examine consumers' social media adoption, adaptation and behavioural outcomes as a composite process based on their joint attitudinal components towards the consequences of their digital footprints and to scrutinise the underlying factors driving this composite process. This research provided background to consumers' technology adoption, adaptation and attitude in Chapters 1 and 2. It highlighted the significant aspects of consumers' interaction with technology, the immense growth in social media adoption and the expansion of digital footprints, creating a rich source of insight for marketers (Henderson and Bowley, 2010; Tuten and Solomon, 2015). To achieve the aim of this research, the researcher formulated the following objectives to determine consumers' adoption, adaptation and outcomes towards the consequences of their digital footprints and to fill the identified research gap. This chapter provides conclusions on the attainment of these objectives and sets out a summary of the study's theoretical and practical contributions. Based on the research conclusions, recommendations are given, followed by research limitations and possible directions for future research. Table 7.1 below highlights the objectives and the chapters in which they are addressed in detail.

Objectives	Chapter
To examine what underlying attitudinal components (cognitive and affective) drive consumers' social media adoption, adaptation and behavioural outcomes as a composite process.	3, 5, 6
To critically assess the impact of the joint attitudinal components (cognitive and affective) on consumers' social media adoption, adaptation and behavioural outcomes.	2, 5, 6
To analyse the adaptation behavioural efforts that consumers undertake to cope with the consequence of their social media digital footprints.	5, 6
To determine the behavioural outcomes of the adaptation behaviour based on consumers' attitudes towards the consequences of their digital footprints.	5, 6
To develop a comprehensive model which focuses on consumers' adoption, adaptation and behavioural outcome as a composite process.	3

Table 7. 1 Research Objectives

7.2 Objective 1

To examine what underlying attitudinal components (cognitive and affective) drive consumers' social media adoption, adaptation and behavioural outcomes as a composite process.

Both the CMUA and the UTAUT gave little attention to the joint attitudinal components that this research has addressed in its examination of both cognitive and affective attitudinal components, which drive consumers' technology adoption and adaptation as a composite process. The results of this research in Chapter 5, and the discussion and analysis in Chapter 6, provide evidence that consumers' social media adoption, adaptation and outcomes as a composite process are driven by Perceived Opportunity, Perceived Social Influence and Perceived Control (cognitive attitudinal components) and by Enjoyment, Self-Enhancement, Trust and Fear (affective attitudinal components). Both the UTAUT and the CMUA focused on cognitive functional attributes, whereas this research, based on the empirical findings in the above chapters, concludes that the joint attitudinal components, including the emotional components manifest in consumers' feelings towards the consequences of their digital footprints, are the factors underlying social media adoption, adaptation and behavioural outcomes as a composite process. Thus, the above attitudinal attributes are the key determinants in the TAAM, which offers predictive power and accounts for the composite process of social media adoption, adaptation and behavioural outcomes.

7.3 Objective 2

To critically assess the impact of joint attitudinal components (cognitive and affective) on consumers' social media adoption, adaptation and behavioural outcomes.

The second objective was to assess the impacts of joint attitudinal components (cognitive and affective) on consumers' social media adoption, adaptation and behavioural outcomes. As discussed above, the results of this research confirm that consumers' composite process of social media adoption, adaptation and outcome is driven by both cognitive and affective attitudinal components referring to consumers' overall attitude towards the consequences of their social media digital footprints. The evidence from this research provides empirical support that consumers' attitude consists of both cognitive and affective attributes towards social media adoption and adaptation behaviour and its outcomes. Therefore, based on the empirical evidence, this research infers that cognitive components of perceived opportunity, perceived social influence and perceived control, and affective components of enjoyment, jointly have a direct influence on social media adoption and adaptation as a composite process. Therefore, it concludes that it is not only cognitive but also affective attitudinal components which drive consumers' social media adoption, adaptation and behavioural outcomes as a composite process. Thus, this research developed and empirically tested the Technology Adoption and Adaptation Model (TAAM) based on the joint attitudinal components and infers that these joint components provide a more comprehensive understanding of the composite interaction of social media adoption, adaptation and outcomes.

7.4 Objective 3

To analyse the adaptation behavioural efforts that consumers undertake to cope with the consequences of their social media digital footprints.

The third objective was to analyse the adaptation behavioural efforts that consumers undertake to cope with the consequences of their social media digital footprints. The results presented in Chapter 5 and the detailed discussion in Chapter 6 provide empirical evidence that consumers undertake the following adaptation strategies to cope with the consequences of their digital footprints. They may engage in adaptation behaviour of Exploration to Maximise or Exploitation to Satisfice Social Media Benefits (EMSMB and ESSMB) if they have a favourable attitude towards the consequences of their digital footprints. Similarly, they may engage in Exploration to Revert (ER) from social media adaptation behaviour or Avoidance of Social Media (ASM) altogether if their attitude towards the consequences of their digital footprints is unfavourable. If their attitude towards the consequences of their digital footprints is positive, they may explore ways to maximise social media benefits and share digital footprints on these platforms. However, they may engage in exploitation to satisfice social media benefits (limited adaptation behaviour) if their attitude towards social media digital footprints is such that they are unable to derive further benefits from these platforms. In such limited adaptation behaviour, they may make the least use of social media functions and features to satisfice social media benefits and share limited digital footprints on these platforms.

In contrast to the above adaptation behaviour, the results of this research provide evidence that consumers may avoid social media altogether if their attitude towards the consequences of their digital footprints is negative (brings them harmful consequences). They tend to both cognitively and emotionally disconnect from the platforms and may engage in social media avoidance adaptation behaviour and stop sharing digital footprints on social media platforms.

Similarly, the results show that both cognitive (perceived control) and affective (fear) attitudinal attributes have an impact on exploration to revert to older technologies as an adaptation behaviour, with the exception of trust. Therefore, this research infers that consumers may engage in exploration to revert from social media if they have less control and high fear, but may not revert from social media to older technologies if they have low trust in these platforms.

Thus, based on the evidence and empirical support, this research infers that consumers may undertake the adaptation behavioural efforts of EMSMB, ESSMB, ER and ASM based on their attitude to cope with the consequences of their digital footprints.

7.5 Objective 4

To determine the behavioural outcomes of the adaptation behaviour based on consumers' attitudes towards the consequences of their digital footprints.

As discussed in detail in Chapter 6, each adaptation effort has an outcome, as given in Figure 7.1 (4C Matrix), based on their joint attitudinal components. The four outcomes are Carelessness, Carefreeness, Consciousness and Cautiousness respectively, depending on the composite process of social media adoption and adaptation behaviour.

Consumers may explore ways to maximise social media benefits and share digital footprints if their attitude towards the consequences of their digital footprints is positive. Based on the evidence and empirical support, this research infers that consumers may be careless towards the consequences of their digital footprints, such that they may not pay attention to the risks of their digital footprints and may not take any precautions against them. They may tend to be negligent and inattentive to their social media digital footprints.

However, they may engage in exploitation to satisfice social media benefits (limited adaptation behaviour) if their attitude towards social media digital footprints is such that they are unable to derive further benefits from these platforms. In such limited adaptation behaviour, this research infers that consumers may make least use of social media features to satisfice social media benefits, may share limited digital footprints and may be Carefree towards their digital footprints. Thus, they may be free from care and they might not be anxious towards the consequences of their digital footprints on social media platforms.

In contrast, consumers tend to engage in social media avoidance as an adaptation behaviour if their attitude towards the consequences of their digital footprints on social media platforms is negative. They may tend to avoid social media platforms altogether, and the empirical evidence produced by this study infers that these consumers tend to be cautious towards the consequences of their digital footprints. They tend to exercise caution and may tend to be alert towards sharing digital footprints on social media platforms.

However, based on the results, this research concludes that perceived control and fear have a direct significant effect on exploration to revert as an adaptation behaviour, with the exception of trust. Therefore, this research infers that in such a situation, consumers would tend to engage in exploration to revert from social media because of less control and high fear, and they would tend to be Conscious towards their digital footprints. They would tend to pay considerable attention towards the consequences of their digital footprints. However, based on the empirical evidence, this research infers that consumers would not tend to revert from social media if they have little trust in social media platforms, and in such a situation, they would not tend to be conscious towards their digital footprints.

		Digital Footprint Sharing	
		High	**Low**
Digital Footprint Concern	**High**	**Consciousness** (Mindfully aware, cognizant and fully considerate about digital footprints)	**Cautiousness** (Suspiciously alert and exercising caution about digital footprints)
	Low	**Carelessness** (Inattentive and heedless about digital footprints)	**Carefreeness** (Indifferent and lighthearted about digital footprints)

Figure 7. 1 4C Matrix (Consumers' Behavioural Outcome)

7.6 Objective 5

To develop a comprehensive model which focuses on consumers' adoption, adaptation and behavioural outcomes as a composite process.

