# Exploring the Impact of AI-Based Innovations in Consumer Products on Consumer Loyalty

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# Exploring the Impact of AI-Based Innovations in Consumer Products on Consumer Loyalty

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**DECLARATION**

I declare that this thesis has been composed solely by myself and the work has not been submitted, in whole or in part, for any other degree or professional qualification. I confirm that the work submitted is my own.

*Monica Chauhan*

July 2024

## Dedication

This is dedicated to my mother, for being my first teacher, the heart of my education.

# Acknowledgements

First and foremost, I would like to express my deepest gratitude to my supervisory team, Prof. Paul Smith, Dr. Saeed Najafi-Tavani and Dr. Konstantia Litsiou (Dina) for your support, constructive feedback, advice, and direction. I will forever be indebted to you for your expertise, I am truly grateful for your insightful contributions. Prof. Jenny Rowley, your guidance and kindness throughout my first year in lockdown was much appreciated. I am honoured to have been part of this excellent research team.

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Finally, I would like to acknowledge the doctors who have demonstrated resilience in their work which has guided me through the darkest days, Dr Ambedkar, Dr King, and Dr Grewal.

## List of Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| BA | Brand Attitude |
| BI | Brand Innovativeness |
| BL | Brand Loyalty |
| BVC | Brand Value Chain |
| CMB | Common Method Bias |
| CVPAT | Cross-Validation Predictive Ability |
| GAIPK | General AI Product Knowledge |
| MGA | Multi-Group Analysis |
| ML | Machine Learning |
| PBC | Perceived Behavioural Control |
| PI | Purchase Intention |
| PK | Product Knowledge |
| PLS | Partial Least Squares |
| SAIPK | Specific AI Product Knowledge |
| SEM | Structural Equation Modelling |
| SN | Social Norms |
| TAM | Technology Acceptance Model |
| TPB | Theory of Planned Behaviour |

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# Abstract

Organisations are increasingly exploring the use of Artificial Intelligence (AI) to innovate in relation to the features of the products and services they deliver to consumers. This research explores the impact of AI enabled innovations within a brand on the consumer perceived brand innovativeness and ultimately brand loyalty, drawing on the theoretical foundation of the Brand Value Chain (BVC). In particular, the impact on brand innovativeness of awareness of the use of AI to enable new functionality (amplifying innovations) or to enable easier use of existing products and services (simplifying innovations) is examined. Also, the extent of awareness of specific new (AI enabled) named features (specific AI knowledge) and general level of awareness of AI features (general AI knowledge) and its impact on relationships is explored.

A conceptual model based on research questions and hypotheses derived from the research gaps related to the above is developed and examined. The research extends theory by using the BVC model and addressing these gaps. To test the model, a quantitative structural equation-based methodology is adopted. The Amazon brand was selected in relation to data collection, based on its strong brand credentials, and its track record of innovation including differing types of AI-enabled innovations. Data collected from 209 UK Amazon Brand App users via an online survey were analysed using PLS-SEM. The results confirm that AI amplifying and simplifying innovations increase the perception of brand innovativeness. Additionally, brand innovativeness was found to be positively related to brand loyalty, as was brand attitude, however, brand attitude did not act as a partial mediator between brand innovativeness and brand loyalty following mediation analysis. Further, there is evidence to suggest that specific AI Product Knowledge positively moderates the relationship between Amplifying AI innovations and Brand Innovativeness, and between Brand Innovativeness and Brand Loyalty, making a valuable new theoretical contribution. The findings of this study provide justification for managers to invest in AI enabled product innovations as this directly improves consumer perceived brand innovativeness and increases brand loyalty. Managers are able to use the findings in this study to focus their marketing efforts on educating consumers about their specific new AI enabled product features and functions, which in turn will strengthen the perception of brand innovativeness and brand loyalty driven by AI enabled innovations.



**Keywords:** Artificial Intelligence, Consumer Behaviour, Simplifying and Amplifying Innovation, Product Knowledge, Brand Innovativeness, Brand Attitude, Brand Loyalty.

# Chapter 1

# Introduction

## 1.1 Introduction to the Study

In general terms, this research hopes to examine the impact of product level Artificial Intelligence (AI) innovations on consumer perceptions of Brand Innovativeness, and ultimately on Brand Loyalty. More importantly, the research explores how much of that impact is based on knowledge of the specific new features introduced through AI enabled innovation as opposed to a general sense of AI enabled innovation driven through marketing.

This chapter provides a rationale for this research and discusses the contribution to knowledge this thesis makes. The chapter outlines the research questions for the study, the most appropriate methodology to explore them, and the high-level results and findings. An outline of the organisation of this thesis is provided.

## 1.2 Research Background and Justification

*"AI is a very significant opportunity – if used in a responsible way. I am a tech optimist and, as a medical doctor by training, I know that AI is already revolutionizing healthcare. That's good. AI can boost productivity at unprecedented speed. First movers will be rewarded, and the global race is already on without any question. Our future competitiveness depends on AI adoption in our daily businesses, and Europe must up its game and show the way to responsible use of AI. That is AI that enhances human capabilities, improves productivity and serves society."*

(Von der Leyen, 2024)

With the rise of consumer and business interest in AI, there is a corresponding demand for more research in relation to AI and its impact on marketing, (Mustak et al, 2021; Vlačić et al, 2021). The interplay of marketing and AI has seen research growth in recent years (Ameen et al, 2021a). In particular, innovation is a key aspect of marketing and marketing strategy, and from driverless cars to robotics in healthcare, AI is a key driver of innovations today (Davenport, 2019). AI enabled innovations have revolutionised the way businesses interact with customers for example enabling; personal assistants (Siri, Alexa), Chatbots, Robots (vacuum cleaners, lawn mowers) and Mobile Apps (Shopping, Banking) to name a few (McLean and Osei-Frimpong, 2019). Users are able to advance their productivity with AI for creativity (Canva) games (FIFA) and writing (ChatGPT). AI has the ability to enhance the online consumer experience though personalised interactions (Verma et al, 2021). Using machine learning and natural language processing, AI innovations are able to provide tailored solutions. Used as a driving force in product and service innovation in marketing, AI provides new and unique tools to improve customer experiences.

Businesses have adapted to embrace AI to interact with customers (Kaplan and Haenlein, 2019) in order to remain competitive in the market. Innovations play a critical role in business and staying abreast of evolving advancements is essential (Danneels and Kleinschmidt, 2001; Pauwels et al, 2004), The impact of innovation is transformative and impacts every business area (Ma and Sun, 2020). AI has disrupted industry. Businesses have used AI to adapt their business models (Ehret, 2021), sales processes, and customer service (Davenport et al, 2020). Product innovations have been characterised as either “Simplifying” (innovation makes using a product easier) or “Amplifying” (innovation increasing what can be done with a product) (Hardie et al, 1996). AI could be used to enable either type (in other words be an AI Simplifying or AI Amplifying Innovation). From rapid technological advances in computation, and consumer availability of 5G, AI has revolutionised consumer expectations and companies invested heavily in AI such as Tesla, who have gained market dominance. The advancements run parallel with consumer behaviour which has evolved in recent years, consumers have less patience and higher expectations, due to facilitation of personalised customer experiences (Kunz et al, 2019). The increasing use of AI in business has enabled marketers to desire to understand consumer behaviour through AI feedback mechanisms resulting in consumer engagement and retention, (Ameen et al, 2021a).

Innovation is especially vital for brands because it helps build strong brand images in consumers' minds (Hetet et al, 2020). Brexendorf et al, (2015) proposed a research agenda with emphasis needed to research to examine and explicate the relationship and linkages among concepts related to brands and innovation. More recently, Oh et al, (2020:158) state: “Furthermore, it is unclear how technologies such as artificial intelligence, virtual reality, and augmented reality will change the relationships customers have with their brands”. The concept of brand innovativeness links innovation and branding and has been defined as “the extent to which consumers perceive brands as being able to provide new and useful solutions to their needs” (Pappu and Quester, 2016:4). Product level innovation has been shown to be an antecedent of Brand Innovativeness, together with other elements such as marketing the sense of the brand being innovative and the use of innovation language (Shams et al, 2015).

The adoption of AI in marketing has generated interest, though the literature suggests a key gap regarding how a brand can be perceived to be innovative and whether it impacts brand attitudes in connection with brand loyalty remains. AI allows a business to advance and grow, influencing how businesses respond to changes in customer behaviour (Mustak et al, 2021) and continuously innovate (Mariani et al, 2023). The increasing relevance in this area is witnessed with the emergence of literature reviews (Mustak et al, 2021; Vlačić et al, 2021). Marketers use AI to enable customer centricity (Latinovic and Chatterjee, 2019). Marketers have recognised the importance of influencing consumer perceptions of behaviours towards AI. Understanding consumer perception of the introduction of new AI features and how this influences attitude is crucial to businesses adapting and updating their AI features (Dwivedi et al, 2021).

As outlined above, Brand Innovativeness can be engendered by both consumer knowledge and perception of actual product innovations, and by more general marketing of the idea of the brand being ‘innovative’. To distinguish between these two elements, a distinction can be made between general impressions of product level innovation taking place, and an ability to recognise specific example of product innovation through product knowledge. Cakici and Shukla (2017) describe how greater product knowledge can change simplified perceptions about brand attributes and hence moderate the impact of brand attributes on brand intentions, either by positively creating stronger belief in the judgements about brand attributes (such as brand innovativeness) or potentially negatively if the reality is inconsistent with the marketing hype (leading to cognitive dissonance).

Recently, marketing scholars have shown an increased interest in AI (Kaplan and Haenlein, 2019). The existing body literature surrounding AI is at a nascent stage, where the number of journal articles have continued rising (Mariani, 2022). Only recently have been calls for future studies for the juxtaposition of Marketing and AI, from researchers to study AI and its effects on consumer behaviour. Davenport et al, (2019) proposed their research agenda to examine the full scope of the impact of AI, and the need for more research on the impact on customer behaviour (brand attitudes and brand loyalty). One of the fundamental findings in this area (Ameen et al, 2021a) studies AI technologies relating to positively enhance customer experience, yet warnings of a lack of understanding of how the innovations impact loyalty in this field.

In the language of the Brand Value Chain Theory (Keller and Lehmann, 2003), Brand Innovativeness is an element of Brand Awareness, that in turn precedes Brand Attitudes and Brand Attachment (or Brand Loyalty). As Keller and Lehmann (2023:28) state: “There is an obvious hierarchy in the dimensions of value: Awareness supports associations, which drive attitudes that lead to attachment and activity”. In this study, the aim is to explore the link from AI enabled product innovations to Brand Innovativeness, and how that ultimately links to Brand Loyalty, taking account of the possible moderating effects of product knowledge and the role of Brand Attitudes.
Due to its close association with social norms and perceived behavioural control, brand loyalty is considered a form of intention. The Theory of Planned behaviour (TBP) has shown that the variables of social norms and perceived behavioural controls can influence intentions (Ajzen, 1980). For this reason, the research also controls for the potential impact of Social Norms and Perceived Behavioural Control in the research model.

### 1.3 Research Gaps

Three key gaps in the literature in the area under consideration are highlighted below as areas where a contribution to knowledge is made in this research. All of the gaps relate to a lack of empirical examination of the relationships between AI product innovation and brand innovativeness, and between brand innovativeness and brand loyalty, and mediation and moderation effects in relation to those relationships.

*AI product level innovations and Brand innovativeness*

The literature has demonstrated the existence of a link between product level innovation and Brand innovativeness (Shams et al, 2015). However, no study can be found empirically examining the impact of AI enabled product innovations on brand innovativeness along the two innovation types of Amplifying Innovation and Simplifying Innovation. The impact of amplifying and simplifying innovation on product affect and ultimately intention to purchase has been examined, without a focus on AI enablement (Hardie et al, 2016).

*Artificial intelligence to Brand Attitudes and Brand Loyalty*

Direct relationships can be found in prior studies between Brand Innovativeness and Brand Loyalty, (Eisingerich and Rubera, 2010), Brand Innovativeness and Brand Attitude, (Sanayei et al, 2013) and Brand Attitude and Brand Loyalty (Liu et al, 2012). All three are importFant elements of the brand value chain as described by Keller and Lehmann (2003) as discussed above.  However, no prior study can be identified that empirically examines the impact of Brand Attitude as a partial moderator of the relationship between Brand Innovativeness and Brand Loyalty.

*AI Product Knowledge as a Moderator*

No prior study can be found that examines the moderating effects of the degree of product knowledge on relationships between AI enabled product innovations and Brand Innovativeness, and on relationships between Brand Innovativeness and Brand Loyalty. Given that there has been no empirical investigation of the link between AI enabled simplifying and amplifying innovations, it is not surprising that no studies can be found looking at moderation of that relationship. In relation to moderation of the relationship between Brand Innovativeness and Brand Loyalty, one study looking at a similar concept is Fazal-e-Hasan et al, (2019). which looked at product knowledge as a moderator of the relationship between Brand Innovativeness and Customer Hope, with Customer Hope as one of a sequence of mediators between Brand Innovativeness and Brand Loyalty – however the model in this study is conceptually different. The concept of knowledge as a moderator of relationships due to its ability to increase confidence in judgements is well established - see for example Berger and Mitchell (1989).

### 1.4 Rationale

Brand Value Chain theory (Keller and Lehmann. 2003) suggests that Brand Awareness leads to Brand Associations, Brand Attitudes and Brand Loyalty. A key Brand Association is that of Brand Innovativeness - seen as how effective the brand is at convincing consumers that they can continue to provide new and improved solutions to their needs (Pappu and Quester, 2016).  Brand Value Chain Theory shows that both marketing programs and actual consumer experience influence Brand Awareness and Brand Associations (Keller and Lehmann, 2003). As shown in research gaps above, the link between AI product level innovation and its impact on Brand Innovativeness is underexplored, and the extent to which AI innovation's impact on Brand Innovativeness is moderated by product knowledge (a mix of the result of general marketing and specific user experiences) is not explored. This is the key rationale for this study.

### 1.5 Research Aim and Questions

Research Aim:

The purpose of this study is to explore and understand how and under what conditions AI innovations influence consumer brand loyalty. The aim of this research is to explore the impact of AI innovations on Brand Innovativeness, and Brand Innovativeness on

Brand Loyalty either directly or indirectly through Brand Attitude. It also seeks to explore the moderating effect of Product Knowledge on these relationships.

In response to the research gaps identified in the literature, the research questions for this study are:

*Research Question 1:*
Do AI enabled Simplifying Innovations and AI enabled Amplifying Innovations increase perceived Brand Innovativeness?

*Research Question 2:*
Does increased Brand Innovativeness lead to increased Brand Loyalty and is this relationship (partially) mediated by Brand Attitude?

*Research Question 3:*

Does Product knowledge have a moderating effect on the relationships described in Research Questions 1 and 2 above?

In examining research question 3, two sub-questions exist: a. does knowledge of specific AI enabled features have a moderating effect (Specific Product Knowledge) and b. does knowledge more generally of the existence AI enabled features (General Product Knowledge) act as a moderator?

### 1.6 Research Method, Model Development and Operationalisation

A positivist research philosophy is adopted in this study, and building on this philosophy a theoretical model of hypothesised relationships between key conceptual variables was constructed to explore the research questions described above. Empirical data to test the hypotheses was collected via an online survey, which utilises the Amazon Brand and the Amazon App as an example, to enable specific questions in a questionnaire to be developed in order to operationalise the model. The Amazon brand and app were chosen due to having both simplified and amplified features and used by a significant number of UK consumers.  A purposive sample of the UK population Amazon app users provided the data.

Testing of the hypotheses with the data was undertaken utilising structural equation modelling, conducted with SMART PLS 3 software.

## 1.7 Results

The results support the hypothesised relationships in most respects, with moderating effects of specific product knowledge being identified. Strong positive relationships between AI enabled Simplifying and Amplifying Innovations and Brand Innovativeness, and Brand Innovativeness and Brand Loyalty were found.

## 1.8 Theoretical contributions

The thesis responds to Davenport's (2020) call to examine the full extent of the impact of AI in marketing, and contributes to addressing the research gaps identified in 1.3 above.

This study makes several significant contributions:

Firstly, this study confirms that both amplifying and simplifying AI innovations have a positive impact on Brand Innovativeness, addressing the first identified research gap. In the study it would appear that amplifying AI innovation has a stronger impact on Brand Innovativeness than simplifying AI innovation, implying that AI enabling new functionality or solving new problems may have more impact on consumer association of innovativeness with the brand than AI making existing functionality easier to use.

Secondly, the study explores research question 2 and the second research gap explored in 1.3 above. In the study, Brand Attitude does not act as a moderator of the relationship between Brand Innovativeness and Brand Loyalty finding only weak and non-significant relationships between brand innovativeness and brand attitude.

Lastly, this research uniquely explores the role of product knowledge as a moderator, addressing research question 3. It shows for the first time that AI specific product knowledge (knowledge of specific AI features) can have a positive impact on both the strength of the relationships between AI amplifying innovation and brand innovativeness, and between brand innovativeness and brand loyalty.

The overall theoretical contribution in the field not only advances the theoretical understanding of AI innovations, AI Product knowledge, and Brand, it offers a practical theoretical model for future researchers to approach. The new set of variables in the theoretical model moves beyond any existing models, with the approach to offer an original advancement of theory in these areas. Using the variables in the model bridges the gap between the interdisciplinary fields of innovation and marketing, by providing a comprehensive foundation for brand and innovation theory.

## 1.9 Structure

The thesis is divided into six further chapters. Chapter 2 discusses the main research and themes in literature to provide a theoretical foundation to the research and establishes the research gaps and research questions to be explored. Chapter 3 develops a conceptual model and research hypotheses to be tested. Chapter 4 describes the adopted philosophical approach to the study and the research methodology to be followed and describes the measures and constructs to be used in a quantitative model testing hypothesis established in Chapter 3. Chapter 5 presents the data analysis and findings. Chapter 6 discusses the research findings in detail. Chapter 7 concludes this research and examines managerial implications and limitations of the study.

The seven chapters within this research are in more detail:

Chapter One

This chapter introduced the importance of the broader topic of AI and Marketing, then outlined how AI product innovations via brand innovation leading to brand loyalty needs to be researched due to the gaps in previous studies. It offers a rationale for the study and discusses high level key contributions to knowledge and practice.

Chapter Two

This chapter is the literature review. This is where key themes related to Innovation, Brand and Product Knowledge are discussed and prior studies and literature examined. Gaps in the literature are highlighted, and the foundations of an exploration of those gaps begun.

Chapter Three

A conceptual model of how AI simplified and amplified innovations impact on Brand Innovativeness, and how that in turn impacts on brand loyalty are developed into a conceptual model. The hypothesised relationships are developed and justified in this chapter.

Chapter Four

This chapter describes the methodology adopted in the survey. Taking research aims into considerations, the methods are justified and evaluated underpinned by the positivist approach deemed the most appropriate philosophical stance. Quantitative techniques are operationalised through a survey as a data collection instrument, using a purposive sampling strategy, and allowing for the most suitable method of data analysis by means of PLS-SEM. The measures used in the survey are developed from the literature, in order to test the model. Finally, the approach to ensuring validity and reliability in the methodology is described – outlining tests to be performed.

Chapter Five

This chapter is the data analysis chapter. This chapter presents the results obtained using the data collected to test the measurement model and hypothesised relationships (the structural model). The hypotheses are then identified as supported, or unsupported.

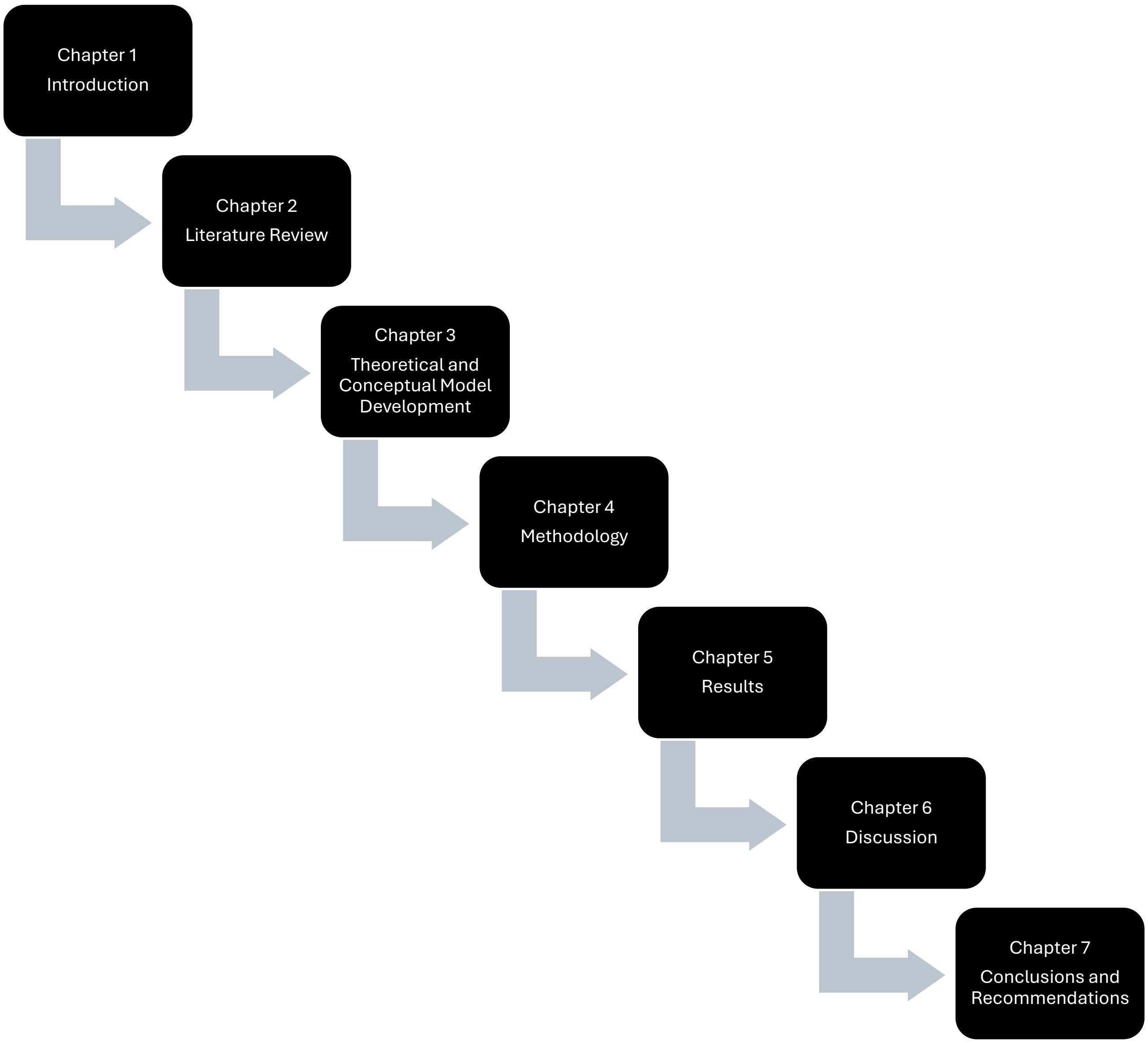
Chapter Six

This chapter is the discussion chapter. This chapter reviews the results and examines the findings of the study. There is a critical discussion of the quantitative data analysis, and discussion of what it might imply.

Chapter Seven

This chapter concludes the thesis. It provides a summary of how the research aims were achieved, alongside theoretical and managerial implications. Furthermore, clear recommendations and limitations ere addressed. Additionally, the contribution to theory and practice are identified. The chapter concludes with suggestions for future research.

*Figure 1: Thesis Outline*



## 1.10 Chapter Summary

This chapter has introduced the three research questions of the thesis. It has given a rationale for the importance of investigating AI product innovations and their impact on Brand Loyalty, and the moderation of product knowledge. It illustrates how empirical findings of this study contribute to addressing the three knowledge gaps giving rise to the research questions addressed. Furthermore, the chapter provides a synopsis of each of the seven chapters in this thesis, thus, signposting the highlights of each stage of the investigation. Finally, a structure of thesis is presented. The next chapter reviews the literature where key themes are identified and reviewed.

# Chapter 2

# Literature Review

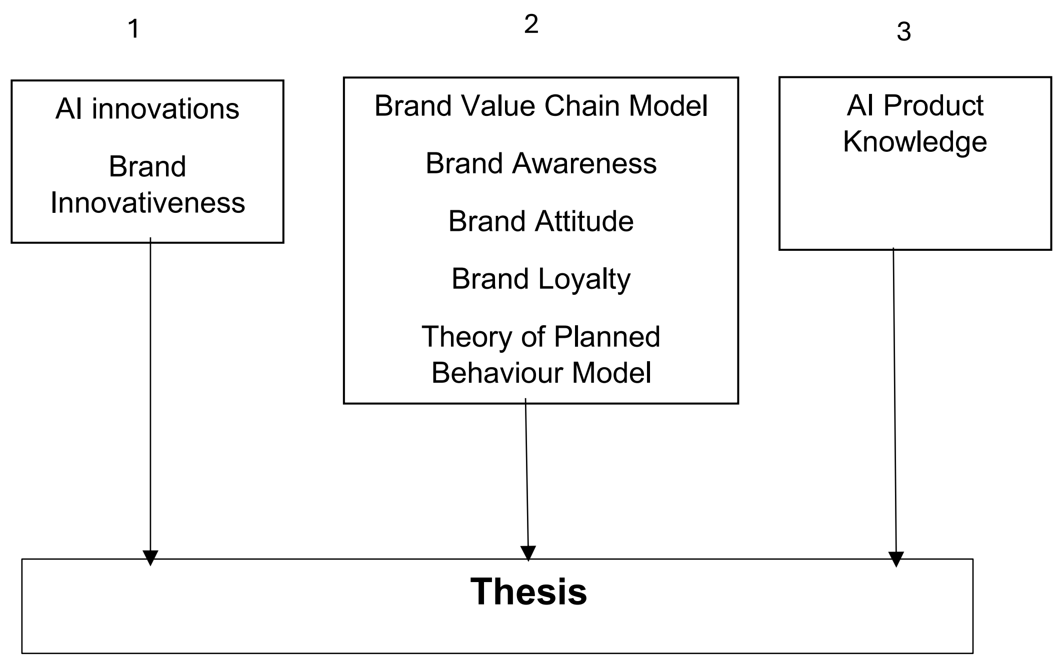
## 2.1 Introduction

Innovation is critical to business success (Tohidi and Jabbari, 2012), and AI in particular has emerged as one of the leading ways businesses can innovate and differentiate themselves in today's market (Mariani and Wamba, 2020). AI is important in order to stay competitive to meet the needs of customers. In this chapter, the literature is comprehensively reviewed to evaluate a collection of theories, focused on innovation, AI and brand research. Furthermore, previous research endeavours have sought to elucidate consumers acceptance of AI innovations, (Zhang et al, 2022; Zhu et al, 2022). This literature review extends and explores key concepts in innovation and brand theory; AI innovations, Brand innovativeness, and Brand Loyalty which have emerged, with particular focus on AI innovations.

First, the topic of Innovations and AI is justified through its growing importance in research and everyday life. Next, brand innovativeness is examined. Knowledge of AI innovation plays a key role in assessing a brands innovativeness. However, there is an apparent gap in the literature on product knowledge of AI innovations and influence on consumers' perception. Exploring this gap allows a deeper understanding of the influence of AI product knowledge, as well as push the boundaries of knowledge in this area. Subsequently, research on brand theory, with a particular focus on the brand value chain, is examined. The standing of the Brand Value Chain model (BVC) is of increased importance in this study as it bonds the branding literature to AI innovations and brand innovativeness, which sets the parameters of the research. Finally, a summary of the chapter highlights the key themes identified in this chapter, to be utilised for hypotheses development.

Concept and theories in the literature review:

*Figure 2: Pillars of the literature review*




Source: Author

The study benefits from utilising the three overarching pillars within a broader framework of the key themes within the literature (Figure 2). The concept of AI innovations and brand innovativeness focus on the AI-enabled innovations and their impact on consumer perception. Shams et al, (2015) distinguish consumer perceptions are based on perceptions of product level innovations, implying product innovation and brand innovation are connected. Amplifying and Simplifying innovations are applied in this section to measure the impact of consumer perception towards brand innovativeness using the two methods of product innovation, through AI-enabled innovations. The literature in this section is modest. The second pillar comprises of brand literature, employing the BVC model to understand consumer perceptions, in particular, how the consumer gathers information though brand awareness and associations to form a brand attitude. Brand attitude and brand loyalty are formed through an interplay of antecedents involving; customer experience, satisfaction, engagement, confidence, involvement, trust and belief (quality, value, image) in relation to the brand. The TPB model contributes through the inclusion of important additional variables of Perceived Behavioural Control (PBC) and Social Norms (SN) with literature strongly associating these in addition to attitude as influencers of loyalty. The final pillar involves AI product knowledge. There is little known on AI product knowledge as a moderator of the relationships between innovations and brand innovativeness, and between brand innovativeness and brand loyalty, as it is untested. The literature supporting product knowledge as a moderator focuses on confidence as a driver of intention (Berger et al, 1994; Peterson and Pitz, 1988).

Pertaining to the research objectives:

**Pillar 1 refers to research question 1:** Do AI enabled Simplifying Innovations and AI enabled Amplifying Innovations increase perceived Brand Innovativeness?

**Pillar 2 refers to research question 2**: Does increased Brand Innovativeness lead to increased Brand Loyalty, and is this relationship (partially) mediated by Brand Attitude?

**Pillar 1, 2 and 3 refers to research question 3**: Does General and/or Specific AI Product knowledge have a moderating effect on the relationships described in Research Questions 1 and 2 above?

## 2.2 Artificial Intelligence (AI)

Can machines think? (Turing, 2009)

Artificial Intelligence (AI) is used in our daily lives, from shopping, to caring, education, to healthcare (Rai, 2020). AI is likely to substantially change both marketing strategies and customer behaviours (Davenport et al, 2020). The term AI is widely used, it is a nebulous concept, due to the complexity of this technology. A variety of definitions of the term AI have been suggested as can been seen in Table 1 below:

*Table 1: AI Definitions*

| **Definition** | **Reference** |
|---|---|
| The use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling | Huang and Rust (2021) |
| An information system (IS) that learns over time by efficiently and effectively performing one or more operations (*e.g.*, acquisition, integration, analysis, and/or interpretation) on information | Manis and Madhavaram, (2023) |
| Computational agents that act intelligently | Vlačić et al, (2021) |
| Automating business processes, gaining insights from data, or engaging customers and employees | Davenport and Ronanki, (2018) |
| Computer programs that can solve problems and achieve goals in the world as well as humans…algorithms as capable as people at solving problems. | McCarthy, (2007) |
| The affordance of human intelligence to machines | Ma and Sun, (2020) |
| The science of creating smart machines using algorithms to help computers solve problems that can be solved by human beings | Bag et al, (2021) |
| It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable | McCarthy et al, (2006) |
| Artificial intelligence is concerned with building computers and machines that can reason, learn, and act in such a way that would normally require human intelligence or that involves data whose scale exceeds what humans can analyse | Google, (2023) |
| AI is the study and development of computer systems that can copy intelligent human behaviour | Oxford Learner Dictionaries, (2023) |

Source: Author

AI is in general defined for the purposes of this study as “a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Kaplan and Haenlein, 2019:5).