This research adopted a composite view of consumers' social media adoption, adaptation and behavioural outcomes and developed a comprehensive model (TAAM) comprising cognitive and affective attitudinal components as antecedents for both adoption and adaptation with outcomes. The model, along with each construct, is discussed in Chapter 3, and tested and validated in Chapters 5 and 6. The model underwent rigorous empirical testing and the empirical evidence confirms that it is an all-embracing, well-fitting model.

7.7 Contributions to Theory

This research makes the following contributions to the literature. First, it offers technology adoption, adaptation and outcomes as a composite process and makes a contribution to the literature by developing a nomological technology adoption, adaptation and behavioural outcome model. Second, this research extends the adoption and adaptation literature by offering the joint attitudinal components (cognitive and affective) as antecedents to technology adoption and adaptation as a composite process. Third, this research contributes to the adaptation literature by examining the adaptation strategies that consumers undertake to cope with the consequences of their digital footprints. Fourth, this research contributes to the literature by examining the impacts of technology adoption and adaptation as a composite process on behavioural outcomes. Finally, it makes a significant contribution to the literature on digital footprints and privacy and security.

First, this research contributes to the literature by extending the technology adoption and adaptation theories into a composite model of Technology Adoption and Adaptation as a composite process. This research builds on the technology adoption (UTAUT) and adaptation (CMUA) models. Both the UTAUT and the CMUA fail to capture the interaction of technology adoption and adaptation as a composite process. This research extends both the models into the TAAM by conceptualising that adoption and adaption form a composite process and introduces consumers' attitudes as the antecedents of this process. Technology does not stop at adoption but goes beyond and integrates into consumers' adaptation and behavioural outcomes. Consistent with prior research, this doctoral study suggests that consumers, based on their joint attitudinal components, would tend to engage in different adaptation strategies towards the consequences of their digital footprints. Moreover, these adaptation strategies are not mutually exclusive: consumers may opt for different adaptation behaviours. Thus, this research has developed an all-embracing TAAM model based on the joint attitudinal components, which offers predictive power and accounts for the composite process of technology adoption, adaptation and behavioural outcomes. This model exhibits the apposite and significant associations among factors, providing valuable insights in determining consumers' underlying adoption and adaptation composite behaviour.

Second, this research contributes to the literature by introducing the joint attitudinal components (cognitive and affective) as antecedents to the composite process of social media adoption and adaptation. It extends prior models (UTAUT and CMUA) by including the affective attitudinal components of enjoyment, self-enhancement, fear and trust as the antecedents of the composite process. Unlike the UTAUT and the CMUA, which focused on cognitive functional attributes, this research introduces both cognitive and affective attitudinal components in the composite process. It contributes to the literature by demonstrating that the joint attitudinal impact, including the emotional components manifest in consumers' feelings towards technology, are the underlying factors in social media adoption, adaptation and behavioural outcomes as a composite process. Consumers' attitudes are driven by both attitudinal components of cognition and affect, conceptualising their overall attitude towards the composite process of social media adoption and adaptation.

Third, this research contributes to the literature by building on adaptation behaviours such that it is a composite process, which is a part of adoption and adaptation, by extending into daily activities. Consumers, based on the joint attitudinal attributes, undertake adoption and adaptation efforts as a composite process to cope with their social media digital footprints. In addition, this research makes a further contribution to the literature by demonstrating that the adaptation efforts depend on the joint attitudinal components such that positive attitudes may result in the adaptation behaviour of exploration of ways to maximise technology benefits and limited adaptation behaviour for exploitation to satisfice technology benefits (inability to derive further benefits from social media). In contrast, it demonstrates that if consumers' attitude towards the consequences of their digital footprints is negative (brings them harm), they would tend to avoid technology and may disconnect from the platforms. Furthermore, this research demonstrates that other affective attitudinal attributes influence Exploration to Revert behaviour, with the exception of trust, which means that if individuals have little trust in technology, they may not revert from social media platforms. In advancing the antecedent scholarship of technology adoption and adaptation as a composite process, this research has extracted and analysed the key antecedents of perceived opportunity, perceived social influence and perceived control as cognitive attitudinal components and self-enhancement, enjoyment, trust and fear as affective attitudinal components having direct impacts on adoption, adaptation and behavioural outcomes as a composite process.

Fourth, this research makes a contribution to the literature by examining the impacts of technology adoption and adaptation behaviour on the four significant individual outcomes given in Figure 7.1 (Carelessness, Carefreeness, Consciousness and Cautiousness) when consumers engage with technology and this research propounds a pioneering 4C Matrix. Based on individuals' expectations of the consequences of technological disruption, extending the UTAUT and the CMUA, each adaptation effort results in an outcome. If their attitude to the consequences is positive, they may tend to explore ways to maximise technology benefits and would be Careless towards the consequences of their digital footprints. However, if they develop the attitude that they are unable to derive further benefits from technology, they may tend to engage in the limited adaptation behaviour of exploitation to satisfice technology benefits and they would not be Carefree towards the consequences of their digital footprints. In contrast, if individuals' attitude towards the consequences of their digital footprints is negative, they may tend to engage in avoidance of technology altogether and would be Cautious towards the consequences of their digital footprints. However, consumers would not tend to revert from social media if they have little trust in social media platforms, and in such a situation, they would not tend to be conscious towards their digital footprints.

Finally, this doctoral research makes a contribution to the literature by demonstrating that these four outcomes exist not only in the context of consumers' social media digital footprints, but also in consumers' attitudes towards the consequences of any other technological disruptions in any context. Furthermore, this research makes a significant contribution to knowledge of digital footprints and the role of privacy and security. Hence, this research offers a strong conceptual underpinning for assessing the dynamic and dichotomous nature of consumers' social media engagement. While the model is suggested for social-media-based interaction, it can also be applied to other technologies.

7.8 Contribution to Practice

This doctoral research makes the following practical contributions. It helps marketers in segmentation, profiling of consumers and developing effective targeting strategies. It allows different stakeholders such as marketers and IS managers to focus on consumers' joint attitudinal components by revealing the key antecedents of the composite process to target consumers both in terms of cognitive and affective attributes. It helps marketers to optimise value propositions for consumers. It also highlights that marketers and practioners need to build strong affective attitudinal relationships with consumers that go beyond the cognitive functional attitudinal attributes. It draws practioners' attention to the affective attributes to create significant value for consumers that influence the generation of digital footprints, which may help them understand patterns of behaviour. It helps practitioners to recognise and comprehend consumers' cognitive and emotional attributes in sharing their digital footprints.

Moreover, it draws attention to consumers' adaptation efforts to cope with the consequences of their digital footprints. By enhancing consumers' positive attitude towards their digital footprints, they tend to share more memories, interests, likes, dislikes and behavioural attributes. This can provide commercial entities with the opportunity to focus on such aspects wherein consumers maximise engagement with social media and tend to become careless and carefree towards their digital footprints. They may tend to share more important digital footprint required by vendors and practitioners. Similarly, it draws attention to certain aspects which may turn consumers attitude unfavourable towards their digital footprints such as lack of trust and control and high fear may lead them to avoid social media altogether. It identifies the roles of fear and trust, which have strong direct effects on adoption and adaptation as well as on their outcomes. Practitioners, by focusing on the emotional factors of fear and trust, could provide more consumer engagement with social media and sharing of digital footprints.

Similarly, it helps other stakeholders such as social media providers to set priorities for social media adoption, adaptation and behavioural outcomes as a composite process and technology in general. In addition, it reveals consumers' attitudinal response to their privacy and security of their digital footprints, which can help both regulators and service providers for policy making. TAAM can be applied in different consumer contexts to enhance understanding and knowledge on technology adoption, adaptation and digital footprints. While the model is suggested for social-media-based interaction, the privacy and security issues can also be applied to other technological applications, such as cloud computing and smartphones. It adds value not only to managerial practice but also to good theory-building.

7.9 Limitations and Future Research Direction

This research makes valuable contributions and offers insightful findings, but there are some limitations that should be acknowledged. This study was carried out using a random sample of social media users to examine consumers' attitudes towards their digital footprints. It was difficult to confine this research to a single social media platform. This can be considered as a limitation to determining findings for an individual platform. Similarly, this research tested the model on social media consumers, but future studies could focus both on general social media users and on users of separate platforms. Furthermore, this research tested the TAAM on social media technologies, but it could also be tested on other technologies and contexts, including cross-cultural contexts. The TAAM has a broader scope regarding technology adoption and adaptation as a composite process. Furthermore, this research studied the joint attitudinal components towards digital footprints, but other technological disruptions could be considered in future research. Similarly, this study used the joint attitudinal components as the antecedents of a composite process. Future research could consider the possibility of the hierarchical and causal nature of cognitive and affective aspects of attitude. The other limitation of this research was measurements of adaptation behaviour, which have both cause and effects embedded in the same statements. This research has advanced scholarship in the literature on technology adoption, adaptation, digital footprints and social media, and its limitations provide further research opportunities. Future research could look at individual platforms separately and also examine them in a cross-cultural context. Secondly, this research mainly focussed on social media consumers, whereas future research could focus on general social media users. Thirdly, future research could use the TAAM with different technologies, contexts and users. Similarly, future studies could examine different technological disruptions using the TAAM, and could also focus on the hierarchy and causality of cognitive and affective attributes.

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Appendix 1. Measurement Items for the Constructs

Construct	Items Adapted for this research	Source
Perceived Opportunity (PO)	• I am confident that social media will have positive outcome for the information I share on these platforms. • I believe social media will open new opportunities for me to share information, memories, interests, likes and dislikes etc. with others. • I believe social media platforms will provide me opportunities to share my likes, dislikes, interests and information etc. with others. • I believe social media will give me opportunities to share my memories, interests and information etc. with others to gain recognition and praise.	Bala and Venkatesh, (2016)
Perceived Social Influence (PSI)	• I think I interact well with others on social media for sharing my memories, likes, dislikes, interests and information etc. • I believe I fit well with others on social media that share the same interests as me. • I believe social media help me establish relationship with others to share information and interests. • I think I maintain close relationships with others on social media for sharing information and interests etc.	Cheung et al., (2015)
Perceived Control (PC)	• I think I have control over sharing information on social media platforms. • I believe I can control sharing information on social media platforms. • I believe I have control over what to share on social media platforms. • I believe I can control sharing my memories, likes, dislikes and information on social media platforms.	Dinev et al., (2013)
Enjoyment	• I feel I have a lot of enjoyment in sharing my memories, likes, dislikes, interests and information with others on social media. • Social media give me a lot of excitement in sharing my memories, likes, dislikes, interests and information with others. • I find social media quite entertaining in sharing my memories, likes, dislikes, interests and information with others. • I spend enjoyable and relaxing time on social media by sharing my memories, likes, dislikes, interests and information with others.	Cheung et al., (2015)
Self-Enhancement (SE)	• I feel social media improve my image by sharing my interests, likes and dislikes etc. with others. • I feel I can influence others on social media by sharing my memories, likes, dislikes, interests and information etc. • I feel I can make a good impression on others on social media through my interests, memories, likes, dislikes, and information etc.	Al-Jabri et al., (2015)

	• Social media platforms help me present my best side to others by sharing my interests, likes and dislikes.	
Fear	• I am afraid of sharing information on social media. • I do not feel comfortable to share information on social media. • I feel social media gather my highly personal information, likes, dislikes interests and memories etc. • I feel social media share my digital footprints with third parties without my consent.	Dinev et al (2013)
Trust	• I feel social media providers are honest and caring about my digital footprints which I share on their platforms. • I feel social media platforms are reliable as they do not share my digital footprints with others. • I feel social media providers are interested in my well-being and they do not share my digital footprints with third parties. • I feel social media do not give access to third parties to have access to my personal information etc.	Dowell et al., 2015; Morrow, et al., 2004
Exploration to Maximise Social Media Benefits (EMSMB)	• I explore social media to find new ways of sharing information, interests and memories with others. • I explore social media for potential new applications to share information etc. • I discover new ways of using social media to share my likes, dislikes, interests and information etc. with others. • I experiment with social media to find new features to share information, interests and memories etc.	Bala and Venkatesh, (2016)
Exploitation to Satisfice Social Media Benefits (ESSMB)	• I use the same social media features that I learnt from others to share information on social media platforms. • I use common social media features to share my memories, likes, dislikes and interests etc. with others. • I use the same social media features suggested to me by others to share my memories and interests etc. on social media platforms. • I use social media features that I learnt from others on these platforms to share my likes, dislikes, interests and information etc.	Bala and Venkatesh, (2016)
Exploration to Revert (ER)	• Due to my privacy and security I now search for old ways of sharing information with others rather than social media. • Due to my privacy and security, I now look for old ways of sharing information with others when social media was not here. • I now use those methods, which were used before social media was introduced to share information with others due to my privacy and security. • Due to privacy and security, I have changed the use of social media now so that I can use old ways of sharing information with others.	Bala and Venkatesh, (2016)
Avoidance of Social Media (ASM)	• I try to avoid sharing information on social media due to my privacy and security. • I find other ways of sharing information without using social media due to my privacy and security. • I try to perform most of my information sharing without social media due to my privacy and security.	Bala and Venkatesh, (2016)

	• I stay away from sharing my memories, interests and information etc. on social media as much as I can because of my privacy and security.	
Carelessness	• I do not care about my privacy and security when I share information on social media. • I do not take any precautions about my privacy and security when I share information on social media platforms. • I am inattentive to my privacy and security of my digital footprints on social media. • I do not pay attention to my privacy and security when I share information on social media.	White, (1961)
Carefreeness	• All things considered, there are no privacy and security concerns in sharing information on social media. • Information sharing is a normal part of social media due to which I am not worried about my privacy and security. • I am indifferent to my privacy and security when I share my digital footprints on social media platforms. • Information sharing is a regular part of social media due to which I have no issues with my privacy and security on these platforms.	Castro et al., (2017); White, (1961)
Consciousness	• I am aware that I will have privacy and security issues if I share information on social media platforms. • I am aware that there are privacy and security issues in sharing information on social media. • I am aware of the fact that sharing digital footprints on social media has privacy and security risks. • I am aware that sharing digital footprints on social media will have negative outcome for my privacy and security.	Dehaene and Naccache, (2001); Tolle, (1999)
Cautiousness	• Sharing information on social media may cause me privacy and security issues in the future. • Sharing information on social media is a big issue for my privacy and security. • Sharing information, interests, memories, likes and dislikes on social media makes my privacy and security vulnerable. • I am alert about sharing information on social media as it may cause me privacy and security issues.	Rodríguez-Castro et al., (2017); White, (1961)

Appendix 2. Questionnaire

Section 1

Dear Participant,

At the outset I would like to thank you for taking time to participate in this academic research survey. My research topic is about Digital Footprints on Social Media and I am looking to examine consumers' adoption and adaptation behaviour and outcome in the context of privacy, security and reputation concerns. The information you provide will make an insightful contribution to my research. Hence, I am inviting you to participate in this academic survey.

The questionnaire will require approximately 5-7 minutes. If you choose to take part in this survey, please answer all questions as honestly as possible. Your participation in this survey is voluntary and you can withdraw if you wish not to participate in it. The survey has been approved by the ethics committee of Brunel University. There are no risks associated with participating in this survey and it collects no identifying information of any respondents. All of the responses in the survey will be recorded anonymously and responses to the questionnaire will be kept confidential.

If you have any questions regarding the survey, you can write to me directly on my email syed.muhammad@brunel.ac.uk.

Thank you for your time and assistance in my research and educational endeavours. Your participation is highly appreciated.

Kind regards

Syed S Muhammad
Brunel University London

Section 2

1. What is your gender?

- Male
- Female

2. What is your age?

- 18-29 years old
- 30-49 years old
- 50-64 years old
- 65 years and over

3. What is the highest level of education you have completed?

- High school
- Graduate
- Postgraduate
- No education

4. Are you a UK resident?

- Yes
- No

5. Do you use social media (Facebook, Twitter, Snapchat, Instagram and WhatsApp etc.)?

- Yes
- No

If you are not a social media user, please don't complete the questionnaire and I would appreciate if you can write below the reasons of not using social media.

6. Which of the following social media platforms do you use?

- Facebook
- Instagram
- Snapchat
- Twitter
- LinkedIn
- Google+
- Flickr
- Pinterest
- YouTube
- WeChat
- WhatsApp
- Yelp
- Tumblr
- Any others please specify below

6. Which records and traces (digital footprints), if any, do you leave on social media? (Select all that apply.)

☐ Shopping ☐ Follow brands

☐ Authoring blog posts ☐ Downloading or listening to music, podcasts

☐ Downloading/Watching movies, TV shows, other videos ☐ Managing money

☐ Playing games ☐ Comment on products/brands

☐ Sharing information ☐ Follow others

☐ Networking ☐ Sharing likes and dislikes

☐ Sharing interests ☐ Sharing memories

☐ Any others please specify below

7. How often do you use social media (Facebook, Twitter, Instagram and WhatsApp etc.)?

☐ Always ☐ Sometimes ☐ Seldom ☐ Never

Section 3.