According to Russell and Norvig (1995) there are four main dimensions to categorise AI – to think like a human, to act like a human, to think rationally or act rationally. AI and 5G in the UK have transformed technologies (Krafft et al, 2020). Specific types of AI include Machine learning and Deep learning. “Versions of machine learning (deep learning, in particular, which attempts to mimic the activity in the human brain in order to recognize patterns) can perform feats such as recognizing images and speech”, (Davenport and Ronanki, 2018:110). Machine learning is defined as:

“*A computational strategy computational strategy that automatically determines (i.e., learns) methods and parameters to reach an optimal solution to a problem rather than being programmed by a human a priori to deliver a fixed solution”* (Dwyer et al, 2018:94).

AI allows sophisticated new ways for businesses to interact with customers include face recognition, voice recognition, search engine optimisation as well as for offering personalised customer experience (Haleem et al, 2022). AI can assist with segmenting customers and sending customised messages, alongside advert optimisation, offering the consumer only suitable adverts to be seen (Huang and Rust 2021). Predictive marketing has become a crucial part of marketing strategy, allowing organisations to understand customer behaviour and preferences whilst predicting future trends and requirements (Rathore, 2023: Sarstedt et al, 2022). “Interactions between firms and consumers are increasingly more individualised and ubiquitous, generating heavily digitised footprints” (Ma and Sun 2020:489).

Machine Learning (ML) enables AI to sift through large amounts of data to searching for trends and patterns to inform decision making. ML is used in social research to predict consumer behaviours (Rana et al, 2022), In addition to this, Davenport et al, (2020) proposed a research framework based on understanding the impact of AI in marketing with ML. ML technologies are used in marketing strategies and applied to the 7Ps

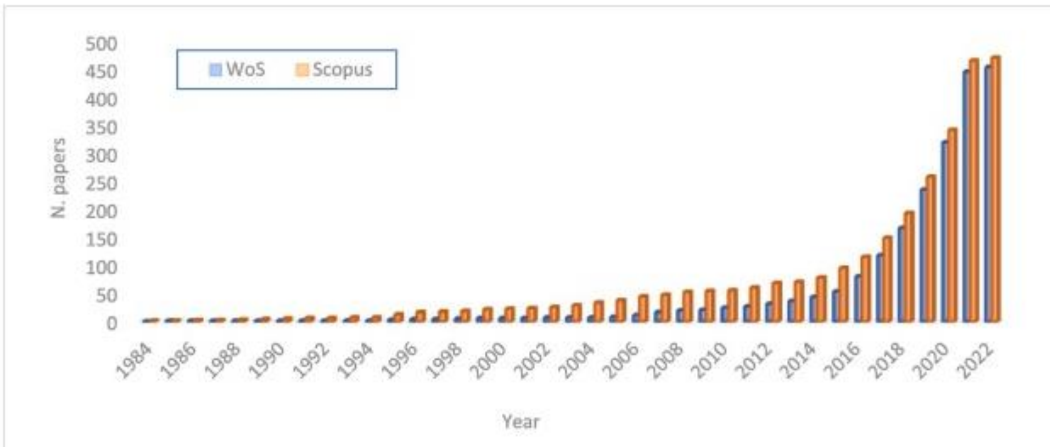
(Figure 5). Recent research shows AI provides recommendations at speed, and consumers perceive product recommendations as more competent than humans (Jin, 2025). ML is used in social research to predict consumer behaviours (Rana et al, 2022). According to Rust (2020), staying current with technological trends, such as AI, is critical for businesses aiming to maintain their competitive edge. By leveraging the power of AI, companies can not only respond to the dynamic market landscape but also proactively shape it. Consequently, the adoption of AI has become a necessary component of recent marketing strategies, ensuring that businesses can navigate to thrive in an increasingly competitive environment. Moreover, using AI within marketing strategy has been empirically proven to positively impact business performance (Wu and Monfort, 2023). This has resulted in a paradigm shift of businesses realising the importance of AI technologies and investing in AI innovations to remain competitive and to increase profits (Grewal, 2020).

### 2.2.1 AI in the context of Branding and Marketing

In recent years, the marketing landscape has experienced significant transformation, primarily driven by rapid technological advancements and evolving consumer behaviours. Scholars such as Nordin and Ravald (2023) emphasise the critical need for businesses to adapt to these changes in order to remain competitive. One of the most profound shifts has been the integration of artificial intelligence (AI) into marketing strategies. AI technologies, offer unique opportunities for businesses to enhance their marketing efforts. These technologies enable companies to analyse data to personalise customer experiences and optimise marketing campaigns with greater precision and efficiency.

The recent focus on AI in marketing has enabled researchers to concentrate on AI and its enabling facility to perform and improve service tasks for consumers (Huang and Rust, 2018). The importance of AI on the research agenda is pertinent to current and future marketing research in new technologies (Kumar et al, 2021). According to Mustak et al (2021) 51 articles were published in marketing journals in 2019, which is a developing trend from 2015. With the rise in interest from consumers with the upsurge in use for ChatGPT, AI has become at the forefront of all industries   Recently scholars have shown interest evidenced in the growth in AI publications, derived from Web of science and Scopus from 1984-2022 (Mariani et al, 2023):

*Figure 3:  Publications of AI Research Articles*




Source: Mariani et al, (2023)

Research in AI in marketing is still under explored (Davenport et al, 2020).  There is growing importance of this subject to the research community, as well as implications for marketers.  The phenomenal growth of AI demonstrates that (1) there is a genuine interest in AI research, and (2) researchers are still learning about it as AI rapidly evolves (Kopalle et al, 2022).

Business have now shifted to a new paradigm for consumer interaction through the integration of artificial intelligence into branding operations. Preliminary studies investigated that AI recommendations expand brand awareness, affecting consumer-brand relationships (Cheng and Jiang, 2022).  Swaminathan et al, (2020) conducted research around hyperconnectivity and recognised the importance of technological advancements in reassessing branding research for scholars.   Through our hyper-connected environments consumers are continuously intertwined with AI and brands.  This interconnectedness requires AI to use data to drive purchasing decisions.  The current discussion amongst scholars on AI and brands lead to an increase of brand offerings and brand value (Mariani et al, 2022) and leveraging AI is the key to enhance customer experience and loyalty (Verma et al, 2021).

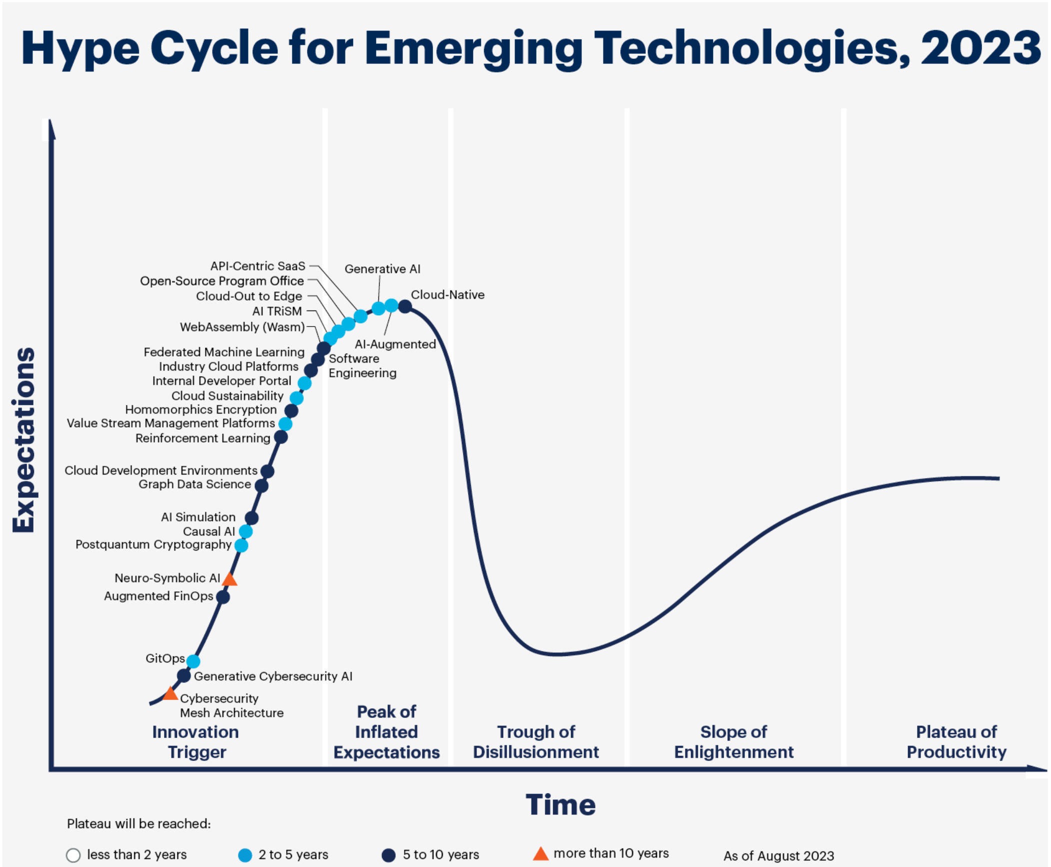
Brands use AI to create personalised experiences at unprecedented levels due to AI being able to analyse and interpret data (Haleem et al, 2022). Brands understand individual user preferences through AI algorithms to develop marketing approaches that connect personally with each consumer. Creating a personalised customer experience enhances loyalty through making consumers feel valued and understood. Brands use AI-driven analytics to obtain predictive insights about market trends alongside consumer behaviour patterns. Companies which adopt real-time branding strategy adjustments using predictive analytics maintain their relevance and competitive market position.  The use of AI technology in branding marketing can create creates ethical issues as consumers feel their privacy is violated when personalised messages are delivered. However, AI technology provides substantial benefits to branding with more precise personalised marketing and predictive outcomes.  AI simplifies applications through sifting through data to implement practices to encourage consumers to engage and interact easier, thus adding value to the customer experience and customer satisfaction (Rohit et al, 2024).  Brands are able to harness the power of AI to build dynamic consumer-brand relationships through crafting engaging communications for a target segment.

### 2.2.2 Consumer Perceptions of AI

Recent research shows AI provides recommendations at speed, and consumers perceive product recommendations as more competent than humans (Jin, 2025). Though this may diminish when anthropomorphised chatbots or robots further improve the acceptance of robots or voice commands as they feel more real (Crolic et al, 2022). In order to understand attitudes towards AI, it is crucial to examine the consumer perspective of the integration of AI into various products.  The AI integration into products has transformed interactions with technology, from virtual assistants to robotic knee surgery to swift purchases via their mobile phone, enables consumers to continuously improve their quality of life (Davenport et al, 2020; Rust, 2020). For consumers, AI has changed the way we "think act and decide" (Hildebrand, 2019:10) AI has made a significant impact; however, many consumers are unaware of how AI has infiltrated the internet to offer ease of use when interacting on a website or anything associated with requiring the internet (Puntoni et al, 2020).

Consumer perceptions include a build-up of observations and experiences which manifest in the consumer mindset. They are important to businesses as the consumer mindset must be favourable in order to remain competitive (Ameen et al, 2021a). Consumer habits and behaviours have evolved with AI and expectations have increased with each development (Jain et al, 2024). The advancement of technologies has enabled consumers to judge brands based on their own AI readiness, with increasing expectations to enable consumers to make swift decisions. As a result, the consumer demonstrates lower patience, with expectations of faster responses. Perceptions may vary depending on level of understanding, and experiences of AI innovations. AI provides an optimal user experience though personalisation, information processing and personalisation. Consumers attitudes towards AI have changed the perceptions of brands as well as service value. Previous studies advocate this with value, which is a determinant of consumers intentions to use AI (Flavián et al, 2024). Consumers have benefitted from AI innovations through useful and convenient AI innovations (Liang et al, 2020). This reflects their opinions building high expectations of technologies to be efficient increasing service quality (Parasuraman et al, 1994), and satisfaction, which shapes of consumer perceptions. Depending on the type of AI innovation, consumers are less willing to use AI for risky tasks. An understanding of the product impacts the propensity on consumer perception of AI (Davenport, 2016). The impact of a business's image is affected by being known to be an innovative brand, or brand with high technology, which influences their perception. Research on AI has seen developments in branding studies (Davenport et al, 2020; Huang and Rust, 2021; Lin and Wu, 2022), however, the literature surrounding perceptions of AI innovations provides scant attention paid to consumer perceived AI in relation to innovativeness of brands. Social networking, reference groups and prior knowledge through social media influence perceptions of AI through online reviews and blogs to create an image in the consumers mind (Riquelme and González-Cantergiani, 2016; Mogaji et al, 2021).

*Figure 4: Gartner Hype Cycle 2023*

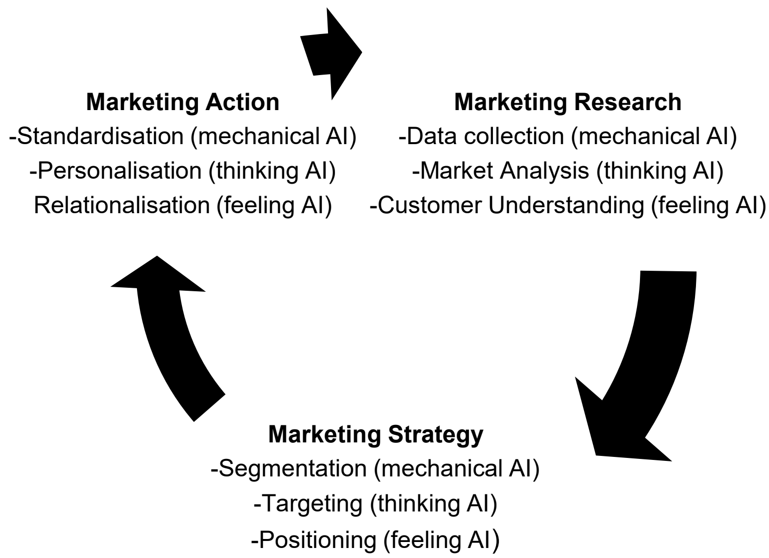



Source: Perri, (2023)

Currently, the Hype cycle reveals that generative AI is at its peak of expectations, and businesses are using Generative AI to enhance digital experiences for consumers (Mogaji and Jain, 2024). Marketing around the new innovations is essential to manage expectations and hype, highlighting a requirement to develop a strategic marketing plan, based on the principles of marketing (Figure 5), (Huang and Rust, 2021). Businesses use the hype cycle to forecast innovations and understand the speed of progress for each innovation. From a research viewpoint, prior studies to explore the hype around consumer perceptions of AI innovations are limited. The level of hype required of an AI function within an innovation is an area for research exploration (Kim et al, 2021). Furthermore, for businesses, emerging research indicates AI is used as a background mechanism for data analytics, such as machine learning to involve the consumer to interact with it, following this, they will “learn” and adapt, listen and question to become better (Di Vaio et al, 2022). Perez-Vega et al, (2021) portray customer engagement as “actor engagement” seen as the actor (consumer) involvement in the interactive activities.

Research advancements in the field show, once a customer has interacted online, the AI algorithms remember the interaction to improve the search for the next customer, thus enhancing both the customer search and experience (CX) (Ameen et al, 2021b). Analogous to how Netflix learns what their customers like to watch, in order to provide a unique and personalised experience. This personalisation makes the user experience enjoyable, as well as increasing the perceived innovativeness of the brand – the consumer often questions themselves asking “how do they know my preferences?”. Consumers interact with AI innovations, knowing and unknowingly (Puntoni et al, 2020). The digital automation behind the design of AI practice ensures companies like amazon and Airbnb go beyond prediction, they solve problems and assist consumers to make decisions faster (Verganti et al, 2020). Research shows AI personalisation and relationship building leads to loyalty (Coelho and Henseler, 2012). Consumers are more likely to return to a brand if they perceive it as representative of their identity or their experience is enhanced with AI, making it more user-friendly or efficient (Leung et al, 2018). An AI enabled marketing strategy can directly impact on consumer perceptions. Figure 5 displays the AI marketing framework where AI is embedded into each element of the marketing mix (McCarthy, 1979).

*Figure 5: AI marketing framework*




Source: Huang and Rust (2021)

The strategic AI marketing framework by (Huang and Rust, 2021) offers a relevant theory of AI's three stages and how it is applied by marketing practitioners to collect, interpret and analyse data to leverage intelligence at each stage. Stage one involves conducting marketing research to analyse the consumers and market, stage two encompasses the creation of a suitable marketing strategy and stage three is the building of the relationship with the consumer. Within the strategy, the tactics are often referred to as 4Ps by Jerome McCarthy (1979) or 7Ps involves Product management through analytics (Dekimpe, 2020) or product design through AI building solutions, recommendations (Cheung et al, 2003). Additionally, literature has included; Pricing algorithms (Misra et al, 2019) or fuzzy logic analytics to forecast and improve e-commerce platforms, Place, though AI distribution (Huang and Rust, 2018), and Promotion through SEO, personalisation and netnography (Verma and Yadav, 2021). Scholars have researched the additional 3 Ps; Process (Timoshenko and Hauser, 2019), Physical evidence (Salminen et al, 2019) and People (Kwok et al, 2020). The 7Ps theory are inherent to building a marketing strategy where AI is making a considerable impact. Furthermore, AI interactions may impact consumer satisfaction and loyalty (Lalicic and Weismayer, 2021). Furthermore, useful information offered as product knowledge is an antecedent of AI transpiring as positive consumer perceptions of the brand (Puntoni, 2021). The importance of utilising a marketing strategy is to communicate the benefits of a brand. Marketers ultimately use AI to build customer perceptions, through communications to position themselves competitively (Huang and Rust, 2021).

### 2.2.3 Critiques of AI

AI is generally well accepted by consumers. However, there are some drawbacks to the perceptions of the technology. Recent studies have found the Adoption of AI is moderated by ethical-related concerns (Guha et al, 2021) such as trust privacy and data issues. Concerns of AI is causing digital disruption through depleting human jobs, or digital technologies which once were popular such as watching Netflix instead of terrestrial television (Palmié et al, 2020). Disruptive innovations impact a firm's performance and pose difficulties for competition to keep up with the new AI innovation.

Ameen et al, (2021b:9) who critiqued AI innovations in their study, warned there are "major sacrifices consumers may face in AI, such as a lack of human interaction, loss of privacy, loss of control, time consumption, and possible negative feelings of irritation, all of which can have a negative effect on AI-enabled experiences ". Thus, impacting negatively on consumer brand perceptions. The research discovered that as a consumer obtains personalised content from a brand, they gain more trust and can lead to positive impressions of the brand.

Social commitment based on subjective norms is also an important variable in the usage of AI in improving customer experience (Ameen et al, 2021b). Previous studies have established privacy is also a growing concern (Rai, 2020). AI's impediments through wrong predictions could prove costly, hindering customer-firm relationships (Berger et al, 2020). Consumers can be wary of AI as it is not a human. According to Belanche (2024) research based on the "Dark Side" of AI summarises the negative perceptions of AI through the distrust, power (fear of manipulation) and bias (Grewal et al, 2021), which is growing for consumers coupled with data breaches widely reported in the UK media from various consumer outlets such as Meta, Amazon and banks. To mitigate these concerns the Hype cycle research by Gartner (Perr, 2023) demonstrates the next wave of AI innovations will involve AI to focus on cybersecurity, encryption and data handling to elevate these concerns. This brings to light the importance of communicating to customers about the new innovations (Heidenreich and Spieth, 2013) to provide the consumer with further product knowledge and tools to evaluate the features of the product, to make an informed perception of the brand. Based on no empirical studies in this area, it is not easy to ascertain the influence of AI innovation on consumer perceptions.

### 2.3 Innovation

The literature on innovation has received enormous attention across every business research area (Palmie, 2023). Technological innovations are "exerting a transformative force on the practice and academic discipline of marketing" (Rai, 2020:137). These technological advances include chatbots, mobile, social media and robotics.

Prior studies by Baregheh et al, (2009) found over 60 definitions of "innovation" in disciplinary literature. Several attempts have been made to define innovativeness, which is often referred to as the degree to which an individual makes his/her innovative decisions independently of the communicated experience of other (Midgley and Dowling, 1978). The definition deemed most appropriate for the present study is:

*"Innovation refers to the process of bringing any new problem-solving idea into use. Innovation is the generation, acceptance and implementation new ideas, processes, products or services"* (Kanter, 2008:703).

With technology evolving rapidly, innovation in organisations is normally a result of the changes in the external and internal environment (Damanpour, 1991). The ability to innovate is crucial in today's rapidly changing global environment, as it allows forms to adapt to evolving customer needs and technological trends (Bessant and Tidd, 2018). AI transforms where and how innovation takes place and is a force of disruption (Davenport and Ronanki, 2018). Businesses realise there is a massive potential to utilise AI innovations in order to meet the requirements of consumer needs (Wamba-Taguimdje et al, 2020). AI is the latest innovation to become at the core of a business (Gerdeman, 2020). Research investment on innovation as part of progression and development, with technology is termed as being the fourth industrial revolution of humankind, (Huang and Rust, 2018). Businesses are leveraging innovation strategies to remain competitive (Spanjol and Welzenbach, 2018). Additionally, it has been reported that the main difference of innovation and innovativeness, is that innovation can be seen is as "the outcome" for an organisation, and innovativeness is understood to be "capabilities and outlook" of a firm, (Hurley and Hult, 1998). Bessant et al, (2005:1366) highlighted the significance of innovations on growth and competitive advantage for business to be:

*"Innovation represents the core renewal process in any organisation. Unless a business changes what it offers the world, and the way in which it creates and delivers those offerings, it risks its survival and growth prospects*".

A technology driven service strategy refers to the systematic use of enhancing services to improve the customer experience. The strategy involves integrating digital innovations to streamline processes and increase efficiency (Rust and Huang, 2014). The importance of using a technology driven service strategy can help businesses to position themselves through connections with consumers to building better customer relationships (Huang and Rust, 2017).

Many scholars argue that keeping up with innovation is essential in order to remain competitive for a brand (Deryl et al, 2023: Campbell and Price, 2021). Central to this area of knowledge is the diffusion of innovation theory (Rogers et al, 2014), which suggests that a set of generalisations and universal factors explain how social change takes place. Innovative decisions made by consumers and their social systems affect the rate of adoption of adoption. Hence, the evermore importance of researching innovation in business. Innovation can lead product modifications which can meet the needs of the customers (Rogers et al, 2014).

"*Innovativeness in the marketing initiatives of the brand can be a function of the contributions made by the brand to its competitiveness*" (Gupta et al, 2016:5672).

Moreover, a successful innovation must be perceived and judged by the consumer to build brand equity. Innovation is important for brands to ensure they stay modern and relevant (Mariani and Wamba, 2020). Innovations have been known to revitalise brands, the product innovations for Apple (iPod and iMac) revolutionised the brand, whilst improving value and profits for the firm (Gemser and Leenders, 2001). AI has played a significant role in product innovation. This innovation can be characterised by being either Simplifying or Amplifying Innovations (Hardie et al, 1996).

### 2.4 AI Amplifying and Simplifying Innovation

AI innovations in general can be defined in many ways, through innovative capabilities in various contexts such as generative AI (Chen et al, 2024) Data Science (Saba et al, 2021) and Fintech (Palle, 2022). However, the consumer centric contextual definition used in the present study is "technological innovations driven by AI" (Mariani et al, 2023; Lin et al, 2024).

Brexendorf et al, (2015) identifies a gap in the AI literature with suggestions future research directions to investigate the way in which brands facilitate the adoption of amplification or simplification. Overall, there is a dearth of literature in this area. The academic discourse on innovation and the concepts of amplifying and simplifying innovations are vital in understanding how new technologies are adopted. Hardie et al, (1996) introduced the concepts of Amplifying innovations and Simplifying innovations, by investigating consumer behaviour changes. This study will use the definition first suggested by Hardie et al, (1996:357):

*"Simplifying and amplifying innovation is the degree to which an innovation makes using a product easier (simplifying) or the degree to which an innovation increases what can be done with a product (amplifying)".*

Simplifying innovations can be described as making the consumer think the product is easy to use, the benefit of this is to attract non-users, focusing on making innovations user-friendly and accessible (Arachchi and Samarasinghe, 2024). This is similar to how Apple Inc. have simplified complex innovative processes to provide ease of use for the consumer. Consumers may choose an aesthetically pleasing mobile phone over features of the phone, due to the ease of use and simplification of the features (Chitturi et al, 2007).

Wood and Moreau (2006) warn marketers not “to promise ease and unrealistic expectations” as this may cause negative emotions towards an innovation – which may be advertised a “simplified” however, if the consumer is unable to use it, they may reject it altogether. Additionally, research has indicated, if the consumer is given too much technical information, this may lead to further negativity towards uptake (Talke and O'Connor, 2011). Recent advancements in the field have enabled researchers to discover a major obstacle for AI consumer adoption, to be the lack of trust and perceived risk (where consumers are concerned with the products new features not working properly) (Gillath et al, 2021; Ameen et al, 2021b). The uncertainty of not knowing how to use AI features can possibly deter consumers, which is why companies like Apple Inc, Microsoft and Tesla have simplifying functions using their AI-enabled innovations such as using their AI assistant “Siri” to make them easier and familiar to the consumer. A broader perspective has been adopted by Bornemann et al, (2015) who adds to the definition that simplifying and amplifying may also be classified as product functionality where the consumer judges the functional features upon evaluation. This is has been criticised as it could be deemed as too many functionalities cause consumers to have “feature fatigue” (Thompson et al, 2005) where too many features of the products or innovation can weigh on the consumer, so they may evaluate it in a negative light. Consumers may be tempted by products which offer greater capability, thus, the greater the capability of the product, the more perceived benefits, (Thompson et al, 2005). This implies that this school of thought may provide more impetus for amplification to be perceived as higher level of work, many innovative features to learn may confuse the consumer, resulting in a negative experience, to compensate for this, simplifying features heighten the process.

On the other hand, amplification can increase the capabilities of a product and increase efficiency such as a CT scanner which “resulted in quantum increase in the diagnostic capabilities of medical specialists” Hardie et al, (1996:357). A prime illustration of this concept in daily routines is the use of Microsoft Office, Microsoft Word for “simplifying” using the AI powered writing assistance tools such as spelling and grammar which have the ability to craft intelligent documents through AI editor suggestions. Consumers may use “Amplifying” via Microsoft Excel’s Ideas function to create AI enabled automated recommendations of graphs and charts for a given data in a sheet to increase productivity capabilities. Gatignon and Robertson, (1989) explore these constructs highlighting both types of innovation to be crucial as they serve different purposes in the diffusion process.

Moreover, the established Technology Acceptance Model (TAM) (Venkatesh et al, 2003) uses perceived usefulness as a key variable to measure how performance at work can be enhanced through productivity by using the simplified system. The Amplification of AI in this study is perceived by consumers to increase productivity. Amplification of AI’s efficiency to increase output is a perception which is growing. Contrary to this, if AI is useful and easy to use, this may impact the perception of the brand due to the ease of use, yet positive use of innovative features, for top innovative brands which makes using their products much easier for users, with the perception of maximum productivity.

Collectively, these studies outline a critical gap in the role of understanding amplifying and simplifying AI innovations influence consumer perceptions towards a brand. Marketing scholars have called for more empirical substantiation in AI and marketing literature to understand AI’s impact on consumers and marketing (Davenport et al, 2020; Rust, 2020). In particular, there are no prior studies, which have examined the influence of amplifying and simplifying innovations enabled by AI innovations on Brand innovativeness.

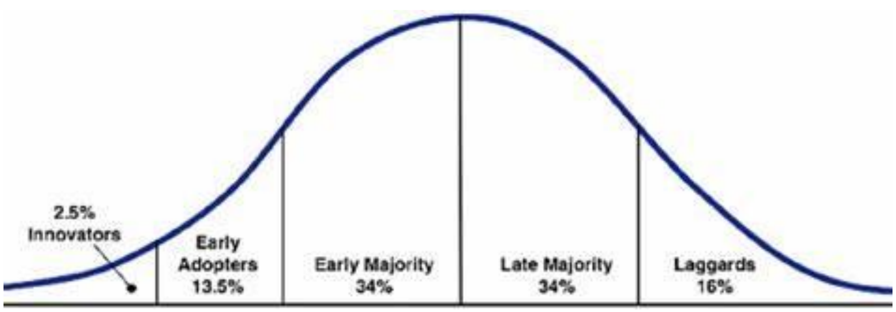
### 2.5 Innovativeness

Different to innovation, Rogers et al, (1971:57) define innovativeness as “the readiness to adopt particular innovations”, and go on to say “relatively earlier compared to other people in his/her social systems” . Within the consumer behaviour research literature, it is defined as being willing and able to understand and adopt a new product. For firms, innovativeness is the distance of the innovation to practice. Innovativeness is used for competitiveness in business performance (Salavou, 2004). Consumer innovativeness relies on the consumers context to undergo and adopt an innovation, in order for them to be deemed as innovative (Dobre et al, 2009).

### 2.5.1 Consumer Innovativeness

Consumer Innovativeness can be described as "the tendency to buy new products in a particular product category soon after they appear in the market and relatively earlier than most other consumers in the market segment" (Foxall et al, 1998:no page). Understanding consumer innovativeness is fast becoming a key instrument in marketing, as businesses rely on growth and profitability through new product development and new methods of communicating, through the innovative consumer (Steenkamp et al, 1999). Consumer innovativeness is an important factor when considering adoption of new technologies (Oliveira et al, 2016).

*Figure 6: Diffusion Theory*




Source: Rogers et al, (2014)

Diffusion theory (Rogers et al, 2014) applies new products to social systems, using time vs adoption factors (Midgley and Dowling, 1978). It is used to understand how brand attitudes form and spread through society, and how new product adoption and diffusion process are influenced by perceived innovation characteristics (Rogers et al, 2014). Whilst categorising consumers through the stages of their innovativeness (as innovators through to laggards) each consumer is branded based upon their communications channels, vs time taken to adopt the new product (Fell et al, 2003). The theory utilises categorisation of diffusion to start with innovators, who have knowledge or want to seek new knowledge of the innovation. These types of consumers are often involved in the innovation process through open innovation from the firm. The early adopters are those who are wanting to take a risk and try the product. They are opinion leaders keen to adopt the product as soon as it is on the market. They use their social influence on their community. This stage is often when all issues should be ironed out to impact the next category. The early majority follow the adopters; they seek clarity from adopters to influence their purchase decision. The late majority and laggards are the followers, who traditionally have lower income, social status and older age (Rogers et al, 2014). The theory postulates Laggards to be resistant to innovation and often have to change due to end of line or terminated products, for example, cassette tapes to CDs. As the timeline shifts through the categories, so does the expense of the product, the demographics, risk factors and compatibility of the consumers. The theory is used in marketing to adopt targeted strategies in each category (Ng, 2023). The proposed innovation attributes, when considering adoption of new products, according to Rogers et al, (2014) are: relative advantage (how much better it is than the replacement), compatibility (how it meets the needs of the adopter), complexity (how easy it is to use and understand), trialability (can it be tested before consumption) and observability (how soon may the tangible results be visible). These all impact the consumers decision to adopt (or reject) an innovation. Some limitations of the theory are that there may not always foster an approach to marketing or takes into consideration an individual's resources or social norms to adopt. Researchers use diffusion theory to categorise consumers into segments, which is a valuable marketing tool (Goldsmith and Foxall, 2003). Consumer AI adoption is growing, with attention diverted towards trust in the company, not just the technology (Frank et al, 2023).

Vandecasteele and Geuens (2010) found four dimensions reflecting innovativeness from their research; hedonic, functional, social and cognitive. This provides reasoning as to why consumers choose to be innovative through the benefits of the innovation for the consumer. Barriers to consumer adoption (De Bellis and Johar, 2020) could be due to the lack of technology readiness (Parasuraman and Colby, 2015) including demographics such as age, ability and income (Im et al, 2003). Hwang et al, (2019) observed novelty seeking, quality experience seeking, hedonic experience seeking, and social distinctiveness to affect a consumer's attitude towards their intention to purchase. This formation of attitude played "an important role" in the formations of the intentions to use the products and ultimately adopt. When measuring consumer innovativeness, (although they had not tested on technology) those consumers considered innovative were familiar and interested in new products (Goldsmith and Hofacker, 1991). The concept of individual innovativeness has much research attention, researchers state that it could be considered part of a personality trait, where consumers are willing to try new products (Agarwal and Prasad, 1998), therefore higher levels of innovativeness links to moderation of intention to use and use of prior knowledge (Steenkamp et al, 1999; Meyer-Waarden and Cloarec, 2022). The Technology Readiness Index (TRI) (Parasuraman, 2000) is a 36 item scale measuring peoples propensity to embrace technology. Research conducted within this study postulates how it facilitates the understanding of the general attitudes towards accepting new technologies. The importance of understanding consumer motivators and inhibitors facilitates the understanding of consumer adoption of technology. A consumer could also be resistant to change (Oreg, 2003), where there are factors leading to a consequence of attitude towards innovation (scales such as “I generally consider change to be negative thing” used). This attitude may also impact a consumer’s yearning to be innovative.

### 2.5.2 Product Innovativeness

According to Lee and O’Connor (2003:296), “product innovativeness has been defined as the degree of novelty of a product’s features, functionality, and benefits”. Though paradoxically found that adoption may not occur with innovation. Similarly, product innovation may be referred to as “a good (or service) introduced to the market that is either new or significantly improved with respect to its attributes” (Mugge and Dahl, 2013:35). These “new” products may be classed as incremental (continuous) or radical innovations forming a new product category. Businesses want their products to be seen as innovative to remain competitive and gain market share, so with this, they invest in innovation, and create innovative products to attract consumers. Danneels and Kleinschmidt, (2001) warned researchers to be cautious which definitions they use to measure product innovativeness, as they arrive at different destinations. A consumers product perception of product innovativeness is the product being “really new” or having new features. Furthermore, the 5 attributes from diffusion theory are key references in previous empirical research on product innovativeness (Calantone et al, 2006). It may also be claimed that not all product innovativeness can result in product/firm success. Product innovativeness and acceptance are connected through determining the success of new innovations or products. Acceptance is influenced by consumer perceptions of the product. There is literature on involvement and product knowledge, as constructs of consumer behaviour (Park and Moon, 2003), however, there is no previous research which examines specifically how knowledge of AI innovations influences brand innovativeness, thus this research contributes to the substantial gap in this area.

### 2.5.3 Firm Innovativeness

Perceived Firm Innovativeness (PFI) can be “conceptualized as the consumers perception and attribution of such an enduring firm capability” (Kunz et al, 2011:816). It can be a subjective notion from the consumers perspective, as it is observed by their subjective knowledge. It is the lens of the consumer, which is the focus of efforts, making it different to corporate reputation which takes into consideration stakeholders and internal factors. It could be contended to increase competitiveness (Awaysheh et al, 2020), and boost the performance of an organisation (Bairrada et al, 2018). Furthermore, firm innovativeness can be emphasised through its green initiatives to reduce cost and increase market share (Rahman et al, 2020). Consumers may perceive a firm to be innovative, and thus greener, gaining a positive perception of the company (Paparoidamis and Tran, 2019). From an organisations internal perspective, the research and development of an organisation can produce the best features and functionality of products (Rubera and Kirca, 2012). The focus on consumers evaluating a firms innovativeness usually direct their experiences from the firm attractiveness, quality consumer intention or loyalty (Kassemeier et al, 2022; Kurtmollaiev et al, 2022). Commercially, global Innovative firms such as Apple, Samsung and Amazon often gain market power which in turn facilitates internalisation (Chiva et al, 2014). Though, the formula for Apple’s success is the perception of a firm’s innovativeness, as iPads were originally invented before 1989 (Bajarin, 2021). CEO’s also play a crucial role in the perception of a firms innovativeness (Ruiz-Palomino et al, 2019) by their leadership and forward thinking. Pioneering leaders, Jeff Bezos and Elon Musk are seen as innovators of their firm, moreover, influencing consumers purchase decisions with their personal views (Dyer, 2019). In general, firms are inclined to be innovative in this fast paced technological environment due to financial implications (Stanko et al, 2013) as well as the impact they play on brand attitude and brand loyalty.

### 2.6 Brand Innovativeness

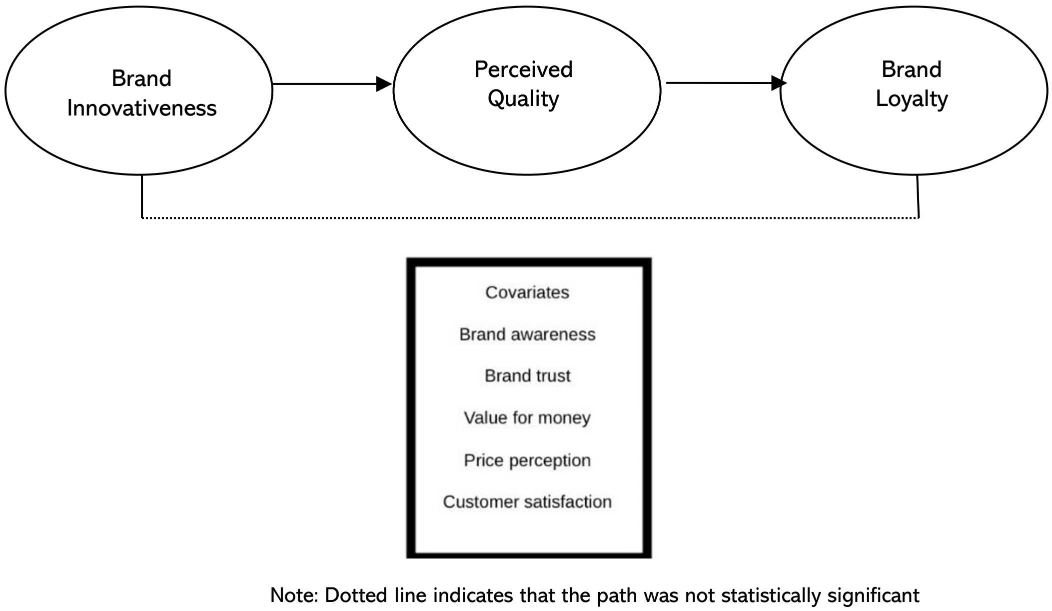
Brand innovativeness refers “to the degree to which consumers perceive a brand to be innovative”(Barone and Jewell, 2014: 309). Pappu and Quester (2016:3) agree with Eisingerich and Rubera’s (2010) definition as “the extent to which consumers perceive brands as being able to provide new and useful solutions to their needs”. The present study will draw on both definitions to refer brand innovativeness to “the extent to which customers perceive a brand to be innovative, by providing novel AI innovations”. Recent studies link the consumer’s perspective of innovativeness to how they view novelty with meaningfulness (Sethi et al, 2001) and how difficult adoption is alongside superiority (Lee and Colarelli O'Connor, 2003). Additionally, the perception of the consumers relative advantage is also well documented. This means it is not always about how the innovation is “sold” to the consumer, but also how they perceive the new innovation to assist them (Lowe and Alpert, 2015). Different from “innovativeness” which is marked by innovation, brand innovativeness can be defined as “referring to consumers’ perceptions of the ability of the brand to introduce innovations into the market” (Pappu and Quester, 2016:7). It “helps a brand stay relevant, thus increasing the present connection a consumer experiences with a brand” (Heinberg et al, 2020:670).

Pappu and Quester, (2016) examined how consumers perceptions of brand innovativeness affected consumer brand loyalty. They examined both the direct effect of Brand Innovativeness on Brand Loyalty, and the indirect effect of Brand Loyalty through the mediator Perceived Quality, measured for the products associated with the brand and defined by reference to reliability, excellence of features and technically advancement. In this context, AI is enhancing the quality of the experience which may impact brand attitude. Clearly perceived quality is a key driver of brand attitude; however, brand attitude is a richer concept which includes consumer satisfaction and brand association more broadly (Keller and Lehmann, 2006). The present study draws upon the key findings of this article and aims to enhance and test their framework further, to understand whether AI influences the perception of brand innovativeness, and if this impacts on consumer brand loyalty.

Although there is little literature in this field, as brand innovativeness is still in its infancy with the more future research required in this field (Brexendorf et al, 2015). The variances in the studies for this area comprise of focusing either on the corporate brand innovativeness (Brexendorf and Keller, 2017; Kunz et al, 2011) or product innovativeness (Fu and Elliott, 2013; Barone and Jewell, 2014) thus, scholars are calling for more research required for consumer perceived brand innovativeness (Shams et al, 2015; Pappu and Quester, 2016).

The literature on brand innovativeness suggests a link to brand innovativeness and brand loyalty is the “perceived quality” of the product or service. Pappu and Quester, (2016) provided a similar interpretation to the works of Shams et al, (2015). The studies generate a level of understanding about what brand innovativeness means to consumers.

*Figure 7: Brand Innovativeness and Brand Loyalty Model*




Source: Pappu and Quester (2016)

The premise behind both studies brought out the clear relationship of quality and brand innovativeness. Their research identified different types of participants which may impact on the result (students vs shoppers at a mall). The link with perceived quality and brand innovativeness can improve the perceived quality as it is "innovative "as part of a customer's experience and therefore improving the perception of a brand. Thus, the addition of using AI innovative features which contribute to the quality of the product, could influence the perception of brand innovativeness. Research by Eisingerich and Rubera (2010) tested the connection between brand innovativeness and commitment on different cultures. The overall findings indicated loyalty is strengthened through brand innovativeness by recommending for managers to emphasise the innovativeness of their brands. More recently, this established connection by Boisvert and Khan, (2020) found product innovativeness increased awareness of perceived quality, which then contributed to a positive attitude to the product. This ultimately concluded in a positive purchase intention. This demonstrates that there is evidence to the connection of perceived quality, attitude and purchase intention within the brand innovativeness research area. The research in these areas indicate the importance of perceived quality forms together with the brand loyalty research. The literature on brand innovativeness suggests a mediator between brand innovativeness and brand loyalty is the “perceived quality” of the product or service (Pappu and Quester, 2016). Shams et al, (2015) however question whether product quality or product innovativeness necessarily has a direct or mediating impact on brand level consumer perceptions. They argue that Brand level concepts such as Brand Attitude represent a better mediator, indicating a gap in the literature, as no prior research has used this variable as a partial mediator of innovativeness and loyalty. A central argument in their research finds a link between innovation and brand innovativeness, using brand theory to conceptualise perceived brand innovativeness. The research signifies the importance of investigating the extent to which types of brand level innovations can influence perception of brand innovativeness at a brand level, moreover, amplifying and simplifying innovation are evaluated at the brand and not the product level in the research model. Research by Hubert et al, (2017) demonstrated the importance of brand attitudes and how purchase intention is a result of perceived brand innovativeness. The significance of brand attitudes cannot be ignored as they influence purchase decisions. Empirical results also indicate a positive corporate image means consumers will buy (and forgive) brands they deem to be innovative (Henard and Dacin, 2010). This indicates the positive association a brand has with a consumer, there is a direct result of brand loyalty. The positive image of a company creates marketing hype to influence a consumer. These associations influence purchase intentions, as the influence of brand innovativeness has proven to raise commitments to an innovative brand. The antecedent to innovation is the capacity to innovate, thus consumer perceived brand innovativeness links back to investments in AI innovations, to influence brand innovativeness. Furthermore, perceived brand innovativeness has a positive effect on new product launches and moderated by social consumer innovativeness (Hetet et al, 2020). In addition to this, the perception of brand innovativeness impacts customer satisfaction levels, where it has been proved to develop repurchasing intentions.

In summary, it can be argued that the major shortcoming of the pertinent literature is the gap in the examination of the impact of AI innovations on brand innovativeness. Despite the abundance of evidence in the value of brand innovativeness, and the link with innovation (Shams et al, 2015) there is a major shortcoming on the findings on the impact of AI enabled product innovations on brand innovativeness, in particular testing the use of amplified and simplified innovations. More importantly, few studies have empirically tested amplified and simplified innovation (Hardie et al, 1996). This calls for further research in this area, to address this significant gap in the literature.

### 2.7 Brand

The topic of Brand has been widely discussed and researched in marketing literature (Keller, 1993). Through their own interpretation of a brand, brand experts have created their own definition on how a brand is recognised (refer to table 2). Since the early civilizations, people branded their sheep to identify their sheep, indicate the quality and source of their products. Marketers have expanded this idea to develop a perception of the business in the mind of the consumer through providing images, associations and attachment with the brand.

*Table 2: Table of Brand Definitions*

| Definition | Source |
|---|---|
| A name, term, sign, symbol, or design, or a combination of them, intended to identify the goods or services of one seller or group of sellers and to differentiate them from those of competitors. | (Alexandar, 1960) – American Marketing Association |
| A brand is a trade name/logo that *identifies* a product or firm, usage of which may be limited by legal structures and practice | (Avis and Henderson, 2022; Gilliam and Voss 2013) |
| The promise of the bundles of attributes that someone buys and provide satisfaction … The attributes that make up a brand may be real or illusory, rational or emotional, tangible or invisible. | (Ambler, 1992) |
| The company is the brand | (Berry, 2000) |
| Brands as an image in the consumers' minds | (Keller, 1993) |
| Brands as value systems | (Sheth et al, 1991) |
| Brands as added value | (De Chernatony and McDonald, 1992) |

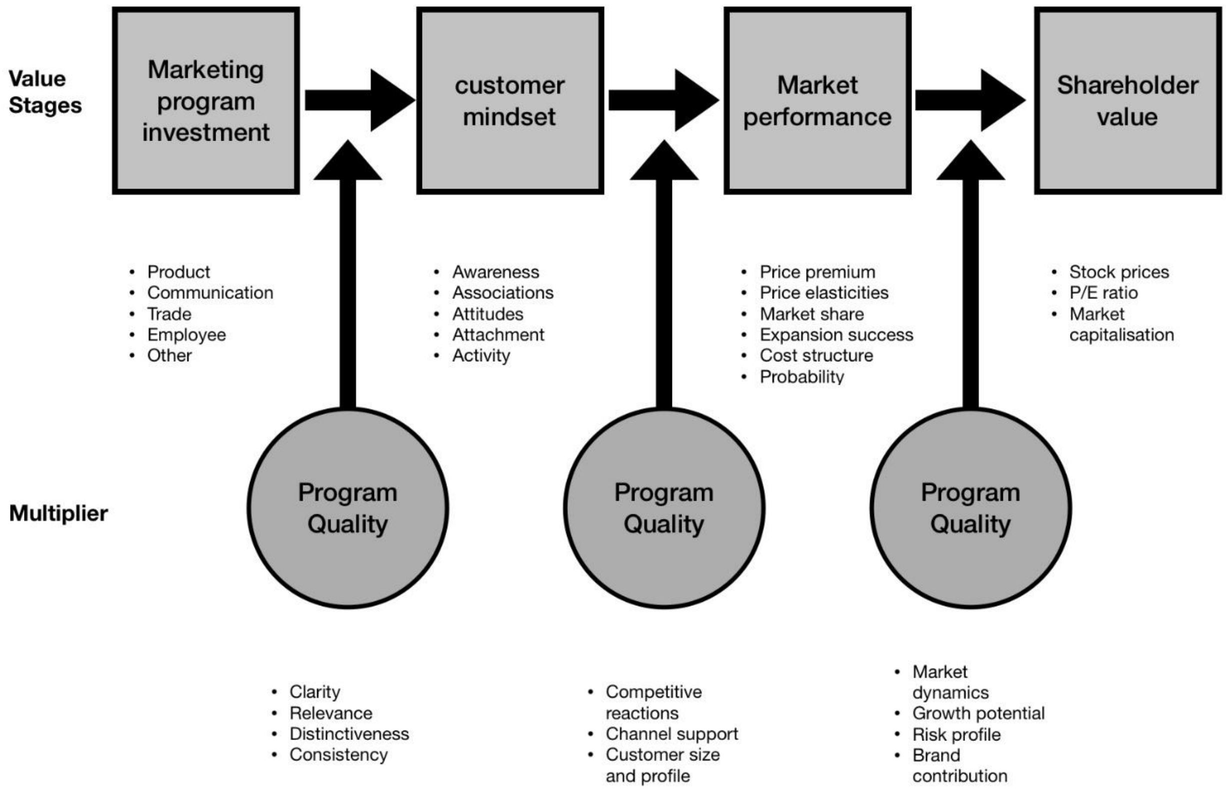
Source: Author

Brand perceptions are to be claimed not just by the products themselves, rather the information features (Strauss and Frost, 2001). From a financial perspective, brand names have been analysed in previous studies to have an impact on brand equity (Ailawadi, Lehmann, and Neslin, 2003), there are scholars who refute this, with an argument for brand to be defined as a consumer's collection of perceptions (Fournier, 1998). The concept of brand equity is established by Customer Based Brand Equity (CBBE) based on the consumer's perception of the brand and Financial Based Brand Equity (FBBE) based on economic growth. A strong brand can reduce the risk of volatility in a financial crisis (Johannson and Brooks, 2010).

Both Keller and Aaker's research on Brand has been well established. The CBBE model uses brand knowledge to affect a consumer behaviour to be integral to build a brand. Authors (Keller and Lehmann, 2006), argue the intangible asset of a brand builds brand equity, thus a deep understanding of the value is created by brands. Furthermore, brand image and customer loyalty are main drivers of brand value (Aaker, 1996; Keller, 2007). Brand equity is a well-researched topic with added value of the brand name and association. The assets and liabilities "can be usefully grouped into five categories: *brand loyalty*, *name, awareness*, *perceived quality*, *brand associations* in addition to perceived quality." (Aaker,2009:16).
The general concept of an external image or corporate identity links with the vision and strategy of a business (Dowling, 2000). Marketers specifically focus this area by studying the ways in which management expresses this key idea to external audiences (e.g. through products, communications, behaviour and environment (Jo Hatch and Schultz, 1997). Kapferers (2008) research in this area states that brands are created to assist consumers decisions, represent qualities and influence levels of quality positioning and differentiation. Prior studies on the Brand value chains have been said to merge financial gains and marketing goals to grow the business. Furthermore, they have stated that marketing activities contribute to the value of a business (Srinivasan and Hanssens, 2009).

### 2.7.1 Brand Value

*Figure 8: Brand Value Chain*




Source: Keller and Lehmann (2003)

Brand and value equity (measurement of consumer assessment of brand) are crucial for business survival (Kim et al, 2020). The progression from brand value to economic value is imperative for businesses. Researchers have found value chains used by businesses can be two-fold, first by looking at internal processes, then outwardly via marketing. A well-established value chain, Porters (1980), is an internal chain for process enhancement used by businesses to provide external benefits to customers. The Customer Relationship Management (CRM) value chain (Buttle, 2004) integrates business processes through CRM strategy. Marketers see modern marketing as creating value for the customer. The marketer is able to choose features services and distribution channels to create value (Kotler, 2020). With increased emphasis on providing competitive offerings for customers, marketers work towards satisfying customers through value creation. With many scholars attempting to measure brand valuation (Fischer, 2007; Rust et al, 2004), the appropriate framework used for the present study is the brand value chain (Keller and Lehmann, 2003) with a structure built from four stages to create value. The brand value chain model is the value creation process for brands to better understand their financial impact of marketing (Keller and Lehmann, 2003). Due to high competition, and lower global barrier, maintaining a sustainable position of a brand in the market is requiring more effort. Therefore, a brand must be able to resonate in the consumers' minds (Keller, 2001). Studies have proved, with the use of value chain models this can achieved (Xie and Shen, 2011). Researchers have found brands to create a value chain to influence customers, to affect how the brand ultimately performs. The chain assumes the value of the brand resides with the customers. A value chain model incorporates the support activities of a business.

The logic of the brand value chain is to improve the progress from the evolution from brand awareness, brand associations, brand trust to attachments through brand loyalty. Keller and Lehmann (2003) present stage one to consists of marketing program investment, where investments at made within the business. From a macro perspective, this is the research and development stage, where capacity for innovations are invested. From a marketing perspective the communication message are sent to position the brand in consumers' minds. With respect to stage two the customer's mindset holds great significance to the present study. Researchers gain valuable insights into the factors influencing consumer choice, buy examining their preferences and motivations. Consumers process information they receive, in different stages. According to the framework, first, they become aware of a brand through advertising and promotion. Previous studies have documented advertising to link to firm value (Sridhar et al, 2016). Next, consumers often connect and develop associations through understanding and learning about a brand whilst feeling and forming an attitude. These attitudes transpire to lead the customer not only to purchase, but to develop an attachment or loyalty to the brand. This study is based on the connections of associations, attitudes and attachments of this part of the framework. The market conditions multiplier depicted in the framework, considers the market conditions. The customer's mindset leads to brand performance, the reactions of the consumer. The third stage refers to market performance indicators which impact of the consumers attitudes. The perception of the brand impacts the price premiums or demand. The worth and willingness to pay for items is derived from the first two stages of the framework. When customer have a positive association, they will purchase and pay more, resulting in a better brand performance. The final stage of the framework indicates, when the brand performs effectively the shareholders are impacted, in turn, shareholders risks are reduced resulting in higher investments for the business.

A critique of the BVC model is that the assumption that one activity precedes the other, it can be seen as simplistic, with a general assumption of mindsets and attitudes are antecedents of performance (Anselmsson and Bondesson, 2015). Though, there is no literature connecting BVC to AI innovations, this exploratory study is satisfied with choosing to focus on the consumers mindset, with the influence of AI factors.

### 2.7.2 Customer Mindset

#### 2.7.2.1 Awareness

*Brand awareness* is defined as the buyer's ability to identify the brand in sufficient detail to make a purchase 1997). Brand awareness is a *necessary precursor* to brand attitude (Rossiter, 2014). Consumers have more access to information through the rise of the information age through the internet, they are empowered to able to process and make informed decisions. Researchers claim this makes consumers more knowledgeable, through only through their own market research interests, also through online forums, reviews and social media (Li, 2019). Businesses not only rely on their own marketing tactics to build their reputation, but they have also had to adjust their marketing strategies to enable consumer feedback to be at the forefront of their tactics. Consumers form impressions about a brand through recognition and familiarity of a product or service relating back to the corporate brand (Delgado-Ballester, 2012). Research has shown that the more brand awareness there is, it is likely they will purchase the product or service. Both brand recall and brand recognition) build brand awareness (Rossiter and John, 2014; Rossiter and Percy, 1997). Brand recall draws on the consumers memory, to enable the consumers to recall their perception about a brand, through knowledge and experience via advertising. Businesses invest in promotion and advertising to build their brand. Brand awareness created values as it carries a reassuring message correlating with quality trust, reliability accessibility and styling (Kapferer, 2008). Recognition refers to how quickly they are able to identify the brand when elements of the brand (logo, font,) are shown (Keller,1993). The familiarity of a brand is derived from their knowledge of a brand or products through communications sent out. Knowledge also refers to the information surrounding technology, and how useful it is for the consumer, and reviews about the technology. Keller and Lehmann, (2003) acknowledge how the consumers judge the brand based on their internal capabilities and information marketed, leading to associations of the brand.

#### 2.7.2.2 Associations

A brand association is anything linked to the perception of the brand in the consumers' mind (Aaker, 1991, Keller, 1993). Brand associations are often attributes of a product, (colour, logo, design) alongside thoughts, feelings and attitudes (Keller, 2003). Previous studies confirm a consumer's evaluation of a brand is formed through brand associations, using their experience, access to media, culture and community around them. An expression of these perceptions often describing a brands personality, which fits into one of the following five dimensions: sincerity, excitement, competence, sophistication and ruggedness (Aaker, 1997). Brand personalities are often used to develop an image through advertising to build an emotional connection to the target market. Thus, using brand associations such as brand personality can lead to favourable outcomes as brand attitude, related to brand satisfaction, and equates to brand loyalty, (Japutra and Molinillo, 2019). A prior brand evaluation can be a basis for segmentation for businesses as well as cement a consumers perception of a brand (Chattopadhyay and Basu, 1990). These brand associations have a positive influence on differentiation a brand and developing an attitude towards a brand (Keller, 2003). Brand associations provide positive outcomes for consumer perceived brand innovativeness, as Shams et al, (2015) found "newness" as a concept users associated with brand innovativeness, consistent with previous research (Henard and Dacin, 2010; Kunz et al, 2011). Studies in the field have stated specific attributes to new functions must be transferred accurately to enable positive brand associations (Aaker and Keller, 1990). According to Bettman and Park, (1980) strong associations meet the needs of the consumer, increasing the likelihood of a return purchase. Purchase decisions are made through positive associations of quality or ease of use through familiarity from advertising and experiences.

#### 2.7.2.3 Brand Attitudes

Wilkie (1994) defines brand attitude as a consumer's overall evaluation of a brand. This then forms a basis for consumer behaviour, such as choice or recommendation of a brand. It has been widely reported how attitudes can be related to beliefs about product related attributes and the functional and experiential benefits consistent with work on perceived quality (Brucks et al, 2000).

Many researchers agree, in order to express that an attitude, it is often described as a feeling, emotion, position or state towards something (Stern, 2006: Avis and Henderson, 2022). In this study, it is interpreted as the consumer's feelings towards a brand. As Brand is a well-researched area, there are many definitions, though De Chernatony (1998) narrows it down to twelve cumulative items, which help to form an attitude towards a brand: a legal instrument, a logo, company, shorthand, risk reducer, identity system, image in consumer's minds, value system, personality, relationship, adding value, an evolving entity. Branding takes place to differentiate and offer a competitive edge. Brand- consumer relationships can affect the brand evaluation, as monetary rewards are not always necessary, other incentives (AI) could increase the attitude-loyalty dimension (Aggarwal, 2004). A brand attitude is often a customer's liking or disliking of a brand. It is often formed of an existing idea or reputation of the brand (Foroudi, 2019). If consumers enjoy a brand, they will build a relationship and love the brand (Batra et al, 2012), in contradiction, negative relationships with brands also facilitates aversive dysfunctional brand associations with a negative impact on brand attitude (Fournier and Alvarez, 2013).   A positive attitude has been linked to loyalty, (Rossiter and Percy, 1987; 1997).  Aaker (2001) observed how brand attitude increases by introducing new products.  He found changes in brand attitude affect the financial situation of a company, thus illustrating its importance for a business to ensure brand attitude is high especially in technology markets.  Brand attitude is an important part of forming an intention as it plays a cognitive and affect role in behavioural intentions. A belief consists of a viewpoint of areas such as; trust, privacy, customer engagement, service quality, customer engagement, satisfaction and customer experience, to all assemble together to form antecedents of brand attitude.

Brand Attitude represents an overall evaluation of the quality of a brand and the satisfaction it generates. Strong brand attitude leads to brand attachment - consumer loyalty to the brand or Brand Loyalty. Two studies conducted by Aaker and Keller (1990) gained insights on how consumers form attitudes towards brands. They conceptualised attitude towards a brand with the consumers perception of overall quality.   This "perceived quality" is also a mediator in Pappu and Questers (2016) brand loyalty model.  The studies presented many findings including; inferred attribute beliefs (examining how some attributes work well in certain contexts, but not all) could enhance or harm a brand.  This underpins the research pertaining to ask questions on how will AI contribute to these beliefs? (for example, are consumer expectations of AI higher when using an IBM website, compared to the NHS website). Additionally, the relationship of positive quality image and quality of the original brand.  The focus on the importance of the search and selection of brands and consideration of the effect AI innovations have towards the perception of the perceived brand innovativeness is of particular interest of this study.

Furthermore, prior studies have found Attitudes have two dimensions: the general valence dimension and the strength dimension (Berger et al, 1994). The strength and valence of attitude could be changed by the level of product knowledge.  For example, a consumer with strong product knowledge may have a positive attitude due to the confidence in the product features and usage.  Consequently, "product knowledge" adds to the formation of an attitude. The knowledge of a product can be seen as a moderator due to its relationship with the strength of an attitude. Laroche et al, (2010) found high product knowledge to create a strong relationship with mental intangibility. They recommend for marketers to communicate key attributes of a brand, so the consumer can make an informed decision about the hidden features in a product. Thus, strengthening the confidence and beliefs to form an attitude towards a brand. To measure the strength of an attitude, confidence, certainty and accessibility is shown. For example, a respondent may have positive thoughts, however, this may not transpire to an actual purchase, however, studies have indicated that the higher the measurement of attitude, the stronger the strength to act on this, as opposed to the lower measurement equating to a negative intention (Berger et al, 1994).

The findings also include brand associations using qualitative research gained insights on brand quality. These associations relate to product quality, specific attributes and overall attitudes. Attitude is a unit of analysis for this study, furthermore, questioning how the enhanced attributes of AI will influence the attitude of the consumer is of interest. The dimensions of brand knowledge (Keller, 1993; Keller, 2003) include brand associations as a connection to brand attitudes, which can vary in strength. Attributes have to be communicated to persuade consumers and create favourable associations. Likewise, this research is customer orientated concerning the "look and feel of the brand" (Keller and Lehmann, 2006:27) whereas the value is the AI function added into the mix. (Keller, 1993) discusses the formation of brand attitudes and "the power of interactive marketing communications as a brand building tool is its versatility". Therefore, for this study, brand attitudes can investigate the influence AI has on the "look and feel" of the brand, and the *value* AI brings to the brand. A model of customer loyalty created by Parasuraman and Grewal, (2000) studied at the role of technology in the quality-value-loyalty chain. With emphasis on "technology (if not the) major force in shaping buyer seller interactions in the future" (Parasuraman and Grewal, 2000:170). AI innovations may influence the consumers perception of "value", thus impacting on their attitudes, intentions and brand loyalty. There is little literature in this area of the impact of AI innovations on Brand associations.

#### 2.7.2.3.1. Brand Attitude and Brand Innovativeness

Previous research has consistently found attitude to be one of the key predictors of behavioural intention (Sanakulov and Karjaluoto, 2015; Sanne & Wiese, 2018). Attitudes toward AI could potentially shape users' acceptance of AI in everyday life (Lichtenthaler, 2020). Recent advancements in the field have shown attitude are positively associated with AI (Chua et al, 2023; Kim et al, 2022). A recent study by Hetet et al, (2020) determined the propensity was higher for consumers to buy products by brands, who had a reputation of being innovative, consequently, they perceived to be innovative. Moreover, when a new product is introduced to the market, they found there was a positive effect of brand attitude on the brands innovativeness. In addition to this, Ashill (2011) examined perceived brand innovativeness to have a strong impact on attitudes toward a product. When an attitude of a brand is innovative, it benefits from being able to diversify and bring out new products and innovations without consumers being surprised by it. Consumers with high brand attitude and high brand innovativeness would expect the firm to be innovative, hence, reducing the resistance to "change" or update their products as technology upgrades. This not only is valuable for the firm, but also for consumers wanting to be ahead of the innovation curve. No research has been identified that empirically examines brand attitude as a partial moderator of the brand innovativeness to brand loyalty relationships.