PO

1. I am confident that social media will have positive outcome for the information I share on these platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I believe social media will open new opportunities for me to share information, memories, interests, likes and dislikes etc. with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I believe social media platforms will provide me opportunities to share my likes, dislikes, interests and information etc. with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I believe social media will give me opportunities to share my memories, interests and information etc. with others to gain recognition and praise. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

PSI

1. I think I interact well with others on social media for sharing my memories, likes, dislikes, interests and information etc. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I believe I fit well with others on social media that share the same interests as me. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I believe social media help me establish relationship with others to share information and interests. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I think I maintain close relationships with others on social media for sharing information and interests etc. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

PC

1. I think I have control over sharing information on social media platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I believe I can control sharing information on social media platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I believe I have control over what to share on social media platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I believe I can control sharing my memories, likes, dislikes and information on social media platforms. Please tick

Enj

1. I feel I have a lot of enjoyment in sharing my memories, likes, dislikes, interests and information with others on social media. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. Social media give me a lot of excitement in sharing my memories, likes, dislikes, interests and information with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I find social media quite entertaining in sharing my memories, likes, dislikes, interests and information with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I spend enjoyable and relaxing time on social media by sharing my memories, likes, dislikes, interests and information with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

SE

1. I feel social media improve my image by sharing my interests, likes and dislikes etc. with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I feel I can influence others on social media by sharing my memories, likes, dislikes, interests and information etc. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I feel I can make a good impression on others on social media through my interests, memories, likes, dislikes, and information etc. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. Social media platforms help me present my best side to others by sharing my interests, likes and dislikes. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

Fear

1. I am afraid of sharing information on social media. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I do not feel comfortable to share information on social media. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I feel social media gather my highly personal information, likes, dislikes interests and memories etc. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I feel social media share my digital footprints with third parties without my consent. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

Trust

1. I feel social media providers are honest and caring about my digital footprints which I share on their platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I feel social media platforms are reliable as they do not share my digital footprints with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I feel social media providers are interested in my well-being and they do not share my digital footprints with third parties. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I feel social media do not give access to third parties to have access to my personal information etc. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

EMSMB

1. I explore social media to find new ways of sharing information, interests and memories with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I explore social media for potential new applications to share information etc. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I discover new ways of using social media to share my likes, dislikes, interests and information etc. with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I experiment with social media to find new features to share information, interests and memories etc. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

ESSMB

1. I use the same social media features that I learnt from others to share information on social media platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I use common social media features to share my memories, likes, dislikes and interests etc. with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I use the same social media features suggested to me by others to share my memories and interests etc. on social media platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I use social media features that I learnt from others on these platforms to share my likes, dislikes, interests and information etc. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

ER

1. Due to my privacy and security I now search for old ways of sharing information with others rather than social media. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. Due to my privacy and security I now look for old ways of sharing information with others when social media was not here. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I now use those methods which were used before social media was introduced to share information with others due to my privacy and security. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. Due to privacy and security I have changed the use of social media now so that I can use old ways of sharing information with others. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

ASM

1. I try to avoid sharing information on social media due to my privacy and security. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I find other ways of sharing information without using social media due to my privacy and security. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I try to perform most of my information sharing without social media due to my privacy and security. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I stay away from sharing my memories, interests and information etc. on social media as much as I can because of my privacy and security. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

Careless

1. I don't care about my privacy and security when I share information on social media. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I don't take any precautions about my privacy and security when I share information on social media platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I am inattentive to my privacy and security of my digital footprints on social media. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I don't pay attention to my privacy and security when I share information on social media. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

Carefree

1. All things considered, there are no privacy and security concerns in sharing information on social media. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. Information sharing is a normal part of social media due to which I am not worried about my privacy and security. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I am indifferent to my privacy and security when I share my digital footprints on social media platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. Information sharing is a regular part of social media due to which I have no issues with my privacy and security on these platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

Conscious

1. I am aware that I will have privacy and security issues if I share information on social media platforms. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. I am aware that there are privacy and security issues in sharing information on social media. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. I am aware of the fact that sharing digital footprints on social media has privacy and security risks.
Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I am aware that sharing digital footprints on social media will have negative outcome for my privacy and security. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

Cautious

1. Sharing information on social media may cause me privacy and security issues in the future. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

2. Sharing information on social media is a big issue for my privacy and security. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

3. Sharing information, interests, memories, likes and dislikes on social media makes my privacy and security vulnerable. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

4. I am alert about sharing information on social media as it may cause me privacy and security issues. Please tick

1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree

Thank you for your time and cooperation!

Appendix 3. Questionnaire Item Coding

Coding	Description
	Perceived Opportunity (PO)
PO1	I am confident that social media will have positive outcome for the information I share on these platforms.
PO2	I believe social media will open new opportunities for me to share information, memories, interests, likes and dislikes etc. with others.
PO3	I believe social media platforms will provide me opportunities to share my likes, dislikes, interests and information etc. with others.
PO4	I believe social media will give me opportunities to share my memories, interests and information etc. with others to gain recognition and praise.
	Perceived Social Influence (PSI)
PSI1	I think I interact well with others on social media for sharing my memories, likes, dislikes, interests and information etc.
PSI2	I believe I fit well with others on social media that share the same interests as me.
PSI3	I believe social media help me establish relationship with others to share information and interests.
PSI4	I think I maintain close relationships with others on social media for sharing information and interests etc.
	Perceived Control (PC)
PC1	I think I have control over sharing information on social media platforms.
PC2	I believe I can control sharing information on social media platforms.
PC3	I believe I have control over what to share on social media platforms.
PC4	I believe I can control sharing my memories, likes, dislikes and information on social media platforms.
	Enjoyment
Enj1	I feel I have a lot of enjoyment in sharing my memories, likes, dislikes, interests and information with others on social media.
Enj2	Social media give me a lot of excitement in sharing my memories, likes, dislikes, interests and information with others.
Enj3	I find social media quite entertaining in sharing my memories, likes, dislikes, interests and information with others.
Enj4	I spend enjoyable and relaxing time on social media by sharing my memories, likes, dislikes, interests and information with others.
	Self-Enhancement (SE)
SE1	I feel social media improve my image by sharing my interests, likes and dislikes etc. with others.
SE2	I feel I can influence others on social media by sharing my memories, likes, dislikes, interests and information etc.
SE3	I feel I can make a good impression on others on social media through my interests, memories, likes, dislikes, and information etc.
SE4	Social media platforms help me present my best side to others by sharing my interests, likes and dislikes.
	Fear
Fear1	I am afraid of sharing information on social media.
Fear2	I do not feel comfortable to share information on social media.
Fear3	I feel social media gather my highly personal information, likes, dislikes interests and memories etc.
Fear4	I feel social media share my digital footprints with third parties without my consent.
	Trust
Trust1	I feel social media providers are honest and caring about my digital footprints which I share on their platforms.
Trust2	I feel social media platforms are reliable as they do not share my digital footprints with others.
Trust3	I feel social media providers are interested in my well-being and they do not share my digital footprints with third parties.

Trust4	I feel social media do not give access to third parties to have access to my personal information etc.
	Exploration to Maximise Social Media Benefits (EMSMB)
EMSMB1	I explore social media to find new ways of sharing information, interests and memories with others.
EMSMB2	I explore social media for potential new applications to share information etc.
EMSMB3	I discover new ways of using social media to share my likes, dislikes, interests and information etc. with others.
EMSMB4	I experiment with social media to find new features to share information, interests and memories etc.
	Exploitation to Satisfice Social Media Benefits (ESSMB)
ESSMB1	I use the same social media features that I learnt from others to share information on social media platforms.
ESSMB2	I use common social media features to share my memories, likes, dislikes and interests etc. with others.
ESSMB3	I use the same social media features suggested to me by others to share my memories and interests etc. on social media platforms.
ESSMB4	I use social media features that I learnt from others on these platforms to share my likes, dislikes, interests and information etc.
	Exploration to Revert (ER)
ER1	Due to my privacy and security I now search for old ways of sharing information with others rather than social media.
ER2	Due to my privacy and security, I now look for old ways of sharing information with others when social media was not here.
ER3	I now use those methods, which were used before social media was introduced to share information with others due to my privacy and security.
ER4	Due to privacy and security, I have changed the use of social media now so that I can use old ways of sharing information with others.
	Avoidance of Social Media (ASM)
ASM1	I try to avoid sharing information on social media due to my privacy and security.
ASM2	I find other ways of sharing information without using social media due to my privacy and security.
ASM3	I try to perform most of my information sharing without social media due to my privacy and security.
ASM4	I stay away from sharing my memories, interests and information etc. on social media as much as I can because of my privacy and security.
	Carelessness
Careless1	I do not care about my privacy and security when I share information on social media.
Careless2	I do not take any precautions about my privacy and security when I share information on social media platforms.
Careless3	I am inattentive to my privacy and security of my digital footprints on social media.
Careless4	I do not pay attention to my privacy and security when I share information on social media.
	Carefreeness
Carefree1	All things considered, there are no privacy and security concerns in sharing information on social media.
Carefree2	Information sharing is a normal part of social media due to which I am not worried about my privacy and security.
Carefree3	I am indifferent to my privacy and security when I share my digital footprints on social media platforms.
Carefree4	Information sharing is a regular part of social media due to which I have no issues with my privacy and security on these platforms.
	Consciousness
Conscious1	I am aware that I will have privacy and security issues if I share information on social media platforms.
Conscious2	I am aware that there are privacy and security issues in sharing information on social media.

Conscious3	I am aware of the fact that sharing digital footprints on social media has privacy and security risks.
Conscious4	I am aware that sharing digital footprints on social media will have negative outcome for my privacy and security.
	Cautiousness
Cautious1	Sharing information on social media may cause me privacy and security issues in the future.
Cautious2	Sharing information on social media is a big issue for my privacy and security.
Cautious3	Sharing information, interests, memories, likes and dislikes on social media makes my privacy and security vulnerable.
Cautious4	I am alert about sharing information on social media as it may cause me privacy and security issues.

Appendix 4. Exploratory Factor Analysis (EFA)

SPSS output for EFA

Communalities		
	Initial	Extraction
PO1	.815	.842
PO2	.738	.744
PO3	.867	.924
PO4	.762	.767
PSI1	.781	.812
PSI2	.765	.780
PSI3	.748	.771
PSI4	.771	.803
PC1	.744	.766
PC2	.772	.775
PC3	.759	.781
PC4	.783	.819
Enj1	.773	.808
Enj2	.743	.774
Enj3	.746	.780
Enj4	.765	.807
SE1	.673	.650
SE2	.755	.763
SE3	.853	.893
SE4	.858	.904
Fear1	.714	.713
Fear2	.805	.847
Fear3	.679	.681
Fear4	.819	.878
Trust1	.626	.637
Trust2	.552	.555
Trust3	.710	.753
Trust4	.736	.823
EMSMB1	.760	.787
EMSMB2	.660	.643
EMSMB3	.759	.792
EMSMB4	.773	.808
ESSMB1	.761	.734
ESSMB2	.772	.749
ESSMB3	.785	.784
ESSMB4	.793	.817
ER1	.746	.709

ER2	.758	.706
ER3	.821	.863
ER4	.809	.848
ASM1	.723	.727
ASM2	.729	.757
ASM3	.775	.817
ASM4	.788	.831
Careless1	.692	.612
Careless2	.692	.611
Careless3	.799	.858
Careless4	.791	.841
Carefree1	.645	.635
Carefree2	.670	.656
Carefree3	.836	.899
Carefree4	.804	.846
Conscious1	.791	.824
Conscious2	.329	.264
Conscious3	.846	.915
Conscious4	.812	.847
Cautious1	.816	.839
Cautious2	.772	.776
Cautious3	.855	.891
Cautious4	.820	.839
Extraction Method: Maximum Likelihood.		

Total Variance Explained

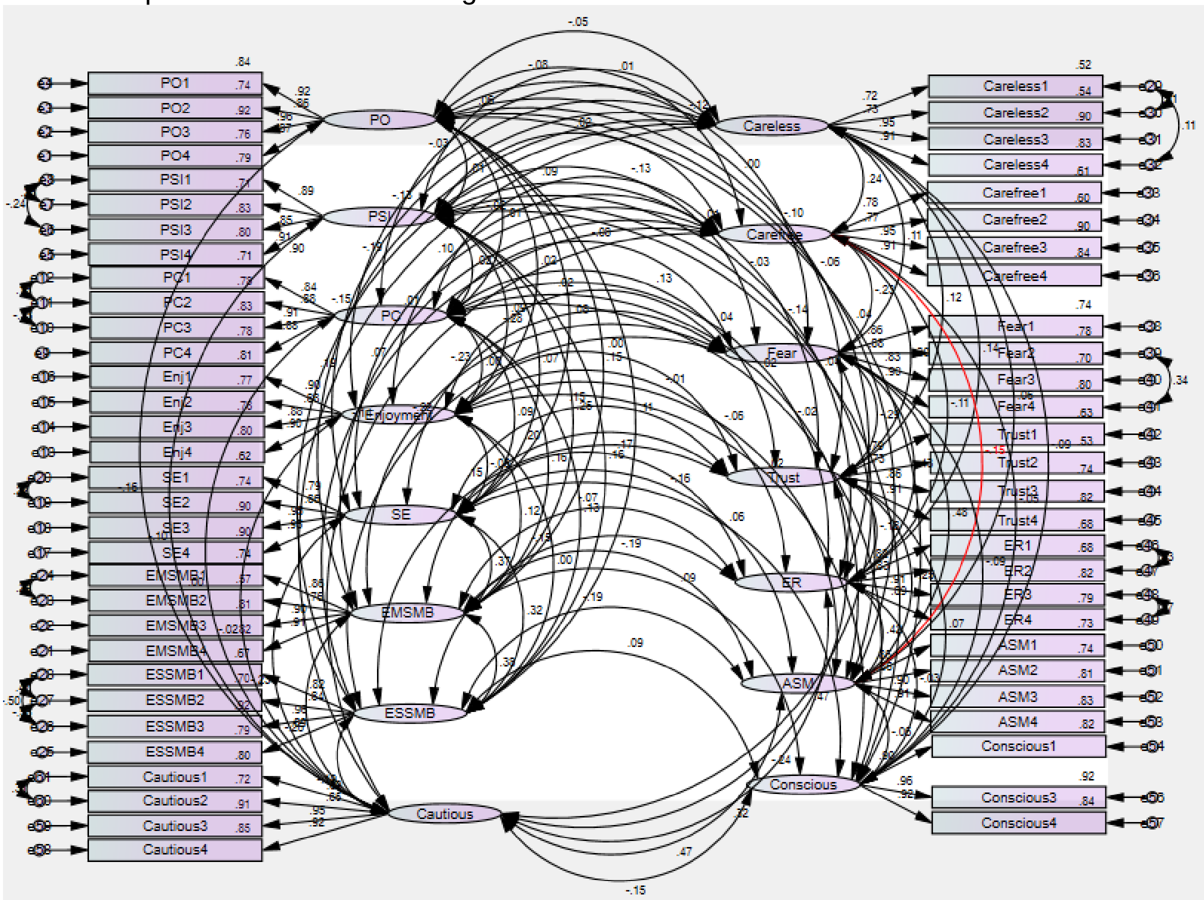
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	10.204	17.007	17.007	9.847	16.412	16.412	6.092
2	4.776	7.961	24.967	4.188	6.979	23.391	3.587
3	4.440	7.400	32.367	3.980	6.633	30.024	4.903
4	3.733	6.222	38.588	3.185	5.309	35.333	3.682
5	3.376	5.627	44.216	2.971	4.951	40.284	3.284
6	3.081	5.135	49.351	3.526	5.876	46.161	5.003
7	2.904	4.841	54.191	2.871	4.785	50.945	5.862
8	2.791	4.652	58.843	2.666	4.443	55.388	3.381
9	2.486	4.143	62.986	2.193	3.654	59.043	4.593
10	2.313	3.855	66.841	2.248	3.747	62.790	6.256
11	2.259	3.766	70.606	2.104	3.506	66.296	3.874
12	2.092	3.487	74.093	1.627	2.711	69.007	5.188

13	1.797	2.995	77.088	1.873	3.122	72.129	3.637
14	1.744	2.906	79.994	1.543	2.571	74.700	4.203
15	1.706	2.844	82.838	1.556	2.593	77.293	2.793
16	.724	1.206	84.044				
17	.517	.862	84.906				
18	.468	.780	85.686				
19	.416	.693	86.378				
20	.398	.664	87.042				
21	.387	.644	87.687				
22	.360	.600	88.287				
23	.352	.587	88.874				
24	.327	.545	89.418				
25	.309	.514	89.933				
26	.300	.500	90.433				
27	.283	.472	90.905				
28	.275	.459	91.364				
29	.264	.440	91.804				
30	.254	.423	92.227				
31	.246	.410	92.637				
32	.237	.395	93.032				
33	.233	.388	93.420				
34	.221	.368	93.789				
35	.214	.357	94.146				
36	.207	.345	94.491				
37	.203	.338	94.829				
38	.198	.329	95.159				
39	.193	.322	95.480				
40	.185	.308	95.788				
41	.178	.297	96.085				
42	.175	.291	96.376				
43	.168	.279	96.656				
44	.165	.276	96.931				
45	.151	.252	97.183				
46	.148	.246	97.429				
47	.144	.240	97.668				
48	.137	.229	97.897				
49	.135	.225	98.123				
50	.130	.216	98.339				
51	.119	.198	98.537				
52	.116	.194	98.731				
53	.114	.190	98.921				
54	.111	.185	99.106				

55	.105	.175	99.281				
56	.095	.159	99.440				
57	.092	.153	99.594				
58	.089	.148	99.742				
59	.081	.135	99.877				
60	.074	.123	100.000				
Extraction Method: Maximum Likelihood.							