#### 2.7.2.3.2 Attitudes towards Innovation (the role of demographics)

Exploring the implications of age-related perceptions of towards innovation can shape adoption of inclusive and effective strategies (Icanu and Icanu, 2020). Attitudes towards innovations have differed with age differences (Schade et al, 2016). Several authors have hailed that their results prove older consumers have declining information processing and adoption (Homburg and Giering, 2001; Hur et al, 2017). Based on this notion, Nunan and Di Domenico (2019) identified a gap in the innovation and marketing literature, in terms of older consumers' use and adoption of digital technologies. According to Ameen et al, (2021a)'s analysis there is a lack of research on generational marketing in new technology.  This recent research implies an obvious gap in the literature of the impact of age on attitudes towards innovations.

Age has been used to measure attitudes as marketers often may often use age as a basis for market segmentation opportunities for managerial implications (Park et al, 2013).  Researchers and marketers have often divided age as part of their segmentation strategies to allow for differences in consumer needs due to generational and behavioural differences.    Segmentation via age groups have been an important variable for a topic of research for marketers (Wolf, 1990; Zeithaml, 1988).

The Technology Acceptance Model (Davis, 1989) is based on the theoretical assumptions of the theory of reasoned action (Ajzen and Fishbein, 1980) which offers a link between technology acceptance and utilization behaviour.  Venkatesh et al, (2003) found age to moderate relationships within their model (UTAUT).  Arning and Zeifle, (2007) postulate that for *age to* play an important role in the explanation of variability in acceptance and performance. They found a*ge* to have considerable differences in the pattern of relationships between technology performance and acceptance between in the two age groups. Many studies have theorised age to have a large bearing on attitudes towards technology acceptance, thus justifying the notion of using age as a control mechanism (Hur et al, 2017; Kumar and Lim, 2008).

Researchers have proved perceived usefulness is key when older consumers adopt new technology.  Yang and Jolly (2008) explored the differences in adoption of both older and younger users' and found older consumers to perceive mobile data services to be difficult (but perception of usefulness was stronger), to use than younger users.

Social generations are Cohorts which can be described as groups of consumers who are born within close time periods, they are linked by similar world views because they share common life-shaping experience (Yoon et al, 2021).  The behaviour and generational divide at around 40 splits the digital natives or Igeneration (under 35) to the baby boomers or generation X (over 40) who were not born surrounded by the internet and AI innovation (Kim et al, 2016).  Researchers have reported how the mature users have had to learn and adapt to the innovative techniques, as opposed to the younger users who may be termed digital natives, who have lived and accepted technology as part of their upbringing as part of their daily life (Yang and Shih, 2020).

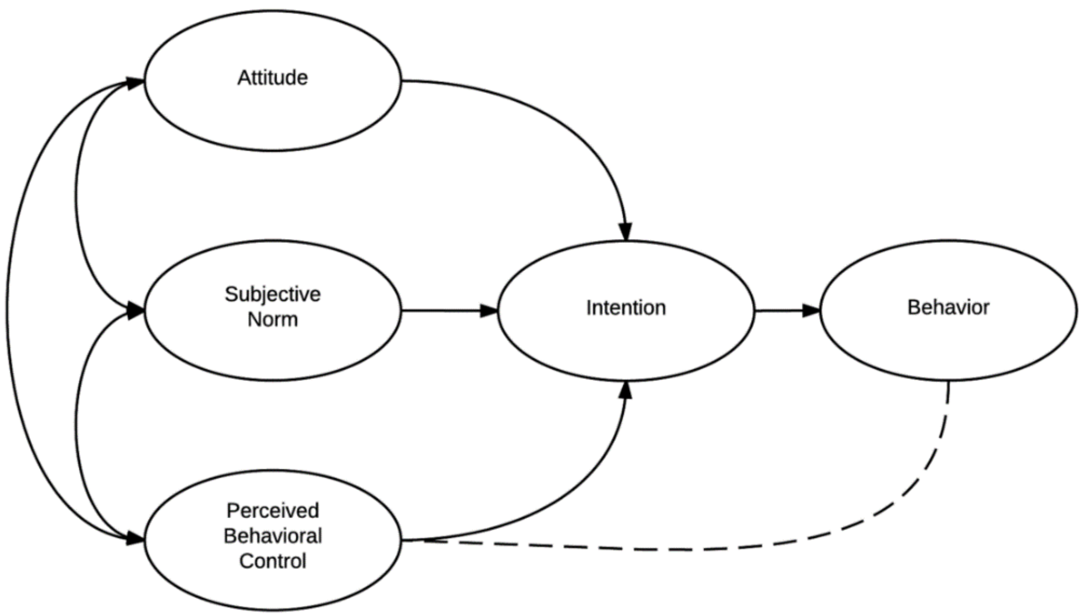
#### 2.7.2.3.3 Age in Brand Innovativeness Research

In an attempt to synthesise the literature of age and concept of brand innovativeness, a study by Helm and Landschulze (2011) found researchers have discovered age to be positively associated with innovativeness, whereas others found age to be slightly negatively associated or even strongly negatively associated. Additionally, their study using FMCG found age differences in consumer behaviour *do* exist, however the experiment has not been undertaken on AI innovations. According to Lambert-Pandraud, and Laurent (2010) when comparing older and younger consumers, the younger set exhibited a greater preference for recently introduced options, demonstrating a favour for innovativeness, and thus risk taking (Rogers et al, 2014). Younger consumers may be more open to new ideas with regards to new technologies (Lustig, et al, 2004).

#### 2.7.2.3.4 Age and Brand Loyalty Research

Age effects brand attitude as different ages have contrary needs at each life stage. Along with the decreasing effect of social influences with age, the motives for consumption with each age group changes (Schade et al, 2016). Research shows mature consumers may need more time to use a new technology, (Koenigstorfer and Groeppel-Klein, 2012). Thus, impacting their decision-making process and attitude towards adopting AI or downloading an app to use. Some elements of behavioural control impact their hesitancy towards innovation, as well as social groups and behaviours, which manifest as an attitude forming towards AI. The older consumer may not feel confident in using new technology or their close circle of friends do not use it. Ventakatraman and Price (1990) indicated that older consumers have a lower tolerance to innovativeness based on their innovativeness index. Conflictingly, a younger user would be willing to learn and use technology as they are more influenced by their peers. Both age categories have a different set of social norms and attitude towards technology. When considering a technology decision, perceived usefulness (Bhattacherjee, 2001) where it could help you enhance your activity or ease of use (where using it would be free of effort) both play in older people mind, as they have already survived without. If attitude is more favourable, then consumers are more likely to use the technology in the future (Davis, 1989). Consequently, the increased levels of consumer satisfaction, equates to an increase of brand loyalty, therefore when consumers find the technology easy to use (Apple, 2022) it has a positive influence on the relationship with loyalty.

*Figure 9: Theory of Planned Behaviour*




Source: Ajzen and Fishbein (1980)

The Theory of Planned Behaviour (TPB) (Ajzen and Fishbein, 1980) and later the Theory of Reasoned Action (Fishbein et al, 2010) has brought together antecedents of intention, and ultimately loyalty behaviour.

*"The model offers a comprehensive, yet parsimonious psychological theory that identifies a causal structure for explaining a wide range of human behaviour, including consumer behaviour*" (Hegner et al, 2017:27).

The main difference is TPB pays attention to external factors, whereas TRA looks internally. This well-established theory has been used to understand determinants of consumer behaviour. The theoretical framework posits that consumer intentions and behaviours are influenced by attitudes, subjective norms and perceived behavioural. These variables are crucial to be integrated into the study as positive attitudes typically enhances intention and loyalty. This is important to the present study as these variables are imperative to link together. The theory postulates having attitude, norms and PBC in place to build intentions. In order to gain confidence, one has either subjective knowledge, where they are aware of the product class (confidence and accessibility) or objective knowledge, where they are able to assess the product on how much they know about it (confidence and accessibility). This area of subjective norms is to be investigated to test the strength of the attitude. Subjective norms are where you desire to act as you "think" you should act in society, drawing from on your beliefs and norms. There may be an issue with the influence of their subjective norms (what society makes them used to). Therefore, the measurement of attitude to commitment will be observed.

Critics highlight the TPB model showing affect and emotions within the model is based on a rational actor (Ajzen, 1980) when in reality this may not be the case. Moods and emotions can affect the behaviour which has not been accounted for in the model (Ajzen, 2011). Affect and emotions are factors influencing behaviour, normative and control beliefs. These beliefs form the basis of an attitude. The role affect can play, can lead an assumption of consequences, (if we do this then we will feel regretful, pleasure, sad). Therefore, taking guidance from Ajzen, who predicted an instrumental attitude belief (useful-useless) is better than experimental measure (interesting-boring) to use this wording for the questions for the data collection. Empirical evidence has shown that past behaviour is the best predictor of future behaviour (Ajzen, 2011). There is unresolved research here in this area with room for widening the study to see if past behaviour towards AI has a relationship with beliefs and attitudes. A criticism of the model has not taken into consideration human *bias,* however, Ajzen (2011) counter-argues that this is a misrepresentation of the theory. The model connects attitudes to behaviour, in particular specific attitudes (as opposed to general) to work well. Some studies have challenged the assumption where intentions are there, however, the behaviour may not transpire due to economic factors (St Quinton et al, 2021). Another criticism is how the model has ostensible neglected the emotions of an actor, (Rapaport and Orbell (2000). Attitude, social norms, intention and PBC are important control variables to explore in this study.

### TPB in Brand Literature

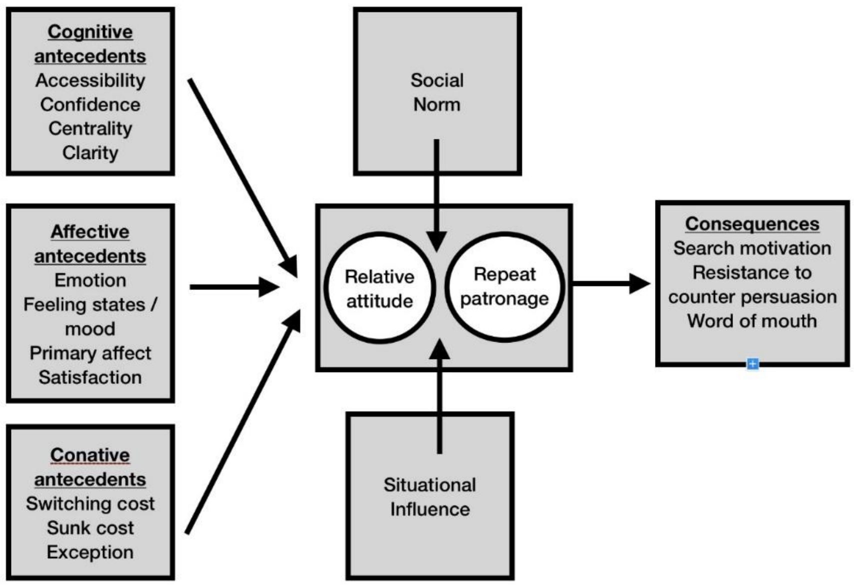
The TPB has primarily been utilised in addressing public health issues (including substance abuse, breastfeeding, smoking etc.) although the health belief model (Rosenstock, 1974) is also an extensively researched behavioural model, as it considers demographic and psychological factors associated with uptake. In marketing and brand consumer research, it is seen as an established model which understands determinants of intentions to behaviours (Hegner et al, 2017). TPB is still influencing recent research. Recent studies have applied the model to a consumer-brand context, using involvement as a moderator (Hegner et al, (2017). Studies in the field include; Cooke and French (2012) found the context of the prediction of intention and subjective norms directly affecting the beliefs (binge drinking is easier in a bar will as opposed to a library). (Hegner et al, 2017) applied variables of the TPB model to a consumer-brand context, using involvement as a moderator. The research used brand love instead of brand attitude and found subjective norms to facilitate high involved customers towards brand love. Many researchers have contributed to the field, although there are similar adoption to loyalty models such as the Diffusion of innovation, UTAT, TRI and TAM, this TPB model has four variables justified using the combination of attitude, social influence, PBC and intention as a basis to look at consumers perceptions and behaviour in this thesis. An assessment of the literature suggests TPB is one of the "most applied frameworks that explain shoppers' responses to technologies" (Wang et al, 2022). Although, the TPB model has demonstrated resilience and versatility (Bagozzi, 1992). Researcher is cautious with limitations to the model and using social norms and PBC as control variables to loyalty. The literature demonstrates how TPB has already been applied to examine customer acceptance in marketing (Kwon et al, 2020; Wang et al, 2020), adding all variables from the whole model to the present study would not be beneficial to provide new knowledge.

#### 2.7.2.4 Attachment – Loyalty (Intentions)

Attachment and loyalty are interconnected (Diallo et al, 2021). Attachment refers to how loyal the customer feels towards a brand through a sense of trust and dependence. Researchers describe it to be where consumers are addicted to a brand, with the ability to withstand bad news (Keller and Lehmann, 2003). Both Brand loyalty and attachment foster commitment and connection with a brand. Many scholars have aimed to define Brand Loyalty: Jacoby and Kyner (2018) define brand loyalty as " (1) biased (i.e., non-random), (2) behavioural response (i.e., purchase), (3) expressed over time, (4) by some decision-making unit, (5) with respect to one or more brands out of a set of such brands, and is a function of psychological (decision-making, evaluative) processes". Whilst the definition used in this study is the closest to Wilkie (1994) who defined brand loyalty as "a favourable attitude toward, and consistent purchase of, a particular brand".

Researchers have argued, as consumers repeat purchase, however they may do due to restrictions, such as availability, location, price etc. Numerous studies have reported on brand loyalty over the years (Fournier and Yao, 1997; Moriuchi, 2019; Villagra et al, 2021; Yi et al, 2003), drawing knowledge from customer satisfaction evolving into repeat purchase behaviour.

*Figure 10: A Framework of Customer Loyalty*




Source: Dick and Basu (1994)

Dick and Basu (1994), characterised loyalty as the development of positive brand attitude creating a loyalty relationship within the brand, moderated by social norms and situational influences. They define customer loyalty as, "The relationship between relative attitude and repeat patronage" (Dick and Basu, 1994:4).

The relative attitude to repeat patronage demonstrates the degrees of loyalty one must possess to be classed as loyal. Seminal research by Oliver (1999) developed the definition further by describing loyalty as "a deeply held commitment to re-buy or re-patronise a preferred product or service consistently in the future, causing repetitive same brand or same brand-set purchasing, despite situational influences or marketing efforts|". Several studies thus far have linked loyalty to attitude, and perceived it as a good predictor towards a consumer's positive attitude (Liu et al, 2012; Ngobo, 2016; Verhoef, 2003; Baldinger and Rubinson, 1996). Moreover, further analysis has proven brand or customer satisfaction consequently leads to loyalty (Reibstein, 2002). Research demonstrates how customer satisfaction is linked to repeat purchase behaviour, leading up the loyalty ladder (Peck et al, 2013) by increasing their commitment through each step. Eventually, brand loyalists advocate the brand through positive sentiments towards the brand or company. Additionally, Lee and Back (2010) confirm satisfaction with a brand affects trust and loyalty. Customer involvement is also a positive indicator of brand loyalty, the drivers of brand engagement (CBE) where brand and consumer relationships have proven to be vital. According to Aaker et al, (2004) the relationships between engagement/involvement with the consumer are very important, (Leckie et al, 2016; Brodie et al, 2011). Furthermore, AI to consumer engagement can positively enhance the perception of the brand (Moriuchi, 2019). The confluence between, brand and customer satisfaction consequently leads to loyalty (Reibstein, 2002). Researchers found satisfied customers move up the loyalty ladder by becoming fully committed to the brand through their advocacy and positive sentiments towards the brand or company (Peck et al, 2013). In their enthusiastic research of the topic, Chaudhuri and Holbrook (2001) explored the chain of outcomes from brand trust to brand loyalty. They also discovered a connection between loyalty, attitude and repeat purchase, supporting the earlier work of Dick and Basu (1993) and Oliver (1999). Trust has been tested to play a part in repeat purchase. Moreover, McMullen and Gilmore (2008) place emphasis on the works of Dick and Basu (1994) with application of customer loyalty development. Intention is about increasing the likelihood of consumers purchasing in the future. Additionally, Harish and Furtado (2019) found a path linking purchase intention to brand loyalty which can be understood as a form of intention. Furthermore, antecedents of brand loyalty are classed as perceived value, trust and satisfaction (Harris and Goode, 2004). Dick and Basu (1994) add "barriers to switching" to this list.

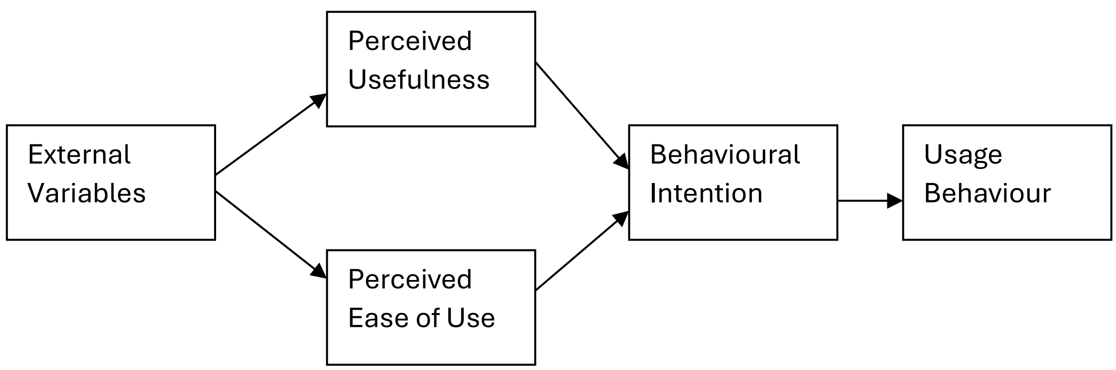
Conclusively, the application of the of the principles of the connection to examine the relationship between brand attitude and brand loyalty (intention). The antecedents to the loyalty relationship draws upon the key variables of the theory of planned behaviour, by Ajzen and Fishbein (1980), where subjective norms were also considered to link to intention. Perceived Behavioural Control also plays a part in forming an intention or brand loyalty as a consumer would need to be confident in the AI features in order to intend to purchase the product and repurchase to identify as a loyal consumer

## Purchase Intention

Purchase intentions can be seen as a precursor to Loyalty. “Purchase intention indicates likelihood that consumers will plan or be willing to purchase a certain product or service in the future” Ajzen, (1980: No Page).

Most research on purchase intention has demonstrated that an increase in purchase intention reflects an increase in the chance of purchasing. If consumers have a positive purchase intention, then a positive brand engagement will promote that purchase (Martins et al, 2019). Online purchase intention of a product through a platform is different (Pavlou, 2003), moreover “purchase intention online as the main antecedent of purchase behaviour from an online retailer”(Peña-García et al, 2020). For online consumers, it could be argued that the familiarity of a website or App can bring fast acceptance, as the consumer has recognised and purchased before. According to Ajzen (1991) intentions are presumed to be an indication of the extent to which people are trying and willing to perform a certain type of behaviour. The TPB model implies that PBC and social norms impact attitudes towards their purchase intention. The stronger the intention, the more likely the performance would take place although this has been proven otherwise (Morwitz, 1997) due to people lying, affordability, circumstances etc. However, not all purchase intention leads to purchase. One may wish to purchase a Lamborghini, however, income levels would prevent them, or a preference for sustainable car or food, which is often related to the attitude-behaviour gap (Vermeir and Verbeke, 2008). Moreover, scholars have added brand commitment to intercept this (Jacoby and Chestnut, 1978). The intention to purchase within the Technology Acceptance Model (TAM) framework (Figure 11) uses the key determinants the perceived ease of use and perceived usefulness (Venkatesh and Davis, 1996). The two factors are critical in the decision-making process of online shoppers. The TPB research has often been affiliated with the TPB model to generate ideas about technology adoption in understanding consumer behaviour and technology adoption. The theory postulates how external variable inform usefulness and ease of use drive intentions to technology. The variables are similar with understanding social norms, intention and usage; however, the perception of usefulness is distinct. This usefulness transpires in the product knowledge and PBC sections, as the consumer will ask whether it is worth carrying out a behaviour, only if it is worthwhile for them to do so. Furthermore, the context of AI has limited research, thus shaping the argument further to investigate purchase intentions, and how the consumer intends to use AI for this research.  It should be acknowledged that not all intentions or behavioural control transpire to a behaviour (De Cannière et al, 2009).

*Figure 11: Final Version of Technology Acceptance Model*




Source: Venkatesh and Davis (1996)

From a marketing perspective cultivating the right communication towards consumers to ensure they understand and form a positive brand attitude, may make the purchase intention stronger. Zeithaml et al, (1996) used customer satisfaction to measure the impact of service quality to examine the relationship with intention. De Canniere et al, (2009) compared the Relationship Quality model with the TPB model, to find the robustness of the TPB model.  Knowing the TPB constructs in marketing is beneficial to gain insights on attitudes and intentions towards brands.  However, the findings of this study advise using past behaviour to predict purchase intentions.  Brand loyalty and positive customer experience increases the chance of a purchase intention, as the consumer is already familiar with a brand and already is acquainted with the perception of the quality, service and trust towards the brand.  Hence, this is the reason bigger brands find it easier to diversify, for example the Virgin brand (airlines, gyms, mobile), as they already have the consumers brand loyalty (Pringle, 2008). Purchase intention and Loyalty have a significant and positive relationship in research, as they can be termed loyalty intentions (Johnson et al, 2006). Jin and Hye Kang (2011) discovered direct paths to purchase intention from Attitudes, PBC and social norms. They found PBC to be an important antecedent of purchase intention, as these relate to the "controllability" of the consumer. An intention to purchase often leads to loyalty.

**2.7.2.5 Activity**

Activity refers to how consumers talk to others about a brand, based on how they use the brand and join clubs to find more information about a brand (Keller and Lehmann, 2003). Engaging in activity is an essential part of consumer behaviour. With the rise of social media and online forums, it is easier for consumers to find out more about a brand, to develop a deeper relationship (Heinonen, 2011). Research has suggested, the increase in the consumer interactions with a brand, the more communications with businesses rise, and eventually they act as brand advocates who shape the opinion of and influence their friends and family (Hollebeek, 2011). With the assistance of mobile technology, consumers have all access to obtain further individual research into understanding AI technology.

*Social Norms*

In this study, the context of social norms are described as the influence of social norms on the consumers attitudes and insights into AI innovations of a brand. According to Ajzen and Fishbein (1980) social norms refer to the perceived social pressure to perform, or not perform a behaviour, the definition deemed most appropriate for this present study. Social norms, or sometimes termed as subjective norms are defined as "rules and standards that are understood by members of a group, and that guide and/or constrain social behaviour without the force of laws" (Cialdini and Trost, 1998:152). Moreover, proposing an individual places their reference groups (friends, family, colleagues, etc) as an important influence when making decisions. It is not termed as an actual law of the land; however, it is built on tradition, customer, culture and way of life. Social norms are known the unwritten rules of life, an example in the UK is customary to be punctual or bowing to say thank you in Japan are all classed as shared items (Legros, 2019). In business, it is pertinent to be aware of social norms, to create a strategy to meet the needs of target audiences, to understand how to communicate with them as well as meet their expectations.

Furthermore, understanding what is “normal” in society helps one to feel accepted. Culture has been associated with social theory research to explain the role of subjective norms within AI (Dwivedi et al, 2021). Within their research, Baker et al, (2007) used TAM model, with gender, age and education as moderators, the study was set in Saudi Arabia, where there are tighter restrictions and cultural divisions in the Middle East in comparison to Western Europe, the study found cultural factors impacted technology adoption in different societies. Within research the social norms variable has been used well in a technology adoption research (Baker et al, 2007). Other factors may influence acceptance geographically, as researchers often cite differences with countries based on cultural values (Individualism/collectivism). This provides impetus to research social norm in a cross-sectional method. With the rise of social media, and influencers in particular, social norms are inflicted in everyday life, when consumers choose what to watch, what to eat and what to buy (Escalas and Bettman, 2003). Literature in this area focuses on understanding a person’s self-concept, and the influence of how friends and family sway decisions based on aspirations or memberships of groups can help to identify their needs. The interplay between social norms and self are related to the adoption of AI (Barnes et al, 2024). Previous studies have found a strong relationship from social norms to brand loyalty (Hung et al, 2020). Research on social norms, suggest they impact the behaviour and attitudes of consumers. Fu and Elliot (2013) tested the construct to measure whether social norms had an impact on perceived product innovativeness and the effect on product adoption. They found the social norm and intention relationship to be significant. Within social norms, the age demographic also affects consumer decisions; if a younger users may respond favourable to the AI features, with more of an intention and craving to purchase the AI innovative product due to social pressures. Younger users are often Heavy users, with a higher reliance on technology (Canziani and MacSween, 2021). Previous studies have found a strong connection between PBC and social norms; Whang and Im (2021) found younger consumers evaluated voice shopping (AI features) as a preferred mode of shopping, and were eight times more dependable on this, than that of 45-year-old and older consumer groups. The reason behind this may be due to their social norms readily accepting and expecting AI features, as opposed to the mature market who may not be willing as their social norms or intentions may prove lower. The perceived behavioural control for various age groups may also differ depending on the strength of the intentions and knowledge of the product and its features. Furthermore, the social class, may potentially have an effect on consumer behaviour. The social and cultural aspect of where and what you purchase, how you purchase is influenced by the social class a consumer belongs to. Marketers have used segmentation to target the differing needs of classes. The social position of a consumer and who and how they spend is determined by their interests as well as socio-economic status and culture around this (Shavitt et al, 2016).

*Perceived Behavioural Control (PBC)*

PBC refers to “The perceived ease of performing the behaviour, assumed to reflect past difficulty of performing the behaviour as well as anticipated impediments and obstacles” (Ajzen, 1988:132). The TPB model has found that attitudes, norms and PBC form an intention, these are then related to a set of beliefs; Behavioural to influence attitudes towards the behaviour; Normative underlying determinants of social norms and control the basis of perceptions of behavioural control. These beliefs form an attitude towards an intention of behaviour; however, a behaviour may not be carried out due to constraints of the act such as money, facilities, opportunity etc. As a result, Ajzen added in PBC to address this issue from the Theory of Reasoned Action (TRA). Intentions are believed to form via an individuals’ evaluation of the behaviour through their attitude. The person believes (through their subjective norms) whether they should engage in this behaviour. Whether the individual feels like they have control over their performance is PBC – and this all forms an intention. The PBC construct was an extension from the theory of reasoned action to TPB. Derived from the concept of social learning, Bandura (1977) highlights self-efficacy, “which is concerned with judgements of how well one can execute courses of action required to dealing with prospective solutions" (Bandura, 1982:122). He stated that one behaviour influences confidence in the ability to carry out an action, furthermore it has a strong influence on motivation, achievement and self-regulations. Confidence influences consumer intent as the ability to perform is higher (Baker et al, 2007: Taylor and Todd (2005). Prior studies have used PBC to predict behaviour (Armitage et al, 1999; Kidwell and Jewell, 2003). Both PBC and intentions assist with forming behaviour patterns. Studies have shown how the individual uses past experiences to form an opinion. These past experiences may also be the experiences of their friends and family (linking with social norms). The higher the resources and information consumers have, the more control they will have over their intentions and actions towards the behaviour (Ajzen, 1980). Thus, controls come from the belief that they are able to use AI and have the resources available to do so successfully. Both PBC and intention play a crucial role in shaping behavioural intention patterns. Research suggests that individuals rely on prior experiences to formulate opinions, which may also be influenced by the experiences of their social network, including family and friends, thereby reinforcing social norms. Ajzen (1980) posits that the availability of resources and information enhances an individual's control over their intentions and subsequent actions. Consequently, the perception of control arises from the belief that one possesses the requisite resources and capability to engage with AI technologies successfully. Moreover, prior studies have identified a relationship between self-control and consumer attitudes and behaviours towards brands (Sela et al, 2017). The introduction of autonomous vehicles exemplifies the profound impact of PBC on technology adoption. This challenges conventional notions of control, as AI-driven innovations may initially diminish the user's sense of autonomy. However, behavioural adaptation occurs gradually; for instance, consumers may first experiment with parking assist features before progressively developing trust in AI-driven functionalities within vehicles. Although product knowledge acquisition—is seen an essential factor in increasing perceived control—can enhance PBC in the adoption of emerging technologies. For example, familiarity with AI-driven tools such as ChatGPT for writing assistance or lane assist systems in vehicles contributes to an increased sense of control and confidence. Individuals exhibiting heightened behavioural control tend to seek opportunities to engage more effectively with technological advancements, through expanding their capacity to undertake complex tasks. Crespo and del Bosque (2008) found that perceived behavioural control (PBC) has no significant effect on adoption intention, attributing this to the principles of flow theory. Flow theory, as introduced by Csikszentmihalyi (1997), describes users' deep engagement with technology, akin to being in a state of heightened focus or immersion—often referred to as being "in the zone." This state facilitates continuous progression, resembling the movement of a river, where individuals advance without conscious awareness of their progress. Social media platforms, particularly TikTok, have garnered substantial academic attention regarding the phenomenon of addiction, specifically users' distorted perception of time while experiencing flow (Qin et al, 2022). This effect can be generalized to other digital touchpoints, demonstrating how immersive technologies shape user engagement. When consumers perceive a sense of control over AI-driven interactions, their perception of a brand is often enhanced, leading to increased brand loyalty and subsequent re-purchase behaviour. However, to enter a state of flow, a minimal threshold of excitement must be met; failure to achieve this results in disengagement and boredom (Hoffman & Novak, 1996). This addictive aspect of engagement suggests that consumer behaviour can, in some instances, be assessed through indicators of addiction. Kidwell and Jewell (2003) examined internal influences by contrasting utilitarian behaviours, such as blood donation, with hedonic behaviours, including substance addiction. Their study distinguished the characteristics of these behavioural tendencies to gain a deeper understanding of behavioural intention, identifying it as a key determinant of behavioural outcomes. Social norms and reference groups have long served as external influences on behaviour. This relationship extends to artificial intelligence, as both utilitarian and hedonic behaviours may exhibit addictive qualities through a state of flow or generate feelings of satisfaction and pleasure, further shaping consumer adoption patterns.

The extant literature specifically on PBC's relationship to AI innovations contribute to addressing the deficiencies in this area. Though one study by Mohr and Kuhl (2021) found PBC was the greatest influence of acceptance for farmers adopting AI systems, followed by attitude. The application of PBC is used by Perri et al (2020) to examine intentions to embrace smart grid technology. The research concluded that PBC is strongly associated with behavioural intent. Finally, PBC is expected to play a role in the study as an antecedent to intention to purchase and repurchase and ultimately lead to brand loyalty.

### 2.8 Product Knowledge

Product knowledge is the information about a product stored in a consumer's memory based on attributes, functions, and features, (Philippe and Ngobo, 1999). Knowledge is a valuable asset to increase confidence to shape behaviours and actions. A broader perspective has been explored by Bettman and Park (1980), though they did not researched in an innovative setting, still obtained valid general findings of how consumers are more likely to use their knowledge of brands and attributes to evaluate choices (Laroche et al, 2012). Consistent with this study, consumers are able to use prior product knowledge to inform price acceptability, for example, low price, for low knowledge subjects, (Rao and Sieben, 1992). The evaluation process for products involves gathering information to make decisions. The product features, quality and durability are assessed. To clarify, for the purposes of this study, the definition used for product knowledge is knowledge about the AI innovations and its features. The emphasis of the importance of customer education (Eisingerich and Bell, 2008), or "knowledge" can transpire in ways such as communicating how the product fits comfortably with the user's lifestyle (Kleijnen et al, 2009) or application-based communication which can bring trust towards AI features (Hengstler et al, 2016).

Prior knowledge has been known to ease evaluations (Zeithaml et al, 1993), which may result in brand loyalty. Alternatively, previous studies have discovered higher prior knowledge consumers are more selective and also have a better comprehension of the attributes (Cowley and Mitchell, 2003). It has been reported; consumers normally base their decision on experience and existing knowledge of the attributes of the product.

Furthermore, Laroche et al, (2012) found customer involvement and prior knowledge to affect the relationship with product categories. On the other hand, Swaminathan (2003) observed too much information hinders consumer decisions. Thus, if there is too much information or recommendations, this can impede consumer decisions and cause confusion and frustration. The discussion on information quality posits a direct link to customer satisfaction (Ashfaq, 2020). Though, the research is based on the quality of information given out by chatbots, and not the brand.

Moreover, although Homberg et al, (2009) tested and found no significant effects of amplifying or simplifying to new product success, the investigation involved product knowledge as a moderator, and found it to be unique and under researched (Moreau et al, 2018). One such study regarding the moderating role of product knowledge on the theory of planned behaviour model (Kim and Hwang, 2020) has found a relationship between product knowledge and attitudes, behavioural intentions and social norms. The investigation involved using drone delivery in a pandemic, which resulted in a change of the social norms and increase product knowledge. Furthermore, a consumer evaluates the adoption of a product through previous knowledge, features and context (Wenben Lai, 1991). Prior research demonstrates marketers may find they need to communicate their AI product features and benefits more effectively, to ensure customers are comfortable with the product knowledge (Zerfass et al, 2020) to enhance customer loyalty. Furthermore, a study by Fazal-e-Hasan et al, (2019) applied product knowledge as a moderator between brand innovativeness and customer hope. Their study verified the link with product knowledge to increase confidence in judgements. They argued that consumers with higher knowledge experience higher levels of customer hope. The expansion of knowledge leads to well-informed actions. This was further supported by Peterson and Pitz, (1998). The empowerment of knowledge further boosts confidence. The relationship between confidence and knowledge leads to satisfaction. Earlier studies on the relationship between confidence and knowledge by Berger et al (1994) explored product knowledge as a moderator to increase attitudes and intentions. Confidence is built on trustworthy information on product knowledge to increases the belief or perception proving to be an antecedent of further beliefs (Berger, 1992; Glasman and Albarricin, 2006).

In an attempt to distinguish between high and low knowledge; low product knowledge occurs when consumers do not have much experience or understanding about an innovation, which may be influenced by Brand names such as Apple, where there is a perception ease of use, or whilst remaining innovative (Biswas and Sherrell, 1993). A consumer with high product knowledge will accept and be motivated by the innovation, they will adopt the innovation in its embryonic stage (Fu and Elliott, 2013) due to their ease of use. Furthermore, familiarity and product innovativeness influence whether a consumer is categorised as having high or low product knowledge. Adding to this, the central argument of the literature in this area concludes customers with higher knowledge are less motivated to learn about a new product, due to inattention when encoding (Wood and Lynch, 2002). It has been implied consumers with higher knowledge would process "technological jargon" and understand attributes better (Lee and Lee, 2011).

Researchers attempting to understand how technology impacts consumers have attempted to research consumer behaviour by understanding their knowledge of product and its features with confidence, and to validate the consumers perception of their perceived ease of use or usefulness of the AI innovation to them. The Technology Acceptance Model (TAM) is often used alongside innovation research (Venkatesh and Davis, 1989; Venkatesh et al, 2003). Together with the Unified Theory of Acceptance and Use of Technology - UTAUT (Venkatesh et al, 2012), and the Theory of planned behaviour (TPB) all gather together consumer acceptance, knowledge, social, behaviour, and usefulness. TAM variables examine whether the consumer deems technology useful, whether they will find it easy to use, resulting in a formation of attitudes, all connected through user motivation. The consumers knowledge of the product plays a larger role in the acceptance of AI (Schepman and Rodway, 2020). Originally TAM was used to study the adoption of computers, similar to the new technologies of AI. Assessing user acceptance through knowledge is fundamental to understand the consumers mindset. The journey the consumer travels on, through their experience perception and understanding influences the perceptions of usefulness of the technology and how easy it is to use. TRA and TAM relate to each other as they both agree attitude is a predictor of intentions. Davis (1980) refined TAM on the basis of TRA whereby attitude will be determined by the user. This updated version of TAM formulated relationships between the variables to evaluate a judgement based on technology adoptions. These key theories are acknowledged in the literature, however, yet lack originality when creating new knowledge. The present study explores the role of product knowledge as a moderator, to evaluate the functions of the AI-enabled innovations. The reliability of Homberg (2009) research presents a new concept to the innovativeness literature. In line with Fazal-e-Hasans (2019) work, the present study argues that confidence leads to satisfaction, which should proceed to brand loyalty.

### 2.8.1 Consumer Knowledge

*"Consumer knowledge is a relevant and significant consumer construct that influences how consumers gather and organize information, and ultimately, what products they buy and how they use them",* (Cordell, 1997:246).

Consumer knowledge shapes product evaluation and attitudes towards a product or brand. The consumer knowledge literature can be traced back to the early work of Brucks (1985) who described three categories of consumer knowledge; (1) subjective knowledge, what the consumer thinks he or she knows; (2) objective knowledge, an actual knowledge construct as measured by some sort of test; (3) and prior experience with the product category. Using these categories can explain that the consumer's perception of their experience forms an attitude towards a particular brand or business. Customer knowledge is related to the customer's purchasing decision, that is, whether they would buy a product or a service and what factors influence their decision (Abrell et al, 2016) The behaviour of customers with prior knowledge boost their confidence in their approach. This can develop a direct impact on their attitudes and intentions and furthermore on acceptance (Li, 2019). The literature aligns with the TAM model to agree that consumer knowledge comes the acceptance of a product, where both the product and brand are accepted through measures of use, experience and usefulness (Stern et al, 2008).

### *2.8.2 AI product knowledge*

"Consumers are not aware of all of a brand's innovations, and they do not keep track of all of a brand's innovations" (Hubert et al, 2017). With a dearth of literature on specifically "AI product knowledge", due to its infancy, product knowledge in general may be perceived from the consumer by looking at the wider context, i.e. the company reputation and quality of the brand.  Judgements by consumers evaluating product quality, found product knowledge as a moderator and indicator of product quality (Blair and Innis, 1996).  However, these results were limited to evaluate the warranty of a brand and not fully representative of product knowledge innovations.  For the purposes of this study, the knowledge of the product or AI product knowledge is the intermediary between the relationships of brand innovativeness and brand loyalty.  The contribution to the knowledge of developing an understanding AI product knowledge will bridge the existing gap in the literature.  In general, perceptions and understanding of AI develop with new information given from media and businesses.  Consumers collect this information to bank into their memory and experience to form building blocks of understanding. When an AI innovation is apparent, there are levels of knowledge and observations which may affect adoption rates (Min, 2023).  Overall, little is known about AI product knowledge, and it is not clear what moderating effects are of AI product knowledge.  Prior studies in this area have evaluated product knowledge through customer hope (Fazal-e-Hasan, 2019). No studies have investigated the influence of AI product knowledge as a moderator on brand innovativeness, brand attitude or brand loyalty.

## 2.9 Literature and Knowledge Gaps Summary

*Table 3: Table to summarise the literature*

| Theme | Author | Definition of key terms | Key Findings | Link to Identified Knowledge Gaps |
|---|---|---|---|---|
| AI | Davenport et al (2020) | AI refers to programs, algorithms, systems and machines that demonstrate intelligence.<br><br>AI is manifested by machines that exhibit aspects of human intelligence | Study on research papers published. Creates a framework for understanding AI in research. | Massive gap identified in AI literature. Proposing AI research agenda |
| AI innovations in Brand and Marketing context | Mariani et al (2022) | AI and innovation is referred to "technology innovation" which refers to the process of creating new and improved technologies that disrupt markets, challenge | Quantitative SLR on AI innovation adoption.  The paper illustrates the ongoing debate of AI literature in innovation management research | Opportunity for research combining behavioural research theories such as TPB and other theory (for example here BVC |

| | | | | |
|---|---|---|---|---|
| | | organizational capabilities, and lead to significant advancements in organisational performance. | | and Product Innovation). |
| AI innovations in products and services | Huang and Rust (2021) | AI as the use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling; the multiple AI intelligence view considers that, rather than treating AI as a thinking machine, AI can be designed to have multiple intelligences, as humans have, for different tasks. | Services previously provided by humans will be partially or fully replaced by AI | Gap in literature for consumer response to AI replacement of humans in services. |
| Simplifying and Amplifying innovations | Hardie et al, (1996) | Simplifying: The degree to which and innovation makes using a product easier.<br><br>Amplifying: The degree to which an innovation increases what can be done with a product. | Amplification and simplification innovations positively impact consumer affect. | Need for further research on the role of these innovations on adoption-decision processes. |
| Brand Innovative ness and Product knowledge | Hubert et al (2017) | Perceived brand innovativeness is the consumers' subjective assessment of a brand as innovative. | Contributors to perceived brand innovativeness is significantly correlated with intention to buy, consumers are not always aware of brand innovations. | A gap identified in the research is AI on Brand innovativeness and BA as a mediator to BL. |
| Brand Innovative ness and product innovation | Shams et al (2015) | Brand innovativeness is a consumers' perception of a brand's track record of product innovations, degree of creativity, and potential for continued innovative activity in the future in a given market. | Product level of innovations impact on Brand innovativeness– including innovation, as well as logo and colours. | No study on impact of AI innovations on brand innovativeness. |
| Brand Innovative ness and Brand Loyalty | Pappu and Quester (2016) | Brand innovativeness refers to the degree to which consumers perceive a brand to be innovative (Barone and Jewell, 2013, 2014). | Consumers perceptions of brand innovativeness affects brand loyalty via perceived quality as a mediator. | No use of Brand Attitude as a mediator between Brand Innovativeness and Brand Loyalty |
| Brand Loyalty | Dick and Basu (1994) | Customer loyalty is the strength of the relationship between relative attitude and repeat patronage | Consumers develop positive attitudes which drive brand loyalty. | Need to consider Brand Attitude as a partial mediator. |
| Product Knowledge | Kim and Hwang (2020) | Product knowledge is the degree of individual knowledge about the pro-environmental role of drone food delivery services. | Used TPB to assess drone delivery – with product knowledge as a moderator to attitudes, behavioural intentions and subjective norms | No study looks at the impact of AI product knowledge as a moderator of the impact of AI innovation on Brand Innovativeness and Brand Innovativeness on Brand Attitude and Brand Loyalty. |

The three main issues in the literature pertain to the following three knowledge gaps:

First the concept of simplifying and amplifying behaviours has been anchored solely on the main research by Hardie et al, (1996). Though some authors have classed it as product functionality, the application of simplifying and amplifying measure is a unique contribution to the usage of AI innovations on brand perceptions. Second the operationalisation of brand innovativeness to brand attitude, and loyalty to brand attitude is complex and well-established in the literature. The advantage of adding in brand attitude to partially mediate these relationships goes beyond the literature to investigate the construct. Finally, there is limited literature around product knowledge as a moderator, and no literature in relation to knowledge of AI enabled products as a moderator in relation to Brands. This research expands the boundaries of the current literature in this field.

## 2.10 Chapter Summary

This chapter presented an overview of the themes of the literature surrounding AI, product knowledge, and brand theory. The chapter reviewed pertinent literature on AI and innovation, its definition and uses. Furthermore, the chapter focused on evaluating brand innovativeness literature and its relationship with brand loyalty. The chapter assessed the Brand Value Chain model, focusing on the brand attitude literature. This literature review found three major gaps in the field. Overall, the academic contributions are growing with AI, posing significant gaps in the field. Within the first gap, no studies have tested AI innovations on amplified and simplified innovations. The second gap highlights the lack of literature using brand attitude as a partial mediator, and the third gap concerns exploration of AI product knowledge as a moderator on brand and innovativeness. The next chapter constructs a theoretical conceptual model and develop hypotheses from the literature and gaps presented in this chapter.

# Chapter 3

# Theoretical and Conceptual Model Development

## 3.1 Introduction

Based on the literature review, key themes emerge regarding the relationships between AI innovations, brand innovativeness and brand loyalty. The review also highlights a substantive gap regarding AI product knowledge as a moderator of the relationship between brand innovativeness and brand loyalty. This presents an opportunity for new empirical research to explore how consumers knowledge of AI-enabled innovations influences perceptions of brand innovativeness and its relationship with brand loyalty. Based on these themes, a conceptual framework is developed and used to explore seven hypotheses. The chapter ends with a summary of the theoretical and conceptual model development and how it enables empirical exploration of the hypotheses in later chapters.

## 3.2 Hypotheses Development

A hypothesis is a tentative explanation of assumption about a causal or functional relationship between entities, concepts, phenomena or data points (Gyllenpalm and Wickman, 2011). Hypotheses can be developed from prior theory or from observation of phenomena, and can tested or falsified (Popper, 2005). Hypotheses can be integrated into an overall conceptual model – "a set of concepts and propositions which integrate the concepts to create a meaningful whole" (Gobbens et al 2010:176).

### 3.2.1 The link between Product Innovation and Brand Innovativeness

Brand innovativeness has been defined as "the extent to which consumers perceive brands as being able to provide new and useful solutions to their needs" (Pappu and Quester 2016:4); Eisingerich and Rubera 2010:66). In this study this definition is adopted and used. Shams et al, (2015) see consumer perceptions of brand innovativeness as subjective and based on perceptions of a stream of brand related product level innovations over time, together with the impact of marketing communications. Clearly this points to the possibility of a positive relationship between consumer perception of product innovations and brand innovativeness.

As outlined in the introduction and literature review chapters, artificial intelligence has been a major source of product innovation in recent years. Product innovation has been characterised along two dimensions being Simplifying or Amplifying Innovations (Hardie et al, 1996). AI could be used to enable either type (in other words be an AI Simplifying or AI Amplifying Innovation. The impact of amplifying and simplifying innovation on product affect and ultimately intention to purchase has been examined, without a focus on AI enablement (Hardie et al, 2016). It seems intuitive however that AI simplifying innovations and AI amplifying innovations may both (as types of product innovation), with differing effect, have a positive relationship with brand innovativeness.

Consequently, the researcher posits:

**H1 AI Simplifying innovation is positively related to Brand Innovativeness**

**H2 AI Amplifying innovation is positively related to Brand Innovativeness**

The amplifying of innovations is the ability to carry out additional tasks beyond expectation (Hardie et al, 1996). With having additional functions, it can extend performance comparable to the Unified theory of acceptance and use of technology (UTAUT) model (Venkatesh et al, 2003) factors affecting consumer behaviour such as performance expectancy and effort expectancy are important to consider. Performance expectancy is referred to as how a consumer perceived the technology will improve their productivity, and effort expectancy is the ease associated with using the technology (Venkatesh et al, 2003). With performance expectancy to be higher with AI-enabled functions, and low effort, users are theorised to be able to elaborate the activity further (Gursoy et al, 2019). With less effort and more functionality, adopters wanting more from AI are willing to use the innovation (through expectancy) and increase their perceived Brand Innovative. Innovative brands have strong associations with excitement (Aaker, 1997). The notion of perceived brand innovativeness is increased through the confidence and impression of it being able to expand activities through the ease of use and productivity. Thus, if the AI innovation is perceived to be productive, the perception of the brand has positive brand associations (Lehmann and Keller, 2003). Together with the novel and utilitarian beliefs of usefulness, (Mclean and Osei-Frimpong, 2019) perceived brand innovativeness increases.

### 3.2.2 The link between Brand Innovativeness and Brand Loyalty

Purchase intention is stronger for consumers who perceive the product to be innovative (Fu and Elliot, 2013). Pappu and Quester (2016) recognise that customer perceived brand loyalty can act as a heuristic (or mental short cut) in relation to the usefulness, quality and benefits of continuing to remain committed to buying and advocating products within a given brand (brand loyalty). Eisingerich and Rubera (2010) observed a strong and direct positive relationship between brand innovativeness and brand loyalty in their study and similarly describe brand innovativeness as a 'signal' to consumers that the brand will continually seek to better meet their needs and wants over time, leading directly to brand loyalty. Keller (1993) in general shows that positive brand associations can lead to brand loyalty, and brand innovativeness is a form of brand association.

Consequently, the researcher posits:

**H3 Brand innovativeness is positively related to Brand Loyalty**

### 3.2.3 The link between Brand Innovativeness and Brand Attitude

Brand innovativeness influences the quality of the brand, affecting the attitude and resulting in a consumer who is loyal (Ashill, 2011). Authors have identified ways in which perceived innovativeness might indirectly influence brand innovativeness. Innovativeness may directly influence consumers' cognitive and emotional satisfaction, thereby indirectly affecting loyalty (Kunz et al, 2011). Alternatively, perceptions of innovativeness may lead to higher consumer involvement with the brand which in turn can lead to brand loyalty (Henard and Dacin, 2010). Finally, innovativeness may directly affect perceptions of brand quality, which has been found to have a positive relationship with brand loyalty (Pappu and Quester, 2016). Each of these (satisfaction, involvement, quality) can be described as elements of a consumer's attitude to the brand.

Consequently, the researcher posits:

**H4a Brand innovativeness is positively related to brand attitude**

### 3.2.4 The link between Brand Attitude and Brand Loyalty

Brand attitude research has a well-established link with loyalty (Ngobo, 2016; Verhoef, 2003; Baldinger and Rubinson, 1996; Liu et al, 2012). Brand attitudes are formed by brand awareness and evaluations of a brand (Rossiter, 2014). Brand awareness leads to brand associations, which form the attitudes towards a brand (Keller and Lehmann, 2003). It is well-known that a favourable attitude towards a brand generally results in repurchase (Oliver, 1999). Increased confidence in consumer evaluation affects attitude confidence (Berger and Mitchell,1989). Attitudinal loyalty is a key component of brand loyalty, which is cultivated by ensuing customer satisfaction and efforts to build customer relationships (Kunz et al, 2011). antecedent of brand loyalty is the quality and the strength of the attitude towards a brand (Pappu and Quester, 2016). Studies have proved brand attitude has a direct relationship with brand loyalty (Liu et al, 2012).

Consequently, the researcher posits:

**H4b Brand attitude is positively related to brand loyalty**

### 3.2.5 The link between Social Norms and Brand Loyalty

The Theory of Planned Behaviour (TPB) model (Ajzen, 1980) has demonstrated in many scenarios through numerous studies of how societal views and behaviours impact consumer intentions and beliefs about the ability to carry out an intention impact consumer intentions (Xu et al, 2022). Social norms have been shown to influence intention to adopt technologies in technology acceptance (TAM) studies (Venkatesh et al, 2000; Pelau et al, 2021; Gursoy et al, 2019) and in consumer buying studies (Kim and Hwang, 2020). Prior studies in this area have confirmed consumers influenced by their families, friends, influencers and colleagues when forming an attitude towards a behavioural intention related to a given technology (Kang, 2014). The norm and intention relationships has been proved to be significant (Fu and Elliot, 2013).

Consequently, the researcher posits:

**H5 Social Norms are positively related to Brand Loyalty**

### 3.2.6 The link between Perceived Behavioural Control and Brand Loyalty

The Theory of Planned Behaviour (Ajzen, 1980) also suggests that perceived behavioural controls can have a negative impact on both intention (such as loyalty) and behaviour – see for example Xu et al (2022) or Kidwell and Jewell (2003). However, only one previous study could be found linking perceived behavioural control to brand loyalty, and in this case only a weak relationship was identified (Lee et al, 2009).

Consequently, the researcher posits:

**H6 Perceived Behavioural Control is negatively related to Brand Loyalty**

### 3.2.7 Exploring potential effects of Product Knowledge on Relationships

It has been identified that attitude confidence can act as a moderator between attitude and behavioural intention (Berger, 1992; Berger et al, 1994). Here confidence is strength of belief that the judgements made to form the attitude are correct, and belief in the accuracy of the attitude should be stronger when the attitude is based on trustworthy information (Berger, 1992).  This is further supported in a meta-analysis by Glasman and Albarricin (2006). In fact, Berger et al (1994) found that product knowledge through the mechanism of increased confidence, had a moderating effect on the relationship between attitude to a product and intention to buy it. In general, it can be argued, by extension, different types of subjective product knowledge may have moderating effects on the relationship between any belief or perception that is an antecedent to another belief or perception if product knowledge might improve confidence in those beliefs, or indeed reduce confidence in those beliefs. Judgments based on more knowledge are made with greater confidence (Peterson and Pitz, 1988).

Consequently, the researcher posits:

**H7 The two types of product knowledge (general AI product knowledge and specific AI product knowledge) may moderate the relationships between the variables in H1, H2, H3 and H4(a and b).**

### 3.2.8 Exploring the Role of Age

Age has been seen to have a moderating or group effect in relation to studies concerning technology and brand intentions – see for example Yee et al (2019), Hwang and Kim (2019) Yoo et al (2021) who defined respondents as younger or older than a median age of 35. Hurst et al, (2007) used age 38 as a mean, whereas many scholars have divided age by generations. However, it may be contended that age may not play a factor in consumer satisfaction or even customer loyalty (Kim et al, 2016 and Walsh et al, 2008). Adding to this argument, Kuppelwieser and Klaus (2020) advise to being less rigid about the age measurement concept to enhance marketing theory. Furthermore, the debates warrant the present study to research age division for under 35 (younger) and over 35 (mature) users. The literature on age in this area suggests the younger groups experiences and perceptions towards AI are engaging. Older groups are more resistant to AI and in some cases only use it when other areas are exhaustive. Age has been used in group analysis studies, additionally as a moderator in recent studies, (Gentina and Kratzer, 2020, and Hwang et al, 2019). The present research aims to test the implication of dividing the respondents into two age groups, to see if they have different viewpoints towards AI innovations.

Consequently, the researcher posits:

**H8 Group Analysis – Does age change any of the proposed relationships?**

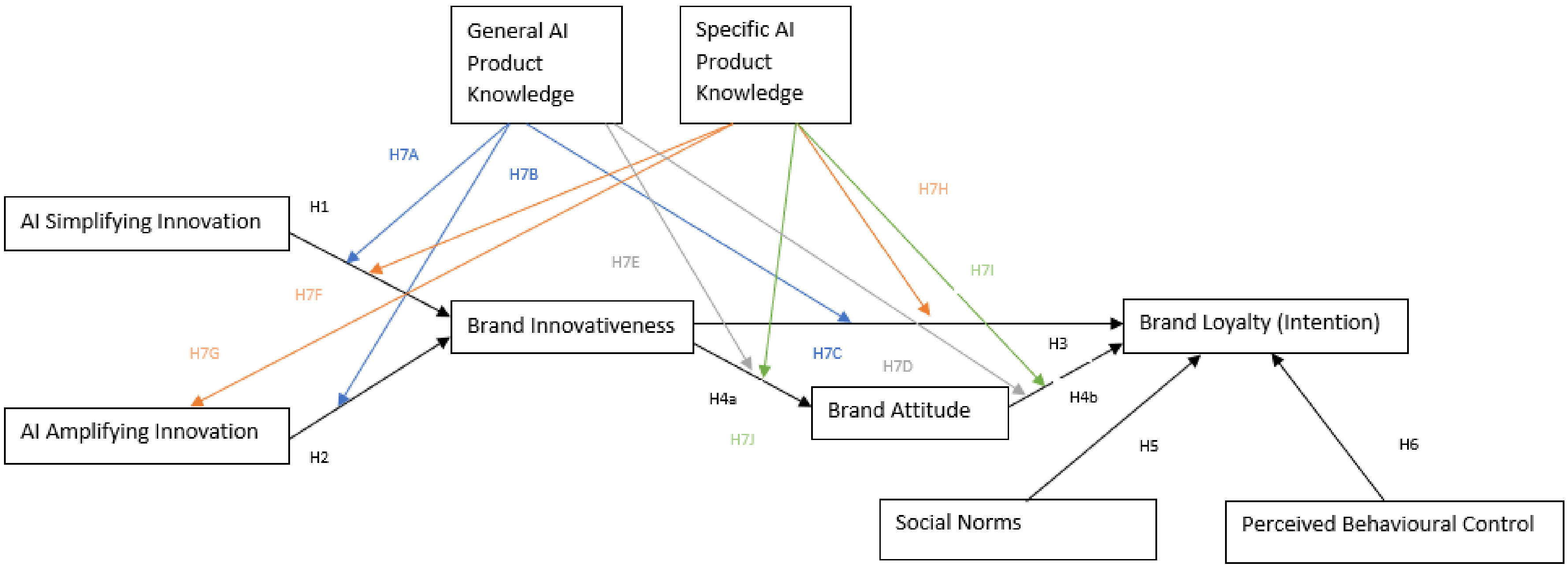
The hypotheses developed reference back to the research questions:

**H1 and H2 refer to research question 1:** Do AI enabled Simplifying Innovations and AI enabled Amplifying Innovations increase perceived Brand Innovativeness?

**H3 H4 (H5 and H6) refer to research question 2**: Does increased Brand Innovativeness lead to increased Brand Loyalty, and is this relationship (partially) mediated by Brand Attitude?

**H7 refers back to research question 3**: Does General and/or Specific AI Product knowledge have a moderating effect on the relationships described in Research Questions 1 and 2 above?

*Figure 12: Conceptual Model*




Source: Author

### 3.3 Conceptual Model

The conceptual model incorporates key constructs and relationships to explore the impact of AI-enabled innovations on consumer perceptions. The model is considered a higher order reflective model, often termed as a second order model, with brand innovativeness, brand attitude and brand loyalty classed as first order constructs. The approach allows the capture of several subcomponents of the construct. Brand innovativeness is operationalised by customer evaluations of AI innovations, focusing on amplifying and simplifying innovations. Customer evaluations form brand attitudes, which transpire into a like or dislike of a brand. Brand attitudes consist of manifestations of beliefs and experience, providing a summary viewpoint, justifying the position of a partial mediator. Brand loyalty has established links with brand innovativeness and brand loyalty, however, testing the partial mediation of brand attitude is a unique contribution. By employing the BVC model to frame the research, the focus on the consumer mindset furthers the understanding of AI-enabled innovations on consumer perceptions.

### 3.4 Chapter Summary

The research from the literature review in the previous chapter analysed scholarly work. Using this as a basis, this chapter has built a conceptual framework with a collection of hypotheses to ensure reliability within the framework. Furthermore, seven hypotheses were proposed to explore links between the variables. The proposed model is to test the relationships between the variable to meet the research aims of exploring the relationships of AI, Brand innovativeness and Brand Loyalty.

The next chapter describes the most appropriate methodology and methods for data collection to be used to test the hypotheses. The methodology chapter uses established measures for each construct within the conceptual model to validate and justify the reliability of the constructs, as well as establishing the steps for data analysis.

# Chapter 4

# Research Methodology

## 4.1 Introduction

The preceding chapters reviewed the existing literature in relation to brand innovativeness, brand loyalty and product innovation, identifying research gaps and questions and then developing a conceptual model and hypotheses to test in order to examine the research questions.

This chapter provides an overview of the chosen research philosophy adopted, and justifies the methodology and methods used in this research. The research philosophy of Positivism is chosen due to the researchers' beliefs, and suitability for analysis of the subject matter examined in this study. Next, a quantitative methodological approach is described and outlined, with a deductive approach to theory and hypothesis testing being adopted and employing the survey method as the data collection instrument.

Adoption of a context and target population of users of the Amazon App (application) is justified to explore the research questions due to its large and wide consumer base in the UK, its strong brand, and the fact that it has frequently released AI enabled simplified and amplifying innovations or features. The chapter identifies a structural equation modelling via partial least squares as an appropriate technique for testing the hypotheses in the conceptual model. The use of PLS-SEM is justified as the most suitable option for data analysis and the steps to assess the model and test the hypotheses are established. Finally, the chapter concludes with a discussion of limitations of the method and ethical considerations.

## 4.2 Review of the Research Aims

In order to provide a clear justification of the adopted methodology, it is important to ensure the methods and methodology fulfil the needs of the research. The research aim is to explore the impact of AI innovations on Brand Innovativeness, and Brand Innovativeness on Brand Loyalty either directly or indirectly through Brand Attitude. It also seeks to explore the moderating effect of Product Knowledge on these relationships.

The aim of this research involves exploring causal relationships in the context of consumer behaviour. The conceptual model of those relationships developed in Chapter 3 clearly demonstrates this. Testing relationships through quantitative methodological approaches in such circumstances is common in the literature, and appropriate subject to the researcher's own philosophical stance being consistent with such an approach.

## 4.3 Research Philosophy

Philosophy plays a fundamental role when designing research because alternative philosophical positions encompass different assumptions which impact the researchers worldly view (Easterby-Smith et al, 2008). A Philosophy or Paradigm can be defined as a system of beliefs or particular worldviews that shape a course of an investigation (Denzin and Lincoln, 1996). A worldview can also be thought of as providing the core set of assumptions the researcher adopts in choosing a particular research philosophy (Denzin and Lincoln, 2011).

By embracing a research philosophy, the researcher embraces their individual perspective and principles to steer the approach as a framework for data collection and analyses with underlying values which drive the process. Through philosophical inquiry, the framework used shapes the research process and approach to the acquisition of knowledge. Three dimensions of the research philosophy are epistemology, ontology and axiology.

The concept of ontology revolves around understanding the nature of reality, delving into exploration of beliefs and perceptions of what the real world is, and how we interpret this. As Richards (2003) suggests, ontology is concerned with unravelling the essence of our understanding of reality.

Epistemology on the other hand, focuses on the nature of knowledge and the ways in which it is acquired and validated. Gall, Gall and Borg (2003) stated that it explores the very nature of knowledge itself and the methods by which we come to know and understand the world. It addresses fundamental questions about how knowledge is obtained, and how we can assess its validity (Scotland, 2012).

Lastly, Axiology plays a crucial role in shaping the research process, looking particularly at the researchers' beliefs around objectivity and subjectivity, impacting on concepts such as bias and ethics in research (Bell et al, 2019).

Five major philosophies which are normally considered in business research are positivism, critical realism, interpretivism, post modernism, and pragmatism. Though, the topic is highly disputed, as Sekaran and Bougie (2016) claim there are just four; positivism, critical realism, constructionism and pragmatism, moreover, Newman and Benz (1998) claim positivism and interpretivism are most used approaches in the social sciences.