Appendix 5. Confirmatory Factor Analysis

AMOS Output for Correlation amongst the Constructs



Appendix 5. Continued

Confirmatory Factor Analysis of the Model
AMOS Output for Correlation amongst the Constructs
Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
PO4	<---	PO	1.000				
PO3	<---	PO	1.075	.027	39.512	***	par_1
PO2	<---	PO	.989	.032	31.303	***	par_2
PO1	<---	PO	1.055	.030	35.758	***	par_3
PSI4	<---	PSI	1.000				
PSI3	<---	PSI	.978	.030	33.137	***	par_4
PSI2	<---	PSI	.967	.032	29.849	***	par_5
PSI1	<---	PSI	1.062	.035	29.958	***	par_6
PC4	<---	PC	1.000				
PC3	<---	PC	1.056	.033	31.831	***	par_10
PC2	<---	PC	1.034	.037	27.761	***	par_11
PC1	<---	PC	1.066	.037	28.857	***	par_12
Enj4	<---	Enjoyment	1.000				
Enj3	<---	Enjoyment	.958	.028	33.865	***	par_17
Enj2	<---	Enjoyment	1.010	.030	33.447	***	par_18
Enj1	<---	Enjoyment	1.076	.031	35.198	***	par_19
SE4	<---	SE	1.000				
SE3	<---	SE	1.005	.020	49.742	***	par_23
SE2	<---	SE	.894	.024	36.836	***	par_24
SE1	<---	SE	.790	.027	29.651	***	par_25
EMSMB4	<---	EMSMB	1.000				
EMSMB3	<---	EMSMB	.957	.028	34.666	***	par_31
EMSMB2	<---	EMSMB	.773	.031	24.853	***	par_32
EMSMB1	<---	EMSMB	.959	.030	31.726	***	par_33
ESSMB4	<---	ESSMB	1.000				
ESSMB3	<---	ESSMB	1.156	.054	21.520	***	par_40
ESSMB2	<---	ESSMB	.858	.045	18.961	***	par_41
ESSMB1	<---	ESSMB	.838	.045	18.615	***	par_42
Careless1	<---	Careless	1.000				
Careless2	<---	Careless	1.007	.037	26.901	***	par_52
Careless3	<---	Careless	1.528	.066	23.306	***	par_53
Careless4	<---	Careless	1.523	.061	24.770	***	par_54
Carefree1	<---	Carefree	1.000				
Carefree2	<---	Carefree	1.134	.051	22.279	***	par_64
Carefree3	<---	Carefree	1.269	.044	28.923	***	par_65
Carefree4	<---	Carefree	1.190	.043	27.789	***	par_66
Fear1	<---	Fear	1.000				
Fear2	<---	Fear	1.026	.035	28.985	***	par_75
Fear3	<---	Fear	1.013	.037	27.541	***	par_76
Fear4	<---	Fear	1.012	.034	29.713	***	par_77
Trust1	<---	Trust	1.000				
Trust2	<---	Trust	.986	.048	20.361	***	par_88
Trust3	<---	Trust	1.260	.051	24.904	***	par_89
Trust4	<---	Trust	1.450	.055	26.329	***	par_90
ER1	<---	ER	1.000				
ER2	<---	ER	1.003	.030	33.520	***	par_101
ER3	<---	ER	1.045	.058	18.023	***	par_102

			Estimate	S.E.	C.R.	P	Label
ER4	<---	ER	1.034	.058	17.760	***	par_103
ASM1	<---	ASM	1.000				
ASM2	<---	ASM	.947	.032	29.471	***	par_117
ASM3	<---	ASM	1.049	.033	31.597	***	par_118
ASM4	<---	ASM	1.025	.032	32.326	***	par_119
Conscious1	<---	Conscious	1.000				
Conscious3	<---	Conscious	1.048	.024	43.123	***	par_132
Conscious4	<---	Conscious	1.008	.026	39.412	***	par_133
Cautious4	<---	Cautious	1.000				
Cautious3	<---	Cautious	1.044	.023	45.555	***	par_147
Cautious2	<---	Cautious	.906	.027	33.140	***	par_148
Cautious1	<---	Cautious	.994	.026	38.139	***	par_149

Covariances: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
PO	<-->	PSI	.012	.042	.284	.776	par_7
PSI	<-->	PC	.025	.044	.583	.560	par_13
PO	<-->	PC	.015	.045	.341	.733	par_14
PO	<-->	Enjoyment	.016	.042	.377	.706	par_20
PSI	<-->	Enjoyment	.090	.042	2.159	.031	par_21
PC	<-->	Enjoyment	.005	.044	.113	.910	par_22
PO	<-->	SE	.096	.047	2.049	.040	par_26
PSI	<-->	SE	.078	.046	1.708	.088	par_27
PC	<-->	SE	.110	.048	2.267	.023	par_28
Enjoyment	<-->	SE	-.088	.046	-1.912	.056	par_29
PO	<-->	EMSMB	.161	.044	3.633	***	par_34
PSI	<-->	EMSMB	.260	.044	5.874	***	par_35
PC	<-->	EMSMB	.179	.046	3.901	***	par_36
Enjoyment	<-->	EMSMB	.121	.043	2.794	.005	par_37
SE	<-->	EMSMB	.427	.051	8.447	***	par_38
PO	<-->	ESSMB	.109	.041	2.683	.007	par_43
PSI	<-->	ESSMB	.158	.040	3.919	***	par_44
PC	<-->	ESSMB	.136	.042	3.224	.001	par_45
Enjoyment	<-->	ESSMB	.004	.039	.102	.919	par_46
SE	<-->	ESSMB	.348	.048	7.307	***	par_47
EMSMB	<-->	ESSMB	.388	.046	8.370	***	par_48
PO	<-->	Careless	-.029	.025	-1.173	.241	par_55
PSI	<-->	Careless	-.050	.025	-2.025	.043	par_56
PC	<-->	Careless	.040	.026	1.532	.126	par_57
Enjoyment	<-->	Careless	-.018	.025	-.736	.462	par_58
SE	<-->	Careless	-.085	.027	-3.110	.002	par_59
EMSMB	<-->	Careless	-.118	.026	-4.506	***	par_60
ESSMB	<-->	Careless	-.086	.024	-3.592	***	par_61
PO	<-->	Carefree	.005	.037	.142	.887	par_67
PSI	<-->	Carefree	.018	.036	.493	.622	par_68
PC	<-->	Carefree	.082	.038	2.146	.032	par_69
Enjoyment	<-->	Carefree	-.015	.036	-.420	.674	par_70
SE	<-->	Carefree	.101	.040	2.514	.012	par_71
EMSMB	<-->	Carefree	.012	.037	.309	.757	par_72
ESSMB	<-->	Carefree	.057	.034	1.653	.098	par_73
Careless	<-->	Carefree	.129	.023	5.664	***	par_74