*Table 4: Table of Research Philosophies*

| | Positivism | Interpretivism | Critical Realism | Post modernism | Pragmatism |
|---|---|---|---|---|---|
| **Ontology**<br><br>**(what is the nature of reality?)** | Objective Independent of social actors | Reality exists in human thoughts beliefs or knowledge Complex and rich | Stratified / layered (the empirical, the actual, the real) | Complex, rich, socially constructed though power relations | Multiple realities are the practical result of ideas |
| **Epistemology (What is it possible to know?)** | Only observable phenomena provides facts and credibility. Scientific Method | Focus on narratives, perceptions and interpretations | Facts are social constructions. Knowledge historically situated and transient | What counts as "truth" and "knowledge" is decided by dominant ideologies | Problem - solving and informed future practice, Focus on problems, practice and relevance |
| **Axiology (What is the role of values?)** | Value-free Research is detached and objective | Researcher interpretations are key to contribution, Value- bound research | Researcher acknowledges bias by world views, cultural experiences and upbringing | Value-constituted research, researcher and research embedded in power relations | Research initiated and sustained by researchers doubts and beliefs |
| **Methods (what are the typical methods used?)** | Deductive, Highly structured Quantitative | Inductive, in-depth investigations, mainly qualitative | Retroductive, range of methods to fit subject matter | Range of data types – typically qualitative methods of analysis | Range of methods, quantitative, qualitative, mixed, multiple, action research |
| **Suitability to meet research requirements** | Suitable as scientific, no bias, and objective | Subjective Time constraints | Too much bias | Subjective | May not obtain the full picture |

Source: Saunders et al, (2019) and Bell et al, (2019)

Of the five main research philosophies, the positivist and interpretivist are the most frequently used in social sciences (Majeed, 2019). Advocates of interpretivism are concerned with in depth meaning in a given context, which is subjective and without generalisations (Scotland, 2012). Contrary to this, positivism is focused on explaining human behaviour in terms of causality by simplifying phenomena and testing hypotheses through scientific methods. The nature of this research is to find reasons in the causal relationships of the conceptual framework thus is consistent with the positivist approach.

### 4.3.1 Justification for Positivist Philosophical Choice

"Positivism relates to the philosophical stance of the natural scientist and entails working with an observable social reality to produce law-like generalisations" (Saunders et al, 2019). This study takes the positivist approach based on the beliefs of the researcher that accord with the ontology, epistemology and axiology of positivism, and because the focus of the research is identifying and casual validating relationships in a way which can be generalised. Positivist research looks for relationships between variables, looking at discovering trends and patterns in relationships. Positivism is best suited to the research for many reasons. Firstly, using quantitative methods have proved fruitful in the past studies of consumer behaviour due to a requirement to be objective when measuring attitudes. Secondly, the philosophy unique contribution to add in product knowledge as a moderator which can gain insights into overviews of society and social trends by optimising facts through figures. Contradictory to this, researchers use interpretivism, which supports experiences through in-depth interviews, however, the statistical power and reliance of positivism develops new findings which is suited to meet the research aims. Furthermore, based on the purpose of the study, in order to meet the research objectives, the positivist method is best suited.

French Philosopher Auguste Comte advocated the positivist approach, which holds great significance in the pursuit of objective knowledge, furthermore, he bases his ideologies on "observation and reason are the best means of understanding human behaviour; true knowledge is based on experience of senses and can be obtained by observation and experiment", (Antwi and Hamza, 2015:218). The positivist body of work originates from ideas of using scientific methods in social sciences as well as the natural science. The original positivist researchers renowned as the "Vienna Circle" based their positivism ideas on yielding optimal measurable data to produce scientific knowledge. According to Malhotra et al, (2013) marketing research is often searching for either exploratory or causal data, which is often measured, and ultimately required for marketing practitioners and presenting to the board. The highly structured methodological approach is applicable to the needs of this particular research due to the neutral objectivity of the researcher, the promise of accurate and unambiguous knowledge (Deleuze and Bacon, 2003). The research gap searches for a causal explanation and prediction as a contribution to new knowledge, thus making it the optimum philosophy to ensure the research objectives are met. As this approach allows for theory building using a deductive approach. Concepts are linked together through hypotheses and tested empirically (Brannick and Coghlan, 2007).

From an ontological perspective, the positivist paradigm assumes of a single tangible reality which can be understood and measured. This allows development of a conceptual framework to predict and explain general phenomena. Epistemologically, knowledge must be developed objectively without researcher influence. There must be a distance from the researcher to the respondent to reduce bias. Moreover, facts are derived from using scientific methods, which is objective and generalised. Based on the purpose of this study and the research aim, positivism develops knowledge by causal explanations and predictions as contributions (Saunders et al, 2019). From an axiological perspective, positivism relies on the objectivity of the researcher. The answers should not be subjective or open to interpretivism. No values of the researcher should be subjected to the respondents.

Moreover, the literature suggests methods using case studies, observations, measurements, statistics and questionnaires are often selected together with this philosophy (Mingers, 2003; Choudrie and Dwivedi, 2005). Furthermore, many brand studies have been quantitative (Liu et al, 2012; Rossiter and John, 2014; Aaker, 2001) with conceptual variables often measured by Likert scales, as they are seen as being objective, reliable and valid subject to methodological testing to show bias is controlled (Kim et al, 2022).

### 4.3.2 Potential Limitations of Positivism

Is marketing a science? Over half a century of debating and this question remains divisive. The discipline of consumer research and marketing has been dominated by positivist, empiricist, and realist philosophies, but some authors have argued for a pragmatic approach, which recognises the role of subjectivity and context. (Majeed, 2019). Positivism has been criticized for making unrealistic assumptions, confusing predictions with explanation, and discard all non-logical reasoning. For the positivist, there is no connection with nature, (Blaikie, 2007).

Despite the potential concerns, given this study engages in theory testing, and exploration of conceptual relationships, and given the authors philosophical beliefs, a positivist approach is adopted.

## 4.4 Approach to Theory – Adoption of Deduction

In social sciences, there are three main approaches to reasoning in relation to theory, being deduction, induction and abduction. Deductive reasoning entails a process of developing theories for explaining, anticipating, and forecasting occurrences in order to manage them (Saunders et al, 2019). Deductive reasoning is highly associated with the positivist paradigm, where the theory is tested in the form of a conceptual or theoretical model, with hypotheses showing the relationships between variables in the model. This method involves development of a research strategy to test the hypothesis, which relates closely to the needs of the research (Bell et al, 2019). This approach is most suitable to either falsify or validate the conceptual model, and to “explaining the casual relationships between the concepts and variables” (Saunders et al, 2019:146). Deduction is beneficial to the study, as it generalises the population, therefore offering a broader scope for the research and derives hypotheses from logic which is tested via quantitative methods using surveys and experiments (Gray, 2019).

In contrast, induction finds gaps in theory and aims to form a new theory through data collected in research – and is associated with interpretivism. Often associated with qualitative data, it normally examines a phenomenon in its context in the social world and makes no theoretical assumptions though the researcher can familiarise themselves with theory in the chosen area of research (Bryman, 2016; Creswell & Creswell, 2017). Abduction is usually the third alternative, often associated with a pragmatism philosophical stance. It is often used to overcome the weaknesses of both induction and deduction (Saunders et al, 2019).

### 4.5 Research Strategy

According to Easterby-Smith et al, (2012) research strategy is a general plan as to how to answer the research questions that have been set by researcher. A research strategy is a comprehensive approach to a research effort that encompasses the research philosophy, research design (the framework for data collecting and analysis), and research questions to be answered (Saunders et al, 2019). Previous studies have contributed to the strategy and methodology body of literature, debating the strengths and weaknesses of qualitative, quantitative and mixed methods (Teddlie and Tashakkori, 2011; Creswell and Creswell, 2018). Previous studies that have determined and explored the relationships connected to Brand concepts were research strategies based on quantitative approaches used to establish causality. Quantitative methods frequently measure consumer behaviour, knowledge, opinions or attitudes (Cooper and Schindler, 2014).

In contrast to this, some marketing researchers have utilised qualitative methods where brand- consumer relationships have traditionally held qualitative research as highly regarded (Aggarwal, 2004). Traditionally the use of qualitative methods such as interviews, focus groups and observations, collects "rich data" to find the meanings behind responses, were often used to develop theories or hypotheses. The limitation of this approach is that it is time-consuming and open to interpretation; thus, researcher bias may prove hard to manage. Furthermore, qualitative is inappropriate for this particular study there is a developed hypothesis to be tested. Moreover, researchers normally use a qualitative method when there is little research to delineate constructs. However, some researchers are in favour of qualitative methods, as these techniques have often proved fruitful in business research to provide deeper understanding of any issues which have remained unclear in quantitative studies (Eriksson et al, 2008). Undoubtedly, a qualitative method is appropriate when interpreting “rich data”. Moreover, in future studies there is scope to combine both methods and use mixed methods for examining the combinations of themes which have not been researched before.

There are eight key research strategies in social sciences (Yin, 1994; Saunders et al, 2019) which include: secondary data (such as archives and historical data), surveys, experiments, case studies, action research, grounded theory, narrative enquiry and ethnography (refer to table 5 below). The survey method is well-established in business research to present detailed analysis in consumer studies. This study uses a survey of Amazon App users in the UK via a questionnaire as a research data collection instrument method to explore the research model.

*Table 5: Key Research Strategies*

| **Research Strategy** | **Description** |
|---|---|
| Survey | Usually in a form of questionnaires with standardised data from a sizeable population |
| Experiment | Uses hypotheses formulate the probability of change from the independent variable to the dependant variable. |
| Case study | Intensive analysis of a single case (A company, Individual, changer process) |
| Secondary and Archival Data | Use of a repository, government records, emails, media, records, visual and audio, and organisational sources. |
| Action Research | Develops solutions though participation and collaboration with real organisations |
| Grounded Theory | Aim to develop theory from behaviours. Data analysis is ongoing, typically inductive. No prior knowledge. |
| Narrative Inquiry | A story or personal account of an event. |
| Ethnography | Studies of culture with a written account of a group |

Source: Bell et al, (2019); Saunders et al, (2019)

### 4.6 Data Collection Method

The data collection approach is briefly outlined below, before a detailed description of questionnaire development and sampling is given in later sections.

### 4.6.1 Unit of analysis

"Unit of analysis answers the question of 'what' and 'who' is being studied in business research. It helps to determine what type of data a researcher should collect from his study and who he collects it from" (Kumar, 2018). The research objective aims to examine the extent to which AI innovation, in the form of simplifying and amplifying innovation, drives consumer perceived brand innovativeness, which in turn (partially mediated by brand attitude) drives brand loyalty. In order to measure the "who" and "what", the unit of analysis to use for this study is UK consumers who utilises the Amazon App. The unit of analysis is an important issue when formulating the research question (Creswell, 2003), and must always be considered as part of the methodology.

### 4.6.2 Data Collection Instrument

This study adopts the Survey research strategy and develops a questionnaire as a data collection instrument. A survey is "a systematic method for gathering information from (a sample of) entities for the purposes of constructing quantitative descriptors of the attributes of the larger population of which entities are members" (Groves et al, 2011:2).

An analytical survey is often used to examine hypothesised relationships, and the differences to test hypotheses (O'Gorman and MacIntosh, 2015). The population of Amazon App users is large and widely distributed, further justifying how using a survey expedites the data collection process. A cross- sectional study was chosen, which is often associated with surveys, and conducted within a particular time period, when AI application was rapidly evolving (2023- 2024). Longitudinal studies were eliminated due to the limited timeframe within the PhD degree period available. An online self- administered survey was adopted for cost and time considerations. These have the ability to generate a fast turnaround, make the participant feel anonymous and can result in more responses (Blumberg et al, 2014). Qualtrics an online survey software provider, was selected to operationalise the questionnaire and collect the data. The attraction of the software is it allows anonymisation of the respondent, can prevent repeat completions of the questionnaire by the same individual, is hosted on secure university servers and so gains trust from respondents as to where their data will be stored, as well as administers questions in a logical and appropriate professional looking manner.

An online approach utilising a link shared via social media was adopted to ensure it reached a wide coverage with fast and efficient collection of responses. Ineffective survey methods via mail, interviews, telephone or in-person, take a substantial amount of time to collect and analyse, also are deemed as ambiguous and the response rates are low (Dillman et al, 2014). Although there may be a gradual response rate, the survey methodologically gathers data which can be quantified. The advantage to this is the data is objective, underlined with the positivist theory alongside measurable outcomes. The surveys objectivity allows the respondent to trust the software and offer anonymous feedback without bias, reciprocally, the researcher makes further use of the software to uncover detailed data analysis. The task of data analysis is simplified with the responses electronically gathered, ensuring accuracy in content.

The researcher recognises the limitations of the survey method and have mitigated these. Surveys are developed through questions, which can limit the answers given through their design or through poor wording (Saunders et al, 2019). To minimise this problem, the researcher conducted a pilot survey with feedback on the time taken, missing questions or factors, and on question clarity to eliminate these limitations. The researcher has added a time bar at the top of the questionnaire, and indicated an amount of time it will take to conduct the survey, to prevent respondents failing to complete the survey. To remove any quick responses if respondents rush through the survey and avoid respondents falling into fixed patterns of response to Likert scale questions, there are questions inserted to common method bias.

### 4.6.3 Reliability and Validity in Data Collection

Reliability and validity are essential to minimise bias and error in data collection and reliability and validity checks ensure the survey provides information to the trustworthiness of the information of the data (Newman and Benz, 1998). Reliability refers to the consistency of a measure, and validity to its accuracy. In the context of this study measures are operationalised as Likert scale answers to questions in the questionnaire. Later in this chapter, tests designed to show reliability and validity are maintained in the approach to analysing the data are described. The table below displays the mitigations to overcome other biases (threats to reliability and validity). The study utilises 7-point Likert scale as studies have shown reliability increases when more points are used  (Symonds, 1924).  Reliability tests using Cronbach's Alpha and Construct Discriminant Validity analyse the data to check for trustworthiness in the data. (Taherdoost, 2016).

*Table 6: Questionnaire Design Mitigations to Overcome Bias*

| **Threat** | **Definition** | **Mitigation** |
|---|---|---|
| Social Tendency Bias | Responding the way most people may do (going with the majority) | Anonymity and a variety of questions with similar meanings. |
| Acquiescence Bias | Respondents replies how they think the researcher will want to see | Anonymity. Randomised question location. |
| Survey and questions | Questions are biased or the respondent does not understand terminology | Pilot study – questions were tested, then amended ready for the larger survey |
| Participant Error | Factors adversely altering the way a participant performs, such as before home time, so it is rushed. | Added in common method bias questions |
| Participant Bias | Factors indicating a false response, such as conducting and interview in open space, where people may overhear, so the respondent offers false positive answers | Survey QR codes were sent out, so the respondent was able to private use their mobile phone to fill out and submit anonymously |
| Researcher Error | Factors altering the researcher's interpretation | Closed questions which cannot be interpreted subjectively |
| Researcher Bias | Bias in the researchers recording of information. | Use Qualtrics to record responses |
| Past or recent events | Responding the way most an event which changes the respondents' perceptions | No recent events have occurred. |
| Testing | Impact of the testing on participants views which changes behaviours or views. | The study had a page on consent and what the survey was about. There were no consequences for participants after the test. |
| Instrumentation | The impact of changing the research instrument between different stages of the project | Only one instrument is chosen – the Survey. No changes were made during this stage.  All respondents received the same questionnaires. |

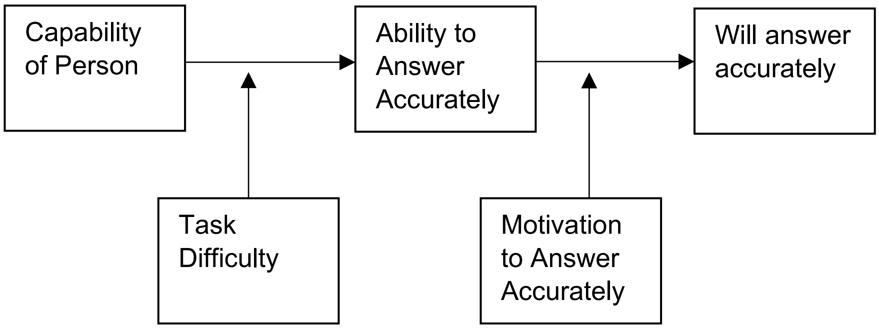
| | | |
|---|---|---|
| Mortality | The impact of respondents withdrawing from the studies | Participants were able to leave the survey and were advised how to leave if they wanted to within a month. |
| Maturation | The impact of change outside the respondents influence of this study | Surveys were sent and anonymous collected via Qualtrics. The respondents could not go back and change their answer |
| Ambiguity about causal direction | Lack of clarity about cause and effect | The respondent was able to freely participate. No cause and effect. |
| Ambiguity in the answer or strength of belief in the answer | Lack of a sense of strength of opinion relative to other topics or questions | The study utilise 7 point Likert scale as studies have shown reliability increases when more points are used (Symonds, 1924) |

Adopted from: Saunder et al, (2019)

### 4.6.4 Common Method Bias (CMB) in Survey Instruments

Common method bias is one of the key sources of measurement error impacting the validity of a study (Podsakoff et al, 2003). Almost every paper that has been written about CMB suggests that detecting CMB is integral as it impacts the relationships between the constructs in the model. Surveys pose a detrimental threat of common method variance and common method bias that affects the validity and reliability of the study (Baumgartner and Weijters, 2012). Moreover, the method bias may appear when both independent and dependant variables are captured by the same response methods affecting the validity (Kock et al, 2021). There is no prescribed solution, as, researchers are still often debating how to deal with CMB (Bagozzi, 2011; Bozionelos and Simmering, 2022; Williams et al, 2010). Common method factors can bias the estimates of the relationships between the many constructs (Podsakoff et al, 2024). The importance of overcoming common method bias is that it affects the integrity and rigour of the results. Podsakoff et al, (2012) offer 26 ways to control CMB, similarly, Baumgartner (1996) complements the work, to add further pre-testing advice, as well as the need to pay attention to careless responses. In order to overcome method bias, Podsakoff et al, (2012) advise to limit questions which make it difficult for the respondent to understand them or demotivate them when trying to answer accurately.  Figure 13 displays the flow of response and barriers which may eliminate responses.

*Figure 13: Response Flow*




Source: Podsakoff et al, (2012)

Podsakoff et al (2012) identified that in the field of marketing, the respondents need to feel motivated and be able to answer the questions accurately.  If they are unable to answer a question, satificating will occur (unwilling to provide an accurate answer).  This causes a problem as the result of CMB will rise.  Satificating conditions include (1) common scale attributes, which were mitigated through giving respondents time for response accuracy, though a Likert scale was present, (2) grouping related items together where questions were minimised, (3) the availability of answers to previous questions were not preset as the software did not allow for this.  The threats to accuracy were eliminated using the advice from figure 14:

*Figure 14: Threats to Accuracy*

| | |
|---|---|
| Lack of Verbal ability | •Adding in Pretest questions<br>•Writing questions in simple terms |
| Lack of experience thinking about the topic | •Selected repondents with Sampling methods, who have used the Amazon App |
| Complex or Abstract Questions | •A definition of AI was stated on the consent page<br>•Simplified questions |
| Item ambiguity | •Clear and concise language used |
| Double-barrelled questions | •No double-barreled questions were used |
| Questions that rely on retrospective recall | •The context was explained at the beginning of the survey.<br>•Only those who had used an Amazon App could enter the survey. |

Source: Podsakoff et al, (2012)

Remedies for factors decreasing motivation, and how they were eliminated:

*Table 7: Mitigation to Motivation*

| **Factor** | **Mitigation** |
|---|---|
| Low personal relevance to the issue | Participation was appreciated and voluntary |
| Low Self efficacy to provide a correct answer | It was empathised that their AI knowledge was not tested, just their personal experience |
| Low need for cognition | Respondents were informed of the research they were participating in, and how important it was for the authors studies |
| Low need for self-expression/ self-disclosure or emotional catharsis | Respondents were told that the authored valued their time and opinion |
| Low feelings of altruism | Respondents were reminded of the importance of their answers to the PhD study. |
| Agreeableness | Participants were told to give honest answers from their own experience to help the study |
| Impulsiveness | Participants were given time and short instructions to reduce quick and impulsive responses |
| Dogmatism, rigidity, or intolerance of ambiguity | Participants were given time to fill out the questionnaire to reduce quick responses |
| Implicit theories | The questionnaire was randomised to limit the answers to be consistent with their theory. |
| Repetitiveness of items | Some items may have seemed repetitive, which is why two questions asked the respondent to tick on agree, demonstrating whether they were actually reading the questions. These were eliminated from the results. |
| Lengthy Scales | On the outset, participant were informed of the timings of the questionnaire. The survey also |

| | |
|---|---|
| | had a progress bar to show how far they have in the survey. The questionnaire had 28 questions which were kept simple and concise. |
| Forced participation | Participants joined voluntarily. No rewards or punishments were given. |
| Presence of an interviewer | The information page told the respondents that their responses will be used for research purposes. |
| Source of the survey disliked | Participants were treated fairly, equally and the survey was anonymised. |
| Contexts that arouse suspicions | The consent page explained the research purpose, how it will be used and who will and how the information will be kept. |
| Measurement conditions that make the consequences of a response salient | Participants were guaranteed anonymity and assured of no “right or wrong” answers |

Source: Podsakoff et al, (2012)

## 4.7 Questionnaire Development in Detail

The questionnaire has been developed using the conceptual model variables described in Chapter 3, which were derived from the literature review in Chapter 2. Table 8 summarises the advantages and disadvantages of using a questionnaire. Next, the Survey measures and scale development questions were articulated from questionnaires from highly ranked journal articles, who have conducted similar studies to find relationships between the variables in the conceptual framework in relation to: (a) attitudes towards AI and brands, and (b) any similarities and differences associated with age. This is best practice as it has already been tested in previous research, thus making the questions effective (Rowley, 2014).

Table 8: Advantages and Disadvantages of Questionnaires

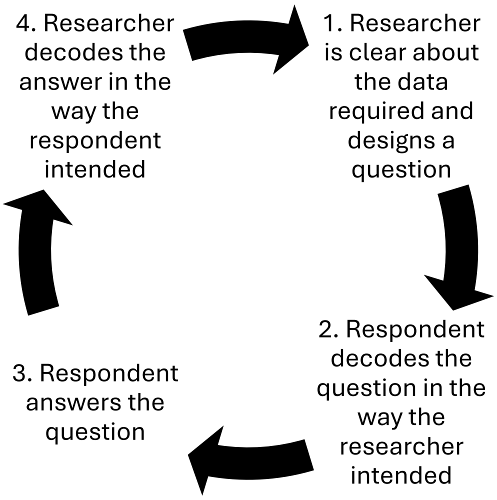
| Advantages | Disadvantages |
|---|---|
| • Valid and reliable - accurate<br>• Quick and easy to fill in<br>• Cheaper and quicker than interviews<br>• Able to validate results quickly<br>• Able to reach large samples<br>• Useful from a wide range of areas<br>• Quick to interpret into statistics | • Linguistic of contextual misunderstandings<br>• Respondents answer carelessly<br>• Depends on researcher assumptions of measure<br>• Researcher sequence of questions<br>• Not in-depth<br>• Inflexible |

Source: Bell et al, (2019); Saunders et al, (2019); Einola and Alvesson, (2020)

### 4.7.1 Questionnaire content

According to Foddy and Foddy (1993), there are four stages that must occur if a question in a questionnaire is to be valid and reliable demonstrated in figure 15.

*Figure 15: Principles to Increase Validity and Reliability in Questionnaires*




Source: Foddy and Foddy (1993)

The questions were structured to ensure they were communicated and encoded by both the researcher and respondents successfully, by using the theoretical principles for constructing interviews and questionnaires, to increase reliability and validity by Foddy and Foddy (1993). Consideration taken to the length of a questionnaire needs to be long enough for suitable data gathering and analysis, yet short enough to ensure the respondent does not get bored and abandon the survey. The questionnaire was self-administered. Although there is a risk of slower response rates or a loss of instructions in self-administered questionnaires, the justification for this is that it saves time, is inexpensive, the purposive group are chosen, and it gives the respondent flexibility to complete when they want to. Another justification is that this completed via Qualtrics online survey software, where respondents feel confident in the software and the researcher is able to collect the information safely. The questionnaire had 10 main categories of question: (1) Consent and information about the survey, (2) Product Knowledge, (3) Brand Innovativeness (4) Amplified Innovation (5) Simplified Innovation (6) Brand Attitude, (7) Brand Loyalty, (8) Social

Norms, (9) PBC and (10) personal (demographics), with 28 questions in total. Questions of the type 2 to 9 above utilise Likert scales.

### 4.7.2 Likert Scales

Likert scales (Likert, 1932) have commonly been used to measure brand attitudes and brand loyalty. According to Malhotra and Birks (2007) Likert scales are easy to comprehend. Likert scales enable the participant responses to be conducted with ease, and less time. It can lower the frustration levels of participants, with providing them with quick "answers", thus reducing response error. The literature suggests 7 point Likert scales are more suited to electronic devices, and the 7 point scale can be used to focus on understanding behaviours (Symonds, 1924; Hair et al, 2012) . According to Hair et al, (2019) Likert scales between point 5-7 are best, if the focus is measuring individual behaviours to measure items. If the scales are less than 5 or higher than 7, they may be deemed less accurate. This study has adopted a 7-point scale. Appendix C exhibits the full questionnaire. The scale items were all anchored on a 7-point scale, "1=strongly disagree, 2=Disagree, 3=Somewhat disagree, 4=Neither agree nor disagree, 5=Somewhat agree, 6=Agree, 7=Strongly agree". The literature review defined the conceptual variables described in Chapter 3; and the measurement items (questions) used for each of the variables were based on, and as appropriate adapted from, previous established research (see below for measurement development).

### 4.7.3 Questionnaire Measurement Items

Based on the theorised conceptual model, nine conceptual or latent variables were identified relating to brands, innovation and product knowledge. Each of these variables need to be evaluated with measures – questions that reflect the conceptual variable and allow it to be evaluated and scored in a quantitative methodology (Sarstedt et al, 2016). The table below displays the questions used in the questionnaire and the established sources from where they were utilised and empirically validated. The wording from established measurement questions in the literature were adapted to apply to the context of the Amazon App and this study. In all cases the measurement questions are part of a reflective measurement model and are Likert scale based. The rationale for choosing Amazon and the Amazon App is set out in the next subsection.

*Table 9: Table to show Measurement scale development*

| Measure | Measurement Item | Adapted from |
|---|---|---|
| General Product Knowledge | PK01. On a scale of 1-7 How knowledgeable are you about Amazon's Artificial Intelligence features on the Amazon App? | (Blair and Innis, 1996) |
| | PK02. On a scale of 1-7 How familiar are you with Amazon's Artificial Intelligence features on the Amazon App? | |
| | PK03 Please rate the relative strength of your knowledge of Amazon's AI features compared to the average consumer from 1-7. | |
| Specific Product Knowledge | PK04 On a scale of 1-7 rate the strength of your awareness of the StyleSnap feature on the Amazon app | (Laroche et al, 2005) |
| | PK05 On a scale of 1-7 rate the strength of your awareness of the Barcode feature on the Amazon app | |
| | PK06 On a scale of 1-7 rate the strength of your awareness of the Image Search feature on the Amazon app (1 being very weak or no awareness, 7 being very strong awareness) | |
| Brand Innovativeness | BI01 Please state the extent to which you agree with the following: "Amazon have introduced technologies that have never been used in online shopping before." | (Pappu and Quester, 2016) |
| | BI02 Please state the extent to which you agree with the following: " Amazon has caused changes to the whole online shopping industry." | |
| | BI03 Please state the extent to which you agree with the following: | |
| Amplified Innovation | AI01 Please state the extent to which you agree with the following: "Amazon introduces Innovations powered by artificial intelligence that let me do things I couldn't do before". | (Hardie et al, 1996) |
| | AI02 Please state the extent to which you agree with the following: "Amazon has created new functionality using artificial intelligence bringing new features and services that previously were unavailable". | |
| | AI03 Please state the extent to which you agree with the following: "Amazon have managed to reinvent their services and deliver different benefits and solutions to me by utilising artificial intelligence". | |
| Simplified Innovation | SI01 Please state the extent to which you agree with the following: "Amazon has been able to use artificial intelligence to help make it easier to use its digital shopping services". | (Hardie et al, 1996) |
| | SI02 Please state the extent to which you agree with the following: "Amazon constantly simplifies its website and app to make it easier to shop using artificial intelligence enabled innovations". | |
| | SI03 Please state the extent to which you agree with the following: "The technology innovations introduced by Amazon and powered by artificial intelligence make it ever easier to work with their apps and websites when shopping and browsing for products". | |
| Brand Attitude | BA01 Rate on a 7-point scale your feelings about Amazon - do you like or dislike Amazon? | (Chattopadhyay and Basu, 1990) |
| Brand Attitude | BA02 Rate on a 7-point scale your attitude towards Amazon - is it favourable or unfavourable? | (Ashill, 2011) |
| Brand Loyalty | BL01 I encourage friends and relatives to shop with Amazon<br>BL02 I say positive things about Amazon to other people | (Nisar and Whitehead, 2016) |

| | | |
|---|---|---|
| | BL03 I intend to shop with Amazon in the next few years<br>BL04 I would recommend Amazon to someone who seeks my advice | (Zeithaml et al, 1996) |
| | BL05 I intend to keep purchasing products from Amazon.<br>BL06 I intend to buy from Amazon the next time I buy online again | (Chaudhuri and Holbrook, 2001) |
| Social Norms | SN01 I believe people important to me would be using Amazon<br>SN02 People I look up to would encourage me to use Amazon<br>SN03 My friends would encourage me to use Amazon | (Fu and Elliott, 2013) |
| PBC | PBC01 Whether I use the Amazon AI is entirely up to me (01)<br>PBC02 Nothing will prevent me from using the Amazon app and its features if I choose to do so<br>PBC03 I believe I have the ability to use the AI Innovation by amazon (SS, Barcode and Image) | (Kidwell and Jewell, 2003) |

Source: Author

*Product Knowledge*

The literature review outlined why Product knowledge has a potential role as a moderator of relationships between product innovation and brand innovativeness, and between brand innovativeness and brand loyalty. The decision was taken to split product knowledge into two types – General product knowledge being knowledge of AI enabled features on the Amazon app without specific examples being mentioned, and Specific product knowledge being knowledge of described actual features (which are enabled by AI). This was to see examine whether knowledge of the actual features and functions driven by AI was a more effective moderator than mere knowledge that AI was in use.

*General PK* - General PK was measured using three items from Blair and Innis (1996) 7-point scale, which originated from Brucks (1985) which explored and confirmed product knowledge as a moderator of brand recall and categorisation of brands by usage situation.

*Specific PK* - Specific PK was evaluated using three items adopted by Laroche et al, (2005) who used a 9-point scale rating the strength of knowledge to be “very weak-very strong” adapted from (Park et al, 1994; Oliver and Bearden, 1983). The three items concerned the ability to use prior knowledge as a moderator to relationships between intangibility and evaluation difficulty concerning retailers, and between evaluation difficulty and perceived risk (the latter being strongly supported). Laroche et al, (2005) suggests that perceived risk is lower with prior knowledge and Zeithaml et al, (1993) add prior knowledge gives a clearer representations which eases evaluation.

*Brand Innovativeness*

Brand innovativeness is to the degree to which consumers perceive a brand to be innovative (Ashill, 2011). Brand innovativeness in this sense refers to the extent to which consumers perceive brands as being able to provide new and useful solutions to their needs (Eisingerich and Rubera, 2010). The construct in this study was measured using original items from Song and Xie (2000) used by Pappu and Quester (2016) who also used this definition to assess whether brand innovativeness affects brand loyalty. They found perceived quality fully mediates the relationship between brand innovativeness and brand loyalty.

Product Innovation

The literature review highlights two key types of product level innovation – amplifying innovation and simplifying innovation. Measures for each category are described below.

*Amplifying Innovation* - Hardie et al (1996:357) define amplifying innovation as “the degree to which an innovation increases what can be done with a product”. The 5-point Likert scale items used by Hardie were adapted to apply to the Amazon brand and the use of AI enabled innovations.

*Simplifying Innovation* - Hardie et al (1996:357) defined simplifying innovation as “the degree to which an innovation makes using a product easier”. The 5-point Likert scale items used by Hardie were adapted to apply to the Amazon brand and the use of AI enabled innovations.

*Brand Attitude*

Brand attitude is defined in this study as a consumer’s overall evaluation of a brand (Wilkie, 1994). To measure Brand Attitude, items from two separate measurement scales were used. The first used by Chattopadhay and Basu (1990) used “like or dislike” to evaluate humour used in advertising. The second used by Boisvert and

Khan (2020) used “favourable or unfavourable to explore attitudes towards service line extensions. Using “favourable” or “like” scales improves understanding attitudes as it commits the responder to voice their opinion to be positive or negative (Davis, 1989). The use of two brand attitude items exercised efficiency to reduce respondent fatigue, and exercise caution not to decrease response rate Bean and Roszkowski (1995). The usage of two items allows for reliability and are sufficient to capture BA as BA has been over-researched and is a clear identifiable valid construct, validating a single or double item construct (Ang and Eisend, 2018). Although limitations of lower internal consistency may occur, mitigations of this included using a pilot test and validation process to ensure the effectiveness of this measure. The two items selected represent brand attitude through favourable/unfavourable, and like/dislike used in literature to establish a consumers overall evaluation of a brand.

*Brand Loyalty*

Brand loyalty is the relationship between relative attitude and repeat patronage (Dick and Basu, 1994). Brand loyalty was measured by questions adapted from three studies to obtain a range of measures. Two questions were adopted from Nisar and Whitehead (2016) who tested if brand loyalty is achieved through social media (measuring behavioural and attitudinal loyalty) and two by Zeithaml (1996) who measured service quality linkages to brand loyalty and purchase intention. Finally, the last two items came from Chaudhari and Holbrook (2001) who adopted their purchase intention loyalty measures from Jacoby and Chestnut (1978) with the intention of investigating brand commitment.

*Social Norms*

Social norms in this study are referred to as the perceived social pressure to perform, or not perform a behaviour. Item scales from Fu and Elliot (2013) were used to measure social norms. The construct were used to measure whether social norms had an impact on product adoption.

*Perceived Behavioural Control (PBC)*

PBC in this study refers to “The perceived ease of performing the behaviour, assumed to reflect past difficulty of performing the behaviour as well as anticipated impediments and obstacles” (Ajzen, 1988:132). PBC is seen as a determinant of intent, and intent is a strong predictor of behaviour (Ajzen, 1988), additionally, Armitage et al, (1999) state that the likelihood of successful performance will alter as a function of the perceived controllability toward performing a particular behaviour. PBC in this study refers to “The perceived ease of performing the behaviour, assumed to reflect past difficulty of performing the behaviour as well as anticipated impediments and obstacles” (Ajzen, 1988:132). A behaviour can be influenced either by internal or external influences, (Kidwell and Jewell, 2003).

PBC internal control encompasses the assessment of utilitarian behaviours, exemplified by actions such as blood donations, alongside hedonic behaviours, such as drug addiction. Distinguishing between these two categories is crucial for a comprehensive understanding of behavioural control. The three measures for PBC were adapted from Kidwell and Jewel (2003), given their focus on both internal and external dimensions.

*Common Method Bias Control Questions (CMB)*

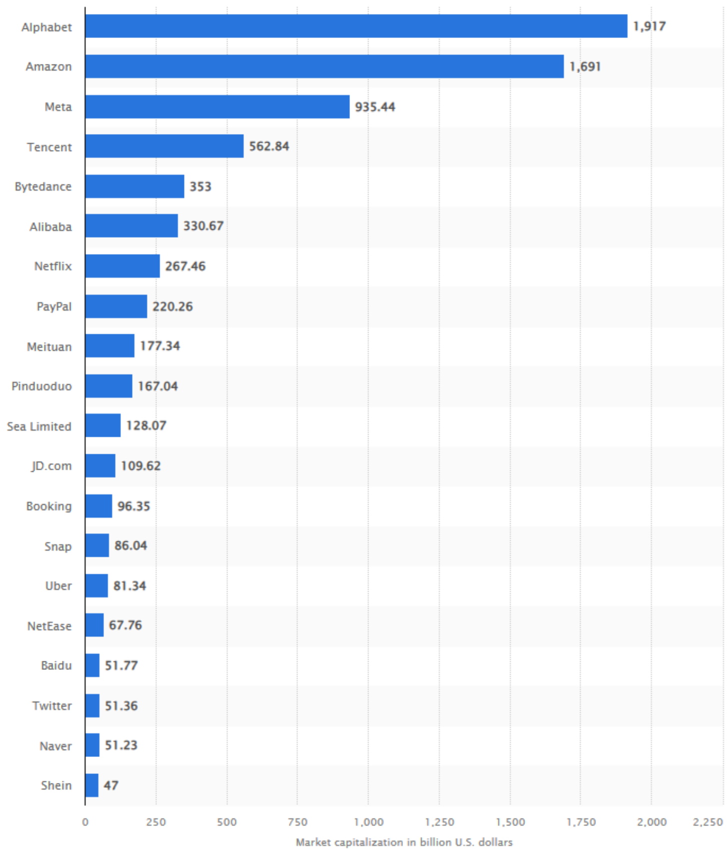
Two questions were added to ensure respondents were carefully reading questions and thinking about their answers. An example is: “Q18 Please carefully read and carry out the following instruction: Please select "Disagree" below”. These can be seen in the questionnaire in the appendices. Any respondent answering these questions incorrectly should be removed from the valid responses due to risks of common method bias in responses.

**4.8 Choice of Brand to Test the Model - Amazon**

Amazon is considered to be one of the most valuable brands in the world, and has high popularity in the UK, being the biggest online marketplace in the UK (Statista, 2023). The brand to be selected was required to be a well-known UK brand, which regularly introduced new innovations and AI enabled features at the time of data collection (to enable maximum participation from the respondents and relevance for the study).

According to Statista (2022), at the time of data collection the largest internet companies in the world are: Alphabet (Google) Amazon, Meta (Facebook and Instagram) Tencent and Byte dance:

*Figure 16: UK Online Brands*




Source: Clement, (2022)

From this data, a table of Ideas for companies to use for this Methodology are available in Appendix A. The UK is selected at the geographical location of the study, as it is the number one in the AI readiness index in Europe and ranked third in the world (Hooson, 2023).

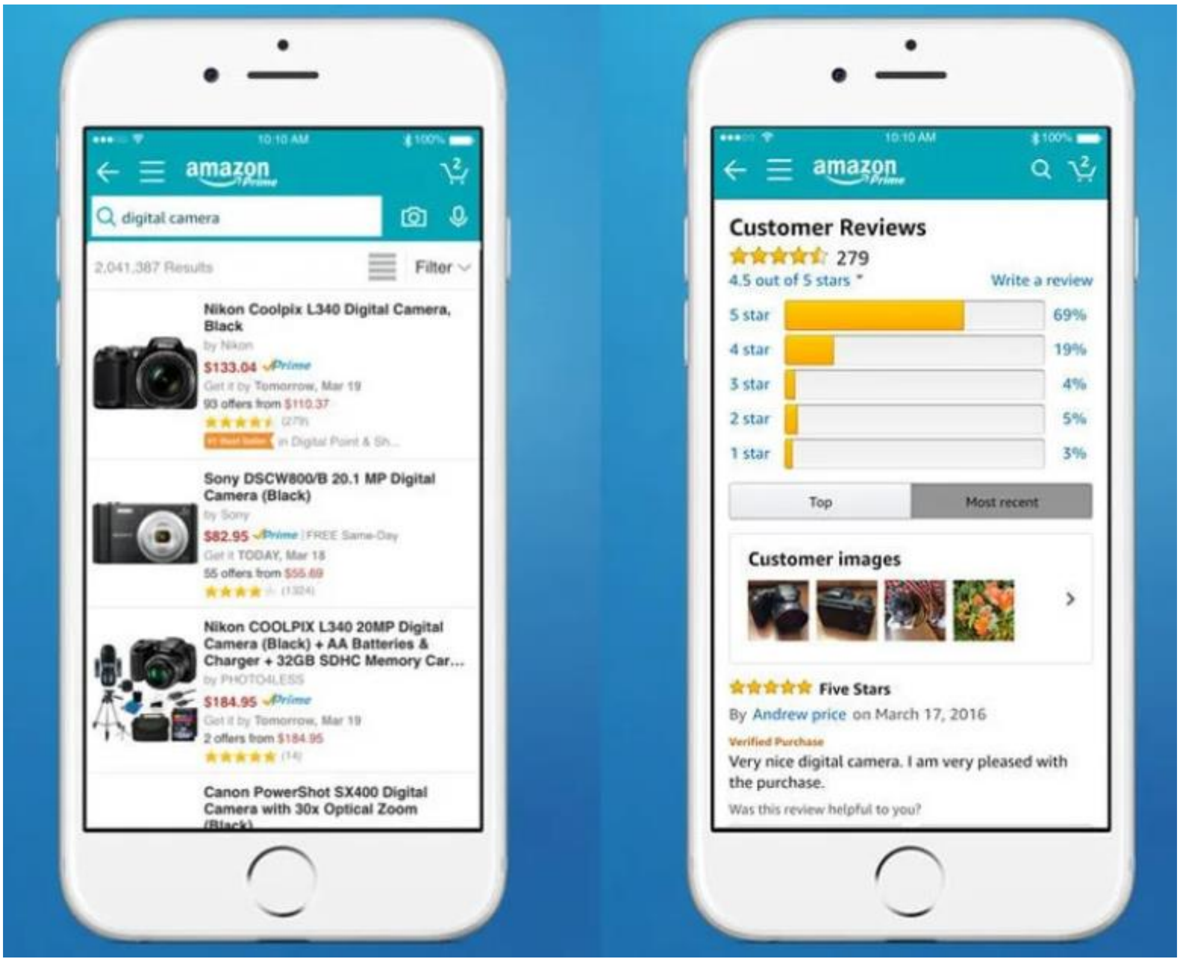
AI innovations range from a selection of areas from healthcare, fashion, computing, banking, social media and entertainment. When deciding from the list in Appendix A, reasons for not using a business is that they may be perceived as too focused on a specific gender, lifestyle or interest. Social media applications, which are heavily used by all genders, ages and backgrounds, were not considered as there is already an extensive body of research on this topic, considered excessive (Li et al, 2023) and introducing unnecessary complexity to the clarity of this study. Both Google and Microsoft were considered in the top three brands for potential selection, however, again all ages may not identify with using Microsoft on a daily basis (especially those over 55,). Although Google and Microsoft are also popular Amazon is the most popular shopping app in the UK (Statista, 2023). With Google, not all respondents may have a Gmail account to use the Google assistant, or the AI text suggestions.

## Mobile Apps

With the rapid growth of Mobile application (App) usage and digitization of engagement via smartphones, businesses are able to offer increased efficiency (Ho and Cheung, 2020). Marketers use branded app to design a brand identity direct onto a consumer's mobile phone or tablet. Branded Apps offer transformational and informational messages, featuring brand related content (Kim et al, 2013). Moreover, studies have demonstrated the impact of repurchase intentions with a brand using an app (Kim et al, 2013). With the development of AI innovations within the App there are many updated AI features to use. The functionalities of an app include; voice recognition, image search, text chatbots, face detection, credit scoring, and text generation to name a few. Moreover, not all mobile apps have the same features, implying their usages are different. A banking app consists of robust safety features with extra security checks relative to a fashion branded app. The Mobile App category has grown in the UK since Apple's inception in 2008, with two major app providers being the Apple store and Google play. A consumer judgement of the quality of an app is based on convenience, loyalty, effectiveness and ease. Bellman, et al (2011) found branded apps to favour Brand attitudes, though, paradoxically reject purchase intentions efficacy. Overall, mobile apps have been known to offer efficiency to consumers.

### 4.8.1 The Amazon App

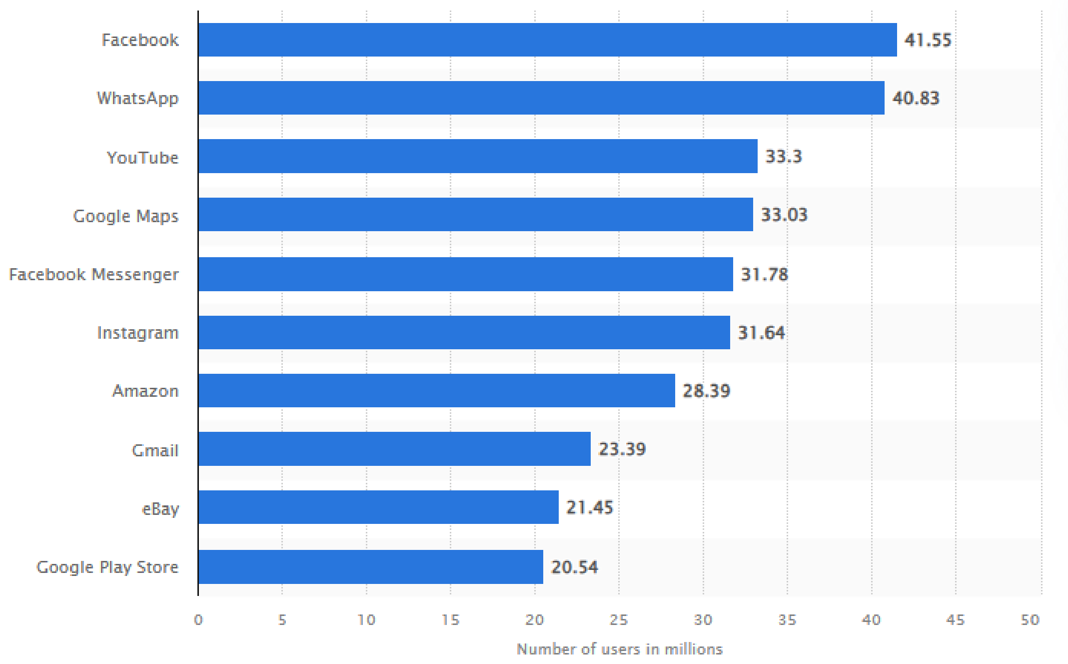
*Figure 17: Amazon App Image*




Source: Amazon (2023)

The established brand is Amazon, proved the most appropriate as it has the most features used by all ages, genders and backgrounds in the UK.  It is deemed the most accessible, popular and identifiable for all the research participants. The participants in the study are asked questions as users of the Amazon App and Amazon Brand. There are over 28m users of the Amazon app in the UK.

*Figure 18: Smartphone App Brands*




Source: Ceci, (2021)

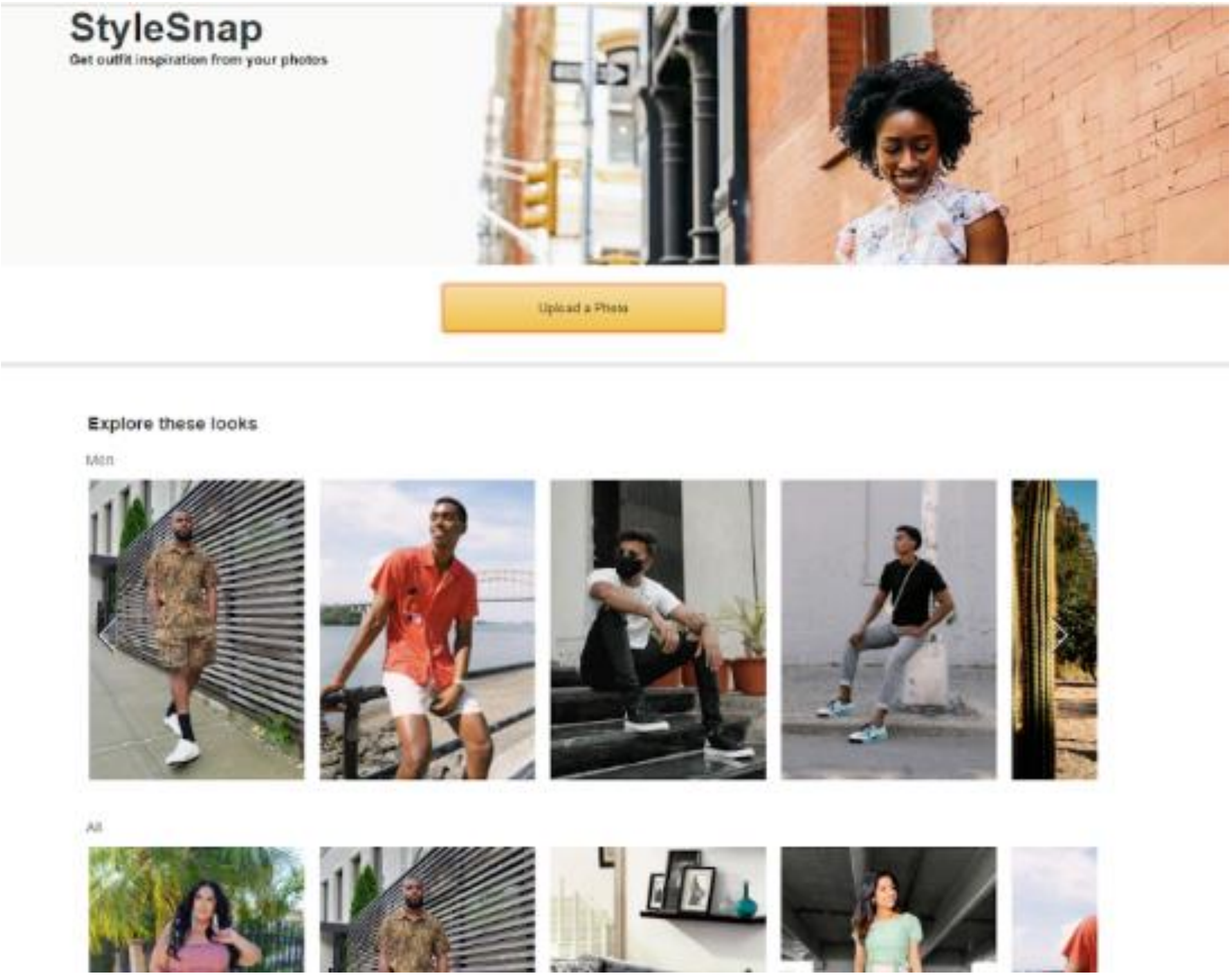
Number of Monthly users of leading smartphone and tablet apps for users in the UK September 2021 (in millions).

The graph above shows that social media apps are commonly used in the UK, after this, Amazon is the most used shopping app in the UK.

### 4.8.2 Specific AI Product Knowledge Features Chosen

The three examples of the AI enabled innovative features from the Amazon App referred to in the questionnaire are as follows:

*Figure 19: Amazon StyleSnap Image*



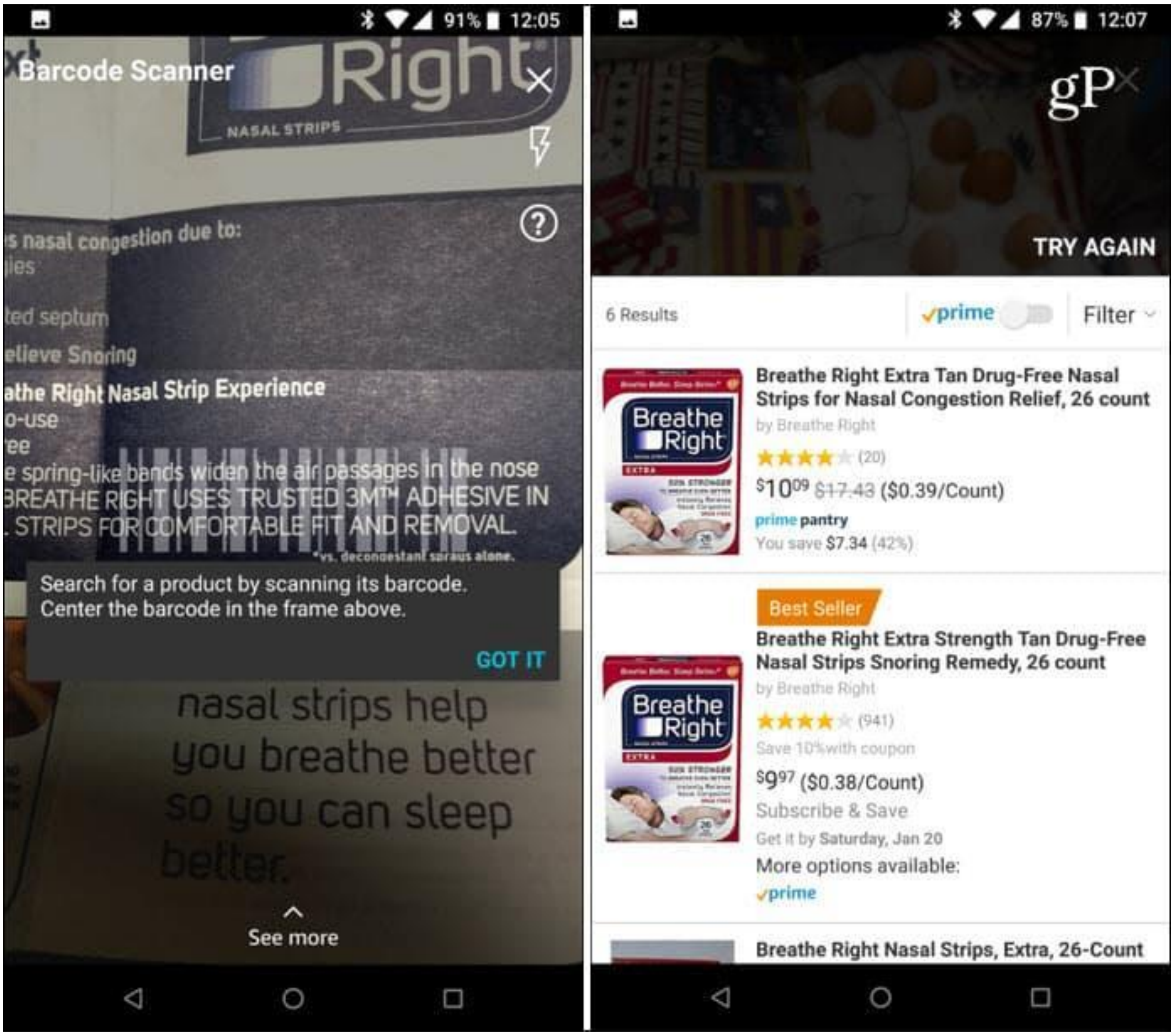

Source: Amazon, (2023)

*Amazon StyleSnap* – An image is taken using a mobile, and the AI algorithms search for similar products, for example where consumers take a photo of the image of mainly fashion and home products, and the AI feature finds similar products using computer vision to search for items relating to the uploaded image.

*Figure 20: Amazon Photo Search Image*


*Amazon Image search* – where consumers take a photo of the image, which is uploaded, and it searches for similar products, which is uploaded, and it searches for similar products.  This visual search engine provides convenience, ease of use, and can be seen as being useful, to save time navigating through websites to search for similar products.

*Figure 21: Amazon Barcode Image*




*Source: Amazon, (2023)*

Using this function users are able to scan the barcode to search for the product for convenience as it takes them straight to the product they are searching for.

By not providing visual aids, participants relied solely on their own knowledge and understanding, which to distinguish between genuine knowledge of the APP and mere recognition of visual cues. The absence of visual aids forced participants to draw upon their actual knowledge rather than relying on visual prompts, which is essential for assessing true understanding. This approach increases the internal validity of the current study by ensuring that responses are based on the accurate measurement of the construct.  This deliberate approach adds methodological rigor to eliminate acquiescence bias.

### 4.9 Pilot Test

A preliminary pilot test refines the questions to ensure validity and reliability of the questioning, as well as ensure they are recorded and answered well.  This analysis can ensure questions are suitable allowing respondents to make suggestions if required (Saunders et al, 2000).  The importance of a pilot study is that it tests the design and type of questions, it assesses the approach to the questionnaire, and ultimately ensure the respondents understand what is expected of them.  For piloting, generally, selecting a small sample size is suitable between 10 to 30 (Luck and Rubin, 1987; Johanson and Brooks, 2010).  According to Bell and Waters (2014) a pilot study aims to ascertain; how long the questionnaire took to complete, clarity of instruction, if any questions were unclear, or they felt uneasy answering, or major topic omissions and any other comments.  The study used a convenience sample of 15 respondents, where the respondents were a mixture of 5 university lecturers, 5 friends and family and 5 undergraduate students, with a 100% response rate.  The survey commenced with obtaining full consent, then four screening questions, as stated in the inclusion sampling criteria.  The participants were excluded from the survey, if they did not agree or consent fully.  The pilot pursued to ensure the questions were comprehensible, concise and timely.  The length of the questionnaire was appropriate, taking under 7 minutes to complete.  The results required a minor amendment as some participants reported difficulties in understanding AI innovations, which included adding the definition of “AI innovations” on the consent page to provide clarity on the meaning of AI Innovations in the context of this survey, and correction to re-order some of the answers.    Overall, the participants responded well and understood the questions.  The insights of the pilot study enhanced reliability and validity of the survey.  The feedback enabled the minor adjustments to the survey to ensure a well-developed data collection instrument was used.

### 4.10 Data Analysis Approach

Quantitative methods of data analysis involve the use of statistical modelling to make sense of the data. Due to the hierarchical nature of the theorised model to be examined as structural equation modelling (SEM) approach to measure the key theoretical variables and test the hypotheses between them is adopted. There are two main types of SEM – covariance based structural equation modelling (CB- SEM) and partial least squares based structural equation modelling (PLS-SEM). PLS-SEM is recommended when the purpose of the research is to investigate or explore theoretical extensions of current theory, where assumptions of normality may not hold (for example where Likert scales are in use for dependent variables as in this research) and the sample size is modest, but the structural model is complicated. It has also been stated that PLS SEM's superior statistical power when compared to CB-SEM permits a more accurate detection of correlations between latent variables (Hair et al, 2019).

With two main types of SEM models, the primary advantages are displayed in Table 10.

*Table 10: PLS-SEM and CB-SEM Differences*

| PLS-SEM | CB-SEM |
|---|---|
| • No assumptions for data distribution<br>• Good for smaller samples<br>• No goodness of fit<br>• Reflective and formative measures<br>• Handles complex models with many constructs<br>• Possible to have nonmetric data and single items | • Rigorous guidelines<br>• Normal distribution is assumed<br>• Necessary to obtain minimum sample size<br>• Goodness of fit criterion required<br>• Just reflective measures<br>• Metric data |

Source: Hair et al, 2014; Hair et al, 2012

Researchers have widely made comparisons with both models, however, it is widely renowned that PLS-SEM provides more flexibility to explore and experiment with a number of configurations for the constructs to be tested (Dash and Paul, 2021). PLS-SEM is good for prediction and explanation of target constructs (Hair et al, 2014:14). The method is argued by scholars to offer analysis between complex interrelationships and constructs (Becker et al, 2023), which is particularly attractive for the conceptual model. The method is increasingly popular in marketing (Guenther et al, 2023) who have developed a detailed checklist for application. In addition to this, in the past ten years, there were 239 PLS-SEM articles in top marketing journals, thus addition to the rigour and popularity of this method. Many models use this method for explanation and prediction oriented (EP) theory while generating practical implications for businesses (Sarstedt and Danks, 2021).

### 4.10.1 Data Collection and Data Screening

With regards to data collection, respondents with any missing data apart from optional demographic data are to be screened out. Suspicious response patterns and outliers were reduced by using common method bias questions, where for example respondents were instructed to tick “disagree” as an answer to a Likert scale question, and those respondents who did not select the instructed answer should also eliminated from the data to reduce common method bias risk.

### 4.10.2 Measurement Model Testing

In structural equation modelling, the structural model describes the relationship between latent variables (such as between Brand Innovativeness and Brand Loyalty), and the measurement model describes the relationship between variables and their measures (such as the relationship between Brand Innovativeness and the 3 questions used to measure it described above) (Hair et al, 2017). In this section we describe the approach to measurement model testing.

As described in the guidelines for choosing a measurement model (Hair et al, 2016), all latent variables in this study use a reflective measurement model, as was the case for the literature they were derived from. In reflective measurement models the indicators (responses to survey questions) are driven by the underlying latent variable.

In order to test the effectiveness of reflective measures, Reliability, Convergent Validity, and Discriminant Validity are three key steps to assess the model in Figure 22.

*Figure 22: Keys steps to assess the model*


Source: Hair et al, (2022)

Assessing a reflective measurement model involves evaluating internal consistency using Cronbach's Alpha and composite reliability scores, then assessing convergent validity using Average Variance Extracted (AVE) scores and indicator reliability, and lastly measuring discriminant validity with HTMT ratios.

**4.10.2.1 Internal Consistency**

Measuring reliability and validity is an essential action to ensure the survey questionnaire is examined using the psychometric properties of acceptable reliable and valid measures (Hair et al, 2006). Testing for reliability reduces bias, enables accurate results and consistent measures, and ensure samples are equal. Reliability evaluates the consistency of a measure as well as a test-retest, where the consistent outcomes are under consistent conditions (Hair et al, 2014). Internal consistency is based on the interrelationships between the indicator variables and assumes that similar indicators are highly correlated on the same construct (Hair et al, 2017). Statistical methods such as split half, the Kuder-Richardson coefficient, alongside Cronbach's Alpha can be considered to measure internal consistency. For the purpose of this study, Cronbach's Alpha is a commonly used test to determine internal consistency.

The formula for Cronbach's Alpha (Cronbach, 1951) is: $\alpha = \frac{N \cdot \bar{c}\_}{\bar{v}+(N-1)\cdot \bar{c}}$

Where:

N = the number of items.
c̄ = average covariance between item-pairs.
v̄ = average variance

The Cronbach's alpha test determines whether the items measure the same characteristic. A value above 0.7 is acceptable. A higher value indicates a greater consistency between the measures.

Composite reliability should be used to assess internal consistency of the measures (which, in the case of PLS, is preferred to Cronbach's alpha) (Hair et al, 2019). This reliability metric accounts for the fact that each indicator variable ($l$) for a construct has a unique outer loading and is defined as follows:

Composite Reliability = ($\sum l$ i)2/ (($\sum l$ i)2 + $\sum$var (ei), (where var(ei) is the variance of the measurement error defined as 1 - $l$ i2.)

Values of between 0.6 and 0.7 are acceptable in exploratory research, and above 0.7 are satisfactory (Hair, 2019).