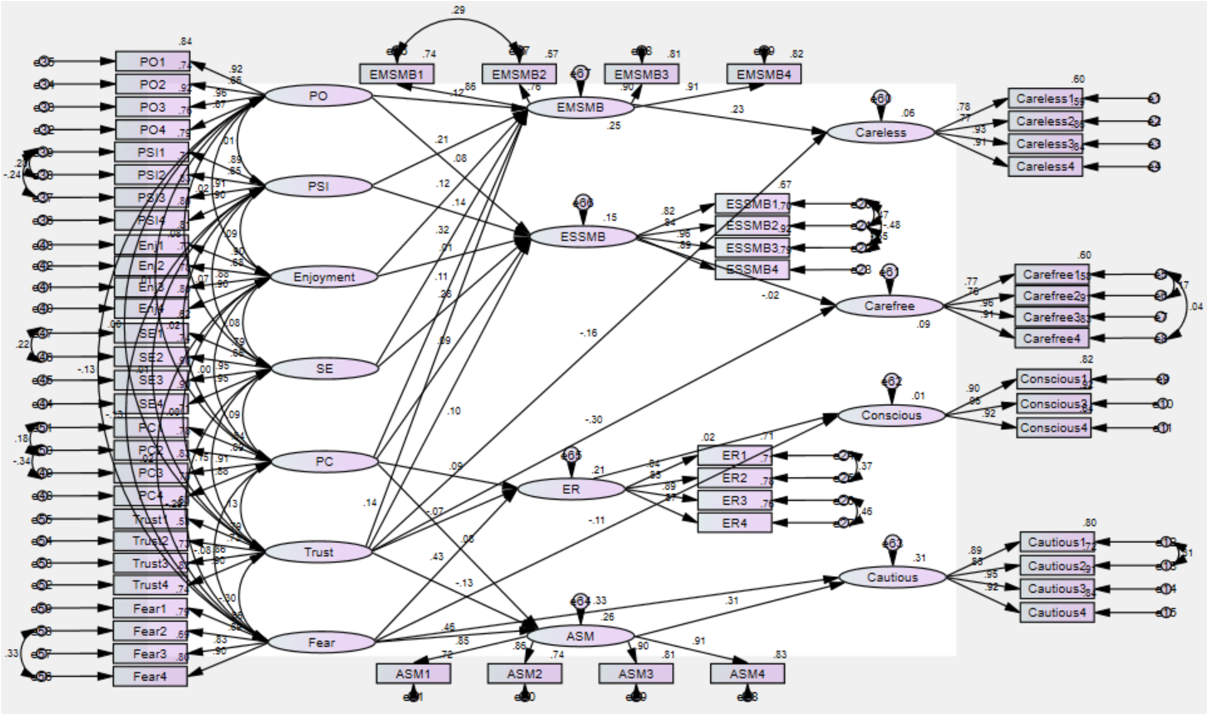
			Estimate	S.E.	C.R.	P	Label
PO	<-->	Fear	-.139	.046	-2.984	.003	par_78
PSI	<-->	Fear	-.141	.045	-3.102	.002	par_79
PC	<-->	Fear	-.093	.048	-1.954	.051	par_80
Enjoyment	<-->	Fear	.023	.045	.508	.612	par_81
SE	<-->	Fear	-.337	.052	-6.484	***	par_82
EMSMB	<-->	Fear	-.261	.048	-5.430	***	par_83
Careless	<-->	Fear	.072	.027	2.673	.008	par_84
Carefree	<-->	Fear	-.217	.041	-5.315	***	par_85
ESSMB	<-->	Fear	-.234	.045	-5.197	***	par_86
PO	<-->	Trust	.001	.034	.038	.969	par_91
PSI	<-->	Trust	.005	.033	.139	.889	par_92
Careless	<-->	Trust	.056	.020	2.774	.006	par_93
Carefree	<-->	Trust	.211	.031	6.701	***	par_94
Fear	<-->	Trust	-.256	.039	-6.590	***	par_95
PC	<-->	Trust	.111	.036	3.111	.002	par_96
Enjoyment	<-->	Trust	-.002	.034	-.073	.942	par_97
SE	<-->	Trust	.136	.038	3.630	***	par_98
ESSMB	<-->	Trust	.121	.033	3.696	***	par_99
EMSMB	<-->	Trust	.170	.036	4.754	***	par_100
Careless	<-->	ER	.068	.021	3.241	.001	par_104
Carefree	<-->	ER	-.083	.031	-2.713	.007	par_105
Fear	<-->	ER	.389	.044	8.815	***	par_106
Trust	<-->	ER	-.119	.029	-4.103	***	par_107
PO	<-->	ER	-.086	.036	-2.408	.016	par_108
PSI	<-->	ER	-.024	.035	-.701	.483	par_109
PC	<-->	ER	.039	.037	1.061	.289	par_110
Enjoyment	<-->	ER	-.005	.035	-.140	.889	par_111
SE	<-->	ER	-.162	.039	-4.113	***	par_112
EMSMB	<-->	ER	-.059	.036	-1.640	.101	par_113
ESSMB	<-->	ER	-.123	.034	-3.610	***	par_114
Careless	<-->	ASM	.040	.027	1.496	.135	par_120
Carefree	<-->	ASM	-.140	.040	-3.533	***	par_121
Fear	<-->	ASM	.574	.056	10.208	***	par_122
Trust	<-->	ASM	-.221	.038	-5.808	***	par_123
ER	<-->	ASM	.382	.044	8.751	***	par_124
ESSMB	<-->	ASM	-.198	.044	-4.512	***	par_125
EMSMB	<-->	ASM	-.219	.047	-4.628	***	par_126
SE	<-->	ASM	-.197	.050	-3.938	***	par_127
Enjoyment	<-->	ASM	-.066	.045	-1.470	.142	par_128
PC	<-->	ASM	.025	.047	.529	.597	par_129
PSI	<-->	ASM	-.149	.045	-3.311	***	par_130
PO	<-->	ASM	-.067	.046	-1.473	.141	par_131
Careless	<-->	Conscious	-.066	.028	-2.325	.020	par_134
Carefree	<-->	Conscious	-.048	.041	-1.151	.250	par_135
Fear	<-->	Conscious	-.118	.052	-2.273	.023	par_136
Trust	<-->	Conscious	.062	.039	1.620	.105	par_137
ER	<-->	Conscious	-.026	.040	-.648	.517	par_138
ASM	<-->	Conscious	-.078	.051	-1.517	.129	par_139
PO	<-->	Conscious	.043	.048	.894	.371	par_140
PSI	<-->	Conscious	.042	.047	.884	.377	par_141
PC	<-->	Conscious	-.023	.050	-.460	.645	par_142
Enjoyment	<-->	Conscious	.027	.048	.557	.577	par_143

			Estimate	S.E.	C.R.	P	Label
SE	<-->	Conscious	.080	.052	1.519	.129	par_144
EMSMB	<-->	Conscious	.107	.049	2.169	.030	par_145
ESSMB	<-->	Conscious	.105	.045	2.317	.021	par_146
PO	<-->	Cautious	-.200	.050	-3.991	***	par_150
PSI	<-->	Cautious	-.122	.048	-2.514	.012	par_151
PC	<-->	Cautious	-.004	.051	-.077	.939	par_152
Enjoyment	<-->	Cautious	-.027	.048	-.562	.574	par_153
SE	<-->	Cautious	-.312	.055	-5.691	***	par_154
EMSMB	<-->	Cautious	-.323	.052	-6.227	***	par_155
ESSMB	<-->	Cautious	-.222	.047	-4.676	***	par_156
Careless	<-->	Cautious	.131	.029	4.460	***	par_157
Carefree	<-->	Cautious	-.147	.043	-3.448	***	par_158
Fear	<-->	Cautious	.606	.060	10.186	***	par_159
Trust	<-->	Cautious	-.233	.041	-5.724	***	par_160
ER	<-->	Cautious	.318	.044	7.176	***	par_161
ASM	<-->	Cautious	.611	.059	10.306	***	par_162
Conscious	<-->	Cautious	-.210	.056	-3.746	***	par_163
e7	<-->	e8	.094	.024	3.856	***	par_8
e6	<-->	e8	-.060	.019	-3.245	.001	par_9
e11	<-->	e12	.077	.032	2.426	.015	par_15
e10	<-->	e11	-.099	.025	-3.997	***	par_16
e19	<-->	e20	.094	.019	4.997	***	par_30
e23	<-->	e24	.118	.021	5.632	***	par_39
e27	<-->	e28	.148	.034	4.356	***	par_49
e26	<-->	e28	-.095	.039	-2.418	.016	par_50
e26	<-->	e27	-.103	.040	-2.583	.010	par_51
e29	<-->	e30	.163	.015	10.948	***	par_62
e29	<-->	e32	.025	.011	2.364	.018	par_63
e39	<-->	e41	.108	.026	4.210	***	par_87
e46	<-->	e47	.140	.035	4.040	***	par_115
e48	<-->	e49	.067	.035	1.893	.058	par_116
e60	<-->	e61	.123	.021	5.958	***	par_164

Note: The above tables provide details about the regression weight and covariances derived for Confirmatory Factor Analysis and shows that most constructs are correlated and relationships in most cases are significant.

Appendix 6. Structure Equation Modelling

AMOS Output for Structural Equation Model in Full



Appendix 6. Continued

Structure Equation Modelling
AMOS Output for Structural Equation Model

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
EMSMB	<---	PO	.112	.034	3.277	.001	par_45
ESSMB	<---	PO	.065	.029	2.240	.025	par_46
EMSMB	<---	PSI	.210	.036	5.830	***	par_47
ESSMB	<---	PSI	.113	.030	3.727	***	par_48
EMSMB	<---	Enjoyment	.117	.036	3.273	.001	par_49
ESSMB	<---	Enjoyment	.011	.030	.373	.709	par_50
EMSMB	<---	SE	.287	.033	8.670	***	par_51
ESSMB	<---	SE	.206	.028	7.322	***	par_52
EMSMB	<---	PC	.099	.034	2.917	.004	par_53
ER	<---	PC	.073	.031	2.400	.016	par_54
ASM	<---	PC	.079	.038	2.108	.035	par_55
ESSMB	<---	PC	.067	.029	2.341	.019	par_56
EMSMB	<---	Trust	.120	.032	3.765	***	par_57
ESSMB	<---	Trust	.073	.027	2.714	.007	par_58
ER	<---	Trust	-.053	.030	-1.782	.075	par_59
ASM	<---	Trust	-.124	.037	-3.350	***	par_60
ASM	<---	Fear	.471	.041	11.619	***	par_63
ER	<---	Fear	.334	.034	9.727	***	par_64
Careless	<---	Trust	-.090	.023	-3.954	***	par_61
Carefree	<---	Trust	-.224	.031	-7.283	***	par_62
Conscious	<---	Fear	-.117	.049	-2.378	.017	par_65
Cautious	<---	Fear	.350	.045	7.820	***	par_66
Cautious	<---	ASM	.329	.043	7.594	***	par_101
Conscious	<---	ER	.031	.064	.486	.627	par_102
Carefree	<---	ESSMB	-.017	.041	-.415	.678	par_103
Careless	<---	EMSMB	.146	.027	5.437	***	par_104
Careless1	<---	Careless	1.000				
Careless2	<---	Careless	.988	.045	21.769	***	par_1
Careless3	<---	Careless	1.394	.051	27.232	***	par_2
Careless4	<---	Careless	1.423	.053	26.908	***	par_3
Carefree1	<---	Carefree	1.000				
Carefree2	<---	Carefree	1.138	.049	23.390	***	par_4
Carefree3	<---	Carefree	1.299	.050	25.890	***	par_5
Carefree4	<---	Carefree	1.205	.044	27.190	***	par_6
Conscious1	<---	Conscious	1.000				
Conscious3	<---	Conscious	1.048	.024	43.124	***	par_7
Conscious4	<---	Conscious	1.007	.026	39.408	***	par_8
Cautious1	<---	Cautious	1.000				
Cautious2	<---	Cautious	.913	.024	37.712	***	par_9
Cautious3	<---	Cautious	1.053	.026	41.165	***	par_10
Cautious4	<---	Cautious	1.007	.027	37.947	***	par_11
EMSMB1	<---	EMSMB	1.000				
EMSMB2	<---	EMSMB	.807	.029	27.891	***	par_12
EMSMB3	<---	EMSMB	.999	.032	31.212	***	par_13
EMSMB4	<---	EMSMB	1.045	.033	31.619	***	par_14

			Estimate	S.E.	C.R.	P	Label
ESSMB1	<---	ESSMB	1.000				
ESSMB2	<---	ESSMB	1.024	.030	33.591	***	par_15
ESSMB3	<---	ESSMB	1.377	.052	26.537	***	par_16
ESSMB4	<---	ESSMB	1.194	.073	16.257	***	par_17
ER1	<---	ER	1.000				
ER2	<---	ER	1.003	.030	33.537	***	par_18
ER3	<---	ER	1.000	.063	15.802	***	par_19
ER4	<---	ER	.991	.063	15.631	***	par_20
ASM4	<---	ASM	1.000				
ASM3	<---	ASM	1.023	.028	36.519	***	par_21
ASM2	<---	ASM	.921	.028	33.169	***	par_22
ASM1	<---	ASM	.973	.030	32.287	***	par_23
PO4	<---	PO	1.000				
PO3	<---	PO	1.075	.027	39.521	***	par_24
PO2	<---	PO	.989	.032	31.333	***	par_25
PO1	<---	PO	1.055	.029	35.778	***	par_26
PSI4	<---	PSI	1.000				
PSI3	<---	PSI	.979	.030	33.183	***	par_27
PSI2	<---	PSI	.967	.032	29.839	***	par_28
PSI1	<---	PSI	1.062	.035	29.949	***	par_29
Enj4	<---	Enjoyment	1.000				
Enj3	<---	Enjoyment	.958	.028	33.869	***	par_30
Enj2	<---	Enjoyment	1.010	.030	33.441	***	par_31
Enj1	<---	Enjoyment	1.076	.031	35.203	***	par_32
SE4	<---	SE	1.000				
SE3	<---	SE	1.004	.020	49.700	***	par_33
SE2	<---	SE	.894	.024	36.842	***	par_34
SE1	<---	SE	.790	.027	29.676	***	par_35
PC4	<---	PC	1.000				
PC3	<---	PC	1.056	.033	31.772	***	par_36
PC2	<---	PC	1.036	.037	27.744	***	par_37
PC1	<---	PC	1.068	.037	28.865	***	par_38
Trust4	<---	Trust	1.000				
Trust3	<---	Trust	.870	.029	30.020	***	par_39
Trust2	<---	Trust	.681	.030	23.073	***	par_40
Trust1	<---	Trust	.690	.026	26.312	***	par_41
Fear4	<---	Fear	1.000				
Fear3	<---	Fear	.997	.035	28.086	***	par_42
Fear2	<---	Fear	1.017	.025	41.133	***	par_43
Fear1	<---	Fear	.986	.033	29.677	***	par_44

Covariances: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
PO	<-->	PSI	.012	.042	.284	.776	par_67
PO	<-->	Enjoyment	.016	.042	.375	.708	par_68
PO	<-->	SE	.096	.047	2.048	.041	par_69
PO	<-->	PC	.015	.045	.339	.735	par_70
PO	<-->	Trust	.002	.050	.039	.969	par_71
PO	<-->	Fear	-.149	.047	-3.168	.002	par_72
PSI	<-->	Enjoyment	.090	.042	2.159	.031	par_73
PSI	<-->	SE	.078	.046	1.706	.088	par_74

			Estimate	S.E.	C.R.	P	Label
PSI	<-->	PC	.025	.044	.582	.561	par_75
PSI	<-->	Trust	.008	.048	.161	.872	par_76
PSI	<-->	Fear	-.149	.046	-3.244	.001	par_77
Enjoyment	<-->	SE	-.088	.046	-1.914	.056	par_78
Enjoyment	<-->	PC	.005	.044	.108	.914	par_79
Enjoyment	<-->	Trust	-.003	.049	-.060	.952	par_80
Enjoyment	<-->	Fear	.017	.046	.376	.707	par_81
SE	<-->	PC	.109	.048	2.261	.024	par_82
SE	<-->	Trust	.199	.054	3.670	***	par_83
SE	<-->	Fear	-.354	.052	-6.747	***	par_84
PC	<-->	Trust	.165	.052	3.185	.001	par_85
PC	<-->	Fear	-.095	.048	-1.970	.049	par_86
Trust	<-->	Fear	-.385	.056	-6.857	***	par_87
e38	<-->	e39	.095	.024	3.898	***	par_88
e37	<-->	e39	-.060	.019	-3.247	.001	par_89
e50	<-->	e51	.074	.032	2.330	.020	par_90
e49	<-->	e50	-.100	.025	-4.022	***	par_91
e46	<-->	e47	.094	.019	4.975	***	par_92
e20	<-->	e21	.147	.040	3.701	***	par_93
e21	<-->	e22	-.103	.049	-2.097	.036	par_94
e20	<-->	e22	-.094	.048	-1.952	.051	par_95
e16	<-->	e17	.120	.021	5.692	***	par_96
e12	<-->	e13	.124	.021	5.973	***	par_97
e56	<-->	e58	.105	.025	4.182	***	par_98
e24	<-->	e25	.109	.042	2.606	.009	par_99
e26	<-->	e27	.098	.041	2.425	.015	par_100
e5	<-->	e6	.103	.027	3.782	***	par_105
e5	<-->	e8	.014	.020	.716	.474	par_106

Note: The above tables provide details about the regression weight and covariances derived for Structural Equation Model and shows that relationships in most cases are significant.