#### 4.10.2.2 Convergent Validity

Validity here refers to the degree to which a question measures what it intended to measure. Convergent Validity is the extent to which the construct converges and is able to explain the variance of its items (Risher, et al, 2019). Convergent Validity is extent to which a measure relates to other measures of the same phenomenon (Hair et al, 2014). Convergent validity is tested in PLS-SEM using two measures, Average Variance Extracted (AVE) and indicator reliability.

AVE for each latent variable is measured as

AVE = ($\sum l_i^2$ / M) where M = number of measures for the construct.

The AVE should have a value of 0.5 or more indicating that the latent variable construct explains more than half of the movement of values in the measures. (Hair, 2019)

In addition, indicator reliability should be met in order for convergent validity to be achieved (convergent validity meaning measures should correlate positively with each other when measures of a reflective construct). In this regard, generally loadings $l$ should be greater than 0.7, and statistically significant. Loadings less than 0.7 and greater than 0.4 should be removed when their removal is necessary to meet composite reliability or AVE (see below) thresholds. Loadings below 0.4 should always be dropped. (Hair, 2019)

#### 4.10.2.3 Discriminant Validity (DV)

Discriminant validity refers to "each measurement item correlating weakly with all other constructs except for the one to which it is theoretically associated", Gefen and Straub (2005:5). Using the Fornell-Larcker (1981) method to measure the Discriminant Validity (DV) (testing to see if each construct is unique). This is important to assess as it ensures the constructs do not overlap. According to Henseler et al, (2015) discriminant validity using Fornell-Lacker criterion do not always assess DV, therefore, they suggest DV must be addressed using the heterotrait-monotrait ratio (HTMT) of indicator correlations, and a value of less than 0.9 is required.

#### 4.10.2.4 Common Method Bias Testing

A test to confirm the absence of common method bias in the measurement model should be conducted, even where steps have been undertaken to minimise its risk (Podsakoff et al, 2024). A test for common method bias using a random number latent variable as a marker variable and as a predictor of all the latent variables in the model (Kock and Lynn, 2012). The VIF scores for the latent variables should preferably be below 3.3, no larger than 5 for an assumption of no common method bias to hold true (Kock and Lynn, 2012: Kock, 2015).

### 4.10.3 Structural model testing

According to Hair et al (2022), there are five steps to assess the PLS-SEM model results:

*Table 11: 5 Steps to Assess the PLS-SEM Model*

| | |
|---|---|
| **Step 1** | Collinearity Assessment |
| **Step 2** | Significance and relevance of the model relationships |
| **Step 3** | Assess the level of $R^2$ |
| **Step 4** | Assess the level of $f^2$ effect size |
| **Step 5** | Assess CVPAT predictive relevance |

Source: Hair et al (2014)

#### 4.10.3.1 Collinearity assessment

First, collinearity assessment involves looking at each latent variable in the model that other latent variables predict, and examining that group of predictors, to ensure they are not too highly correlated with each other. This is achieved using a VIF test to ensure collinearity is not too high (Hair et al, 2022). To assess collinearity the VIF levels need to be below 5.00 (Hair et al, 2022).

#### 4.10.3.2 Significance and relevance of path coefficients

The subsequent test is to measure the significance and relevance of the structural model relationships. The PLS-SEM algorithm estimates the model relationships in the form of path coefficients that have standardised values falling between -1 and +1, with +1 representing a strong positive relationship and -1 representing a strong negative relationship between constructs (Hair et al, 2022).

The significance of path coefficients can be assessed through use of bootstrapping in PLS SEM, to generate t scores and p values for all path coefficients. In marketing, p values of less than 0.05 typically mean a statistically significant relationship exists between the variables concerned are the path coefficient is statistically significant. (Hair et al, 2017).

#### 4.10.3.3 Evaluating predictive power in the model ($R^2$)

According to Hair et al, (2017), it is important to measure the coefficient of determination ($R^2$) to determine the predictive accuracy of the model. As reliable goodness of fit indices are not available in PLS, $R^2$ is used instead to examine the explanatory power of the model. The $R^2$ explains the variance of the endogenous (predicted) variable explained by the exogenous (predictor) variables. $R^2$ values may vary depending on the research discipline, however in consumer behavioural studies values of 0.2 can be considered as high (Hair et al, 2017). Generally Hair et al, (2017) suggest that in research focusing on marketing issues $R^2$ above 0.75 are substantial, 0.50 moderate and 0.25 weak.

The formula used to calculate $R^2$ is: $$R^2 = 1 - \frac{SSresiduals}{SStotal}$$

#### 4.10.3.4 Effect size

Effect sizes assess the change in $R^2$ for an exogenous variable that occurs when a predictor (endogenous) variable is dropped, hence the importance of a predictor variable in the model (Hair et al, 2017). According to Cohen (1988) the $f^2$ effect size is 0.02 small, 0.15 medium or 0.35 large effect on an endogenous construct. However, recent research in the field by Aguinis (2015) who conducted a literature review revealed the mean effect size to be 0.009 over a span of 30 years. Larger effect sizes indicate a better understanding of a phenomenon (Bosco, 2015).

The formula for $f^2$ is: $$f^2 = \frac{R^2\ included - R^2\ excluded}{1 - R^2\ included}$$

#### 4.10.3.5 Predictive relevance (CVPAT)

The final examination of the structural model assessment allows for evaluation and testing of the predictive capabilities of the model. This can be d

one using the Cross Validated Predictive Ability test (CVPAT) (Hair et al, 2022). CVPAT, developed by Liengaard et al, (2021) and Sharma et al, (2022) uses prediction error or average loss as its basis for analysis. For prediction-based model assessment, this average loss value is compared to the average loss value of a prediction using indicator averages (IA) as a simple benchmark and the average loss value of a linear model (LM) forecast as a more conservative benchmark. The model's average loss should be lower than the average loss of the benchmarks which is expressed by a negative difference in the average loss values. This average loss difference should be significant at a p value of 0.05 for the model to demonstrate predictive power (Ringle, 2024). Using the CVPAT reduces the generalisability error of the model and is commended for marketing scholars to strengthen prediction orientated models (Sharma et al, 2022). Predictive modelling is important to constructing theory as well as generalising approaches or policies for commercial uses (Shmueli et al, 2016; Ruddock, 2017).

### 4.10.4 Summary of Measures

Table 12 summarises the required tests and performance measures for the measurement and structural model.

*Table 12: Summary of Measures*

| CMB Test | Purpose/Analysis | Value | Reference |
|---|---|---|---|
| Common Method Bias Questions | Avoid bias in the construction of the measurement approach. | VIF <3.3 or 5 | Kock and Lynn, (2012) |
| **Reliability Tests:** | | | |
| Composite Reliability | Measure are internally consistent | Composite Reliability scores >0.7 (Higher than 0.6 for exploratory research) | Hair et al, (2022) |
| Indicator Reliability | Measures are valid indicators of the latent variable | Outer loadings >0.7 (or >.4 and their removal causes failure of composite reliability or convergent validity tests) | Hair et al, (2022) |
| **Validity Tests:** | | | |
| Convergent Validity | The measure correlate with one and another. | AVE > 0.5 | Hair et al, (2022) |
| Discriminant Validity / HTMT | Ensuring the constructs are distinct from each other | <0.90 | Hair et al, (2022) |
| **Structural Model Tests:** | | | |
| Collinearity Assessment - VIF | Ensure constructs are not too highly correlated with each other | VIF < 5 | Hair et al, (2022) |
| Path Coefficients | Path coefficients are statistically significant | P <0.05 | Hair et al, (2022) |
| $R^2$ | Amount of variance explained in the predicted variable by the model | $R^2$ is of a meaningful value, preferably over 0.2 | Hair et al, (2022) |

| | | | |
|---|---|---|---|
| $F^2$ | Effect size – impact on $R^2$ of removing a predictor variable | Greater than 0.02 | Hair et al, (2022) |
| CVPAT | Assesses the predictive relevance of the model | P value <0.05 | Hair et al, (2022) |

## 4.11 Mediation Analysis

*Specific Indirect Effects*

Mediation analysis begins by looking at the significance of specific indirect pathways by which one latent variable indirectly has a causal effect on another latent variable. This can be seen in terms of Specific Indirect effects in the PLS output. (Hair et al, 2017).

## 4.12 Age Group Analysis and MICOM

**Multigroup analysis (MGA)**

To evaluate and investigate whether there are differences in the model relationships between age groups, a multigroup analysis is tested. According to Henseler et al, (2016), before proceeding to perform the multigroup analysis, it is necessary to perform a MICOM analysis. The objective of the MICOM analysis is to confirm that any differences between the two groups are, in fact, due to differences between the structural model and not due to differences in the measurement model (Henseler et al, 2016).

MICOM is a three-stage process that includes: (1) configuration invariance (Step 1); (2) compositional invariance (Step 2); (3) the equality of composite mean values and variances (Steps 3a and 3b) (Henseler et al, 2016).

*Configural invariance*

Configural invariance consists of a qualitative assessment of the composites' (constructs) specification across all the groups. Specifically, the following criteria must be fulfilled:

- Identical indicators per measurement model: each measurement model must employ the same indicators across the groups.
- The indicators' data treatment must be identical across all the groups, which includes the coding (e.g. dummy coding), reverse coding, and other forms of re-coding, as well as the data handling (e.g. standardisation or missing value treatment). Outliers should be detected and treated similarly.
- Identical algorithm settings or optimization criteria: group-specific model estimations should not result from dissimilar algorithm settings.

Source: Henseler et al, (2016)

*Compositional Invariance*

Compositional invariance is established when the scores of a composite variable using the weights of one group do not differ from those created using the weights of another group. Therefore, to verify composite invariance, it is necessary to examine the correlation between scores of each latent variable, using permutation approach and testing that correlation between groups is not significantly different from 1 using permutation analysis (similar to bootstrapping). This is the case when the p value is insignificant (greater than 0.05).

If it cannot be established for all variables then either:

1. A revised model excluding the variables that do not have compositional invariance can be created and retested via group analysis, or
2. Each group can be analysed separately and multi-group analysis ignored.

(Hair et al, 2024)

*Equality of means and variances*

Examination of the equality of means, and, subsequently, the equality of variances of latent variables, is the final test It should be noted that failure of this test does not prevent multi-group analysis, but means that pooled data analysis is not possible. Again meeting this test requires the p value to be insignificant (greater than 0.05) (Henseler et al, 2016).

### 4.13 Sampling Strategy

#### 4.13.1 Sample Size

The size of the sample determines the statistical power, generalisability and reliability of the data. A sample is a portion of the population chosen to represent the whole population. In order to approximate the sample size, the data analysis method using Partial Least Squares-Structural Equation Modelling (PLS-SEM) theory is used to calculate the number. According to Hair et al (2014) PLS-SEM has higher levels of statistical power with smaller sample sizes, thus using PLS-SEM for this study is a good choice (Reinartz et al, 2009). According to Barclay et al (1995) the general rule of thumb, the sample size is required to be 10x the maximum number of arrowheads pointing at a latent variable anywhere in the PLS path model (Hair et al, 2014). Building on Cohens (1998;1992) seminal work on power tables, the R-squared method provides a framework to calculate the number of independent variables in a regression model. The present study has a maximum of 6 placed in a single variable, implying the model requires a minimum R square of 0.10 at 5% to achieved 80% statistical significance power. A necessary sample of 130 responses are requires. The sample size is comfortably over this threshold. As recommended by Hair et al (2014), the Cohen power table approach is appropriate to this study, consequently, the sample size is adequate for the study as a sample size of 209 respondents was achieved.

#### 4.13.2 Sampling

In the present context of the study the data collected from a purposive sample is suited to the data collection method. Sampling is used to select a group to represent the total population. When choosing a sample, the main types are probability and non-probability sampling (Bell et al, 2019). Non-Probability sampling (Table 13) is the most suited as the target population are required to have certain characteristics. If probability sample were chosen, there is a risk of a low response rate or of impractical time and cost in finding a truly randomly selected sample who use the Amazon App.

*Table 13: Probability Sampling Types*

| Non-Probability Sampling | Description |
|---|---|
| Convenience Sampling | Selecting readily available respondents |
| Quota Sampling | Sample represents target population within strata of variable of the target population. |
| Purposive Sampling | Selecting cases to best answer the research questions |
| Snowball Sampling | Participant volunteer to research, then they identify further participants interested in participating |

Source: Saunders et al, (2019) and Bell, (2019)

Purposive sampling refers to the researcher selecting sample members to conform to the criterion set (Cooper and Schindler, 2014). With a clear inclusion criterion (refer to Table 14) purposive sampling was used to screen respondents with criterial to fulfil and ensure the respondents conform to the survey with informed knowledge. For this study, purposive samples were sought, as the target population were readily available to the researcher, which makes the respondents more relevant, in order to meet the research objectives. Purposive sampling offers richer data to be observed as the participants have clear inclusion criteria based on their knowledge or experience of AI innovations within the Amazon App.

### 4.13.3 Sampling Frame

A sampling frame is a critical part of the sampling process (Cochran, 1977). The target population defined for this project are participants (See table 14) who use the Amazon app, aged over 18, without any barriers to communication such as English, without an impairment or disability and are happy to consent to part-take in the study. The exclusion of people with disabilities from the survey was a deliberate methodological choice aimed at protecting vulnerable populations from potential research-related stress or harm. The MMU ethical guidelines require special considerations for approval of people from vulnerable groups. Those with disabilities may also require special accommodations within the Amazon App which the researcher does not have access to, additionally, the use of the App by disabled users may alter the standardisation of the survey, meaning the consistency of the results were higher.

*Table 14: Inclusion and Exclusion Criteria for Purposive Sampling*

| **Inclusion Criteria** | **Exclusion Criteria** |
|---|---|
| Have an Amazon App | Do not have an App |
| Aged over 18 | Under 18 |
| Have no disabilities | Disabled |
| Able to speak English | Unable to communicate in English |
| | Does not consent /want to participate |

Source: Author

To ensure this, consent questions were asked before participation. If they did not meet the frame, they were automatically removed. Using non-probability sampling ensures the audience has a sample within the pool of participants and can reduce sample bias through representation of the population. Using purposive convenience sampling to gain over 200 respondents in a cross-sectional study is a practical solution to fulfilling data collection to explore and examine all the research objectives and questions.

### 4.13.4 Age groups

Age based segmentation have been an important variable for marketers (Wolf, 1990; Zeithaml, 1985). In particular, the concept of brand innovativeness and age, Helm and Landschulze (2011) found researchers have discovered age to be positively associated with innovativeness, whereas others found age to be slightly negatively associated or even strongly negatively associated. Their study on FMCG found age differences in consumer behaviour do exist, however the experiment has not been undertaken on AI innovations. Age has been a demographic with research attention. The assumptions of older consumers have declining information processing and adoption (Homburg and Giering, 2001), is of interest to researchers.

In comparison to income, Age is accessible and discoverable.  The most accessible to the researcher is to use participants aged over 18.

#### 4.13.5 Data Distribution

Following Rowley's (2014) guidance on distributing questionnaires, the look of the welcome screen and presentation of questions were portrayed in a professional manner, through data collected via online survey portal Qualtrics (Qualtrics, 2023). This ensures the participant felt comfortable with using an established professional website, as well as remaining anonymous. Qualtrics is mobile optimized, which makes it easier for respondents to participate in the survey.  The design and data management are collected by the company which is used and approved by MMU. The survey link and QR code was sent via the researcher's social media contacts via LinkedIn (Appendix B), as well as face to face to university staff and students, and also using the online survey panel Prolific.  Additionally, the QR code was distributed face to face at conferences and poster presentations. The total number of respondents from networking were 433.  The 69 Prolific users earned 60p per survey with 5 minutes on average, thus making it fast and trackable.  The survey filter asked if they shopped online using Amazon, then they were able to use the survey with their ID.  Those who did not pass the consent questions were excluded from the survey.  To ensure there was no sample bias from Prolific users, the specific respondents from the UK and Amazon Users (purposive sampling to use the target population) were pre-screened and on the Prolific website.  The use of Prolific leveraged increased participation numbers of the sample.  Prolific is commonly used in empirical research.  Quality control measures included attention checks reducing common methods bias, and speed detection which also were encompassed through CMB questions eliminating the unthoughtful participants.  Clear instructions of participation and sample usage were removed if they did not comply, for example, "do you have the amazon app?", if the answer was "no" it ended the survey.

### 4.14 Ethical and Data Protection Issues

Ethics reflect the standards of the researchers behaviours in relations of those who are part of the research project (Saunders et al, 2019). The research has pointed out, ethical considerations are important for all researchers involved with the integrity of the research subjects and how they are treated, fairly and equally. Ethical considerations are valuable to a study and should be considered seriously (Maylor et al, 2017). Ethical approval gained from Manchester Metropolitan University's Ethics committee offered a guarantee in research compliance aligning with the research code of ethics. This rigorous process involved providing information on the organisation of the management of data, consent form creating and managing the data online via Qualtrics.

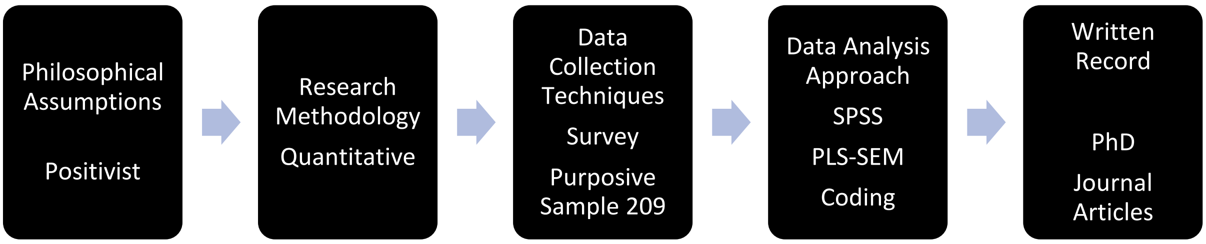
The research avoided conflicts of interest, with approval gained before the commencement of data collection. All participants were informed of the nature of the research and participated voluntarily. To avoid issues of deception, and offer transparency to participants, the questionnaire commences with a consent information sheet with advice on confidentiality, participant anonymity, also indication of the withdrawal process. The respondents were obliged to acknowledge the consent and information boxes to ensure they have read the consent to the conditions. Upon launch of the design instrument, participants were informed as to where and how their data will be saved and used is provided. This assured participants of how their data was to be handled and stored responsibly. In addition to this, to ensure unbiased results; the survey questions were carefully structured using established measures and Likert scales. Moreover, all participants were provided with a university contact email of the researcher and the supervisor at MMU allowing them further reassurance, for the right to withdraw or decline at any time in this research.

### 4.15 Limitations

The methodological approach to this study has a few limiting factors. The focus of using the brand Amazon, may be seen to limit the population sample as not all respondents had used the brand. However, with the use of a purposive sample, this ensured respondents who participated did so with honest replies. Additionally, geographically, with the use of a UK focus could be seen to reduce the sample size, however, it ensured the purposive group was generalised. The length of the survey may have impeded the opportunity to obtain a larger sample. However, a cross-sectional survey ensures a wider population is sought. A shortfall of literature and prior studies specifically on AI innovations on product knowledge may be seen as a limitation, as there are no measures in place, though, this can be interpreted as a strength and major contribution to the literature in this field.

### 4.16 Summary of Methodology

*Figure 23: Research Design*




Source: Author, Adapted to this study (Myers, 2020)

The purpose of the study is to explore the variables on conceptual model derived from the literature review. Therefore, this methodology is the correct fit for this project, in order to test the theory and develop hypothesis, using deductive reasoning to explain the casual relationships in the model. The confluence of the positivist approach which offers objectivity and measurable outcomes, together with quantitative surveys, collaborates well, in order to ensure the research aims and objectives are met. The questionnaire was developed in a 7-point Likert scale format, with measures from previous high-ranking journals. The using purposive convenience sampling of over 200 was collected using social media and researcher networks, to ensure the data were fulfilled. Data analysis was using Qualtrics, SPSS and SEM-PLS on SmartPLS software. Data were measured using values which met criteria from previous established research. Finally, ethical issues were considered, and ethical approval was met from MMU.

### 4.17 Chapter Summary

Initially, the chapter reviewed the research objectives and aims. Following this the philosophy of positivism was adopted to offer an objective approach to the task. The methodology was discussed, with the survey method being used for optimum results. The questionnaire used 7-point Likert scales which was sent to a purposive sample who had to have used the Amazon App which is the justified brand of choice. The Amazon app is the most suitable as it has both amplifying and simplifying features and is one of the most popular Apps in the UK. Measurement scale items were presented and adapted from the pertinent literature. Concerns about reliability, validity and CMB were addressed and mitigated. Ethical considerations were examined. Next, the pilot study were sent to 15 participants. The results from the pretest indicated good understanding of the questions. Finally, the chapter concluded with limitations. The next chapter discusses the quantitative data analysis, presenting the results of the survey.

# Chapter 5

# Data Analysis

## 5.1 Introduction

Following the methodology chapter which highlighted the methods most appropriate to meet the needs of the research aims, this data analysis chapter examines the data collected from the survey utilising SPSS statistical software (SPSS 15) and PLS-structural equation software (SMARTPLS 4). Ultimately the model suggested from the conceptual framework, established from the literature, is empirically tested.

Firstly, the data was summarised and screened using SPSS software, to understand demographic aspects of the data, screen for missing values and outliers, and check for normality (though this is not essential for successful PLS-SEM modelling as described in the methodology chapter. Secondly, the measurement model is examined in accordance with the approach and tests set out in the methodology chapter utilising SMARTPLS PLS-SEM software. Next, the structural model and hypotheses are examined, again in accordance with the approach and tests set out in the methodology chapter utilising SMARTPLS PLS-SEM software. Finally, the chapter ends with a summary of the key findings from data analysis.

## 5.2 Data Summarisation and Screening

In this section data screening for incomplete or unreliable respondents, missing values, outliers are discussed. Next the data is examined for normality. Finally, the demographic characteristics of the retained sample are described.

### 5.2.1 Data Screening

From a total of 532 responses, the data were cleaned and resulted in 209 error-free samples to use in this study. As outlined earlier, the data must be checked and cleaned for missing data, errors, outliers and suspicious patterns in the data in multivariate analysis (Hair et al, 2006). Any respondents with missing data (apart from optional demographic data) were excluded from the final sample.

The low response rate in from 532 to 209 can be attributed to the implementation of common method bias (CMB) questions. This approach, while improving data quality, also reduced the number of invalid responses. CMB questions are designed to detect and eliminate careless or patterned responses, as they are there to ensure participants are reading and comprehending the questions before answering (Podsakoff et al, 2012). The respondents who answered pattern questions and did not respond correctly (For example, tick "disagree") were eliminated, as it suggested that participants were not fully engaged with considering the questions before their final answer. This reduced the overall responses, whilst increasing the reliability of the data. The remaining data used leads to clearer and accurate results eliminating the statistical noise. The quality of the responses leads to stronger and accurate representation of conclusions (Podsakoff et al, 2012). Ethically, genuine participant output is all that remains in the data.

According to Podsakoff et al (2003), the design of the procedures and statistical controls can reduce common methods bias, however it is difficult to fully eliminate. Suspicious response patterns were controlled for using common method bias questions as described in the methodology chapter. Where respondents answered the common method bias control questions incorrectly, those respondents were excluded from the final sample. A review of the data identified 132 responses that were invalid due to incorrect common method bias questions.

In relation to outliers, due to the use of Likert scale questions, no outliers outside the fixed Likert scale range of 1 to 7 were identified, and no deletions of outliers were required.

### 5.2.2 Normality

PLS-SEM analysis is a non-parametric test that does not require normal distribution of data (Hair et al, 2019). However, it is recommended to check for normality to prevent skewed data issues (Hair et al, 2017). Though, according to Vailthinglam et al, (2024) only 1 in 10 business studies articles (between 2016 and 2021) assessed normality of their data. The variables in the present study were tested for skewness and kurtosis to be in the rage of +/-1 (Leech and Onwuegbuzie, 2002). The model demonstrated all the variables to be within this range, thus passing the robustness check, with normally distributed variables.

### 5.2.3 Demographic Analysis

The total number of respondents retained after the above steps was 209. Not all respondents answered all demographic questions, which were optional. The age, income, employment, education and ethnicity of respondents are shown in table 15. The respondents in the age category of 18-34 were predominate in this sample with 77.5%. Over 34's reported with only 22.5% responses. This distribution of age may result in age-bias when interpreting the results. The total amount of respondents willing to share their age were 209. The total response for income, education and employment was 201, with most responses (58%) earning less than £30,000. There were 25 responses (12%) which earned £30,000 – £50,000, although 49 people left the answer blank and 41 people (22%) preferred not to share their income. 22% of people work full-time and 17% people part-time. When asked about their education there was an even distribution of highest qualification with 25% school leavers, 34% undergraduates and 32% postgraduate students. This demonstrates that most respondents are university educated. When asked about ethnicity, less people were willing to share this data. Only 172 people out of 209 were willing to share. This optional information was left open, with no categories, for the respondent to fill in their ethnicity. The figure of the dominant ethnicity to be 34% British Asian respondents compared to 32% white respondents, clearly does not represent the UK population, as the data from the Office of national statistics has presented 74.4% of the UK population as white (Garlick, 2022). This highlights potential bias of answers not fully representing the UK population.

*Table 15: Demographic Response Data*

| Age | Respondents Characteristics | Total % | Overall Total Responses |
|---|---|---|---|
| | 18-34 | 77.5 | ***209*** |
| | 35+ | 22.5 | |
| **Income (£)** | Less than 30,000 | 58 | ***201*** |
| | 30,000 – 50,000 | 12 | |
| | 50,000 – 70,000 | 5 | |
| | 70,000+ | 3 | |
| | Prefer not to say | 22 | |
| **Type of Employment** | Full-time | 26 | ***207*** |
| | Part-time | 17 | |
| | Self-employed | 3 | |
| | Student | 43 | |
| | Unemployed | 6 | |
| | Other | 1 | |
| | Prefer not to say | 4 | |
| **Education Level** | School | 25 | ***207*** |
| | Undergraduate | 34 | |
| | Postgraduate | 32 | |
| | PhD | 5 | |
| | Prefer not to say | 4 | |
| **Ethnicity** | Asian | 12 | ***172*** |
| | Black | 9 | |
| | British | 5 | |
| | British Asian | 34 | |
| | Humanity Respected | 0.5 | |
| | Mixed | 5 | |
| | European | 2.5 | |
| | White | 32 | |

### 5.3 Reflective Measurement Model Examination

The reflective measurement model is examined to ensure the measurement questions in the survey properly reflect (or measure) the main variables in the theoretical (structural) model. The relevant tests were described in the methodology chapter and are examined in three stages being internal consistency and convergent reliability, discriminant validity and finally common method bias.

#### 5.3.1 Internal Consistency and Convergent Reliability

As discussed in the methodology chapter, assessing a reflective measurement model involves evaluating internal consistency using Cronbach's Alpha and composite reliability scores, then assessing convergent validity using Average Variance Extracted (AVE) scores and indicator reliability.

The Cronbach Alpha, composite reliability and AVE scores are examined for each latent variable in Table 16 below. The Cronbach alpha for Perceived Behavioural Control is low at 0.58, but the test for composite reliability is met at 0.78, and all other values are greater than 0.7, so internal consistency is achieved.

All AVE scores exceed the minimum value of 0.5, so the first test for convergent validity is met. In Table 16 below, the loadings of indicators are shown, and all loadings exceed 0.7, showing that test of convergent validity is met.

*Table 16: Measurement Model Internal Consistency and AVE values*

| | **Cronbach's alpha** | **Composite reliability (rho_c)** | **Average variance extracted (AVE)** |
|---|---|---|---|
| **AI** | 0.84 | 0.9 | 0.75 |
| **BA** | 0.89 | 0.95 | 0.90 |
| **BI** | 0.73 | 0.84 | 0.63 |
| **BL** | 0.9 | 0.93 | 0.68 |
| **PBC** | 0.58 | 0.78 | 0.55 |
| **GAIPK** | 0.92 | 0.95 | 0.86 |
| **SAIPK** | 0.82 | 0.89 | 0.73 |
| **SI** | 0.85 | 0.91 | 0.77 |
| **SN** | 0.81 | 0.89 | 0.72 |

All measurement loadings exceed 0.7, with the exception of two items in bold that exceed 0.6. The removal of these is not necessary to improve internal consistency or AVE scores above the required threshold, so they are retained (Hair, 2019).

Table 17: Measurement Model Indicator Loadings

Outer loadings

Mean, STDEV, T values, p values

| | Outer Loadings | Standard deviation | T statistics | P values |
|---|---|---|---|---|
| AI1 <- AI | 0.87 | 0.03 | 34.52 | 0.00 |
| AI2 <- AI | 0.90 | 0.02 | 49.49 | 0.00 |
| AI3 <- AI | 0.84 | 0.03 | 29.77 | 0.00 |
| BA1 <- BA | 0.95 | 0.01 | 115.79 | 0.00 |
| BA2 <- BA | 0.95 | 0.01 | 97.73 | 0.00 |
| BI1 <- BI | 0.79 | 0.04 | 19.68 | 0.00 |
| BI2 <- BI | 0.67 | 0.09 | 7.56 | 0.00 |
| BI3 <- BI | 0.91 | 0.02 | 56.79 | 0.00 |
| BL1 <- BL | 0.84 | 0.02 | 34.41 | 0.00 |
| BL2 <- BL | 0.85 | 0.02 | 36.56 | 0.00 |
| BL3 <- BL | 0.71 | 0.06 | 11.29 | 0.00 |
| BL4 <- BL | 0.89 | 0.02 | 43.74 | 0.00 |
| BL5 <- BL | 0.85 | 0.03 | 31.57 | 0.00 |
| BL6 <- BL | 0.79 | 0.04 | 21.67 | 0.00 |
| PBC1 <- PBC | 0.84 | 0.05 | 16.27 | 0.00 |
| PBC2 <- PBC | 0.75 | 0.11 | 6.81 | 0.00 |
| PBC3 <- PBC | 0.61 | 0.14 | 4.34 | 0.00 |
| PK1 <- PK | 0.95 | 0.05 | 19.13 | 0.00 |
| PK2 <- PK | 0.95 | 0.04 | 21.53 | 0.00 |
| PK3 <- PK | 0.87 | 0.07 | 11.75 | 0.00 |
| PK4 <- PKDetail | 0.84 | 0.05 | 18.02 | 0.00 |
| PK5 <- PKDetail | 0.88 | 0.03 | 27.80 | 0.00 |
| PK6 <- PKDetail | 0.84 | 0.04 | 18.83 | 0.00 |
| SI1 <- SI | 0.87 | 0.02 | 37.19 | 0.00 |
| SI2 <- SI | 0.86 | 0.03 | 31.63 | 0.00 |
| SI3 <- SI | 0.91 | 0.02 | 52.25 | 0.00 |
| SN1 <- SN | 0.74 | 0.06 | 12.33 | 0.00 |
| SN2 <- SN | 0.91 | 0.02 | 53.73 | 0.00 |
| SN3 <- SN | 0.90 | 0.02 | 47.52 | 0.00 |

### 5.3.2 Discriminant Validity (DV)

Discriminant validity can be assessed using either Fornell-Larker or HTMT criteria, however according to (Henseler et al, 2015) Fornell-Larker criterion does not always correctly assess DV in PLS-SEM modelling, therefore, they suggest DV must be addressed using the heterotrait-monotrait ratio (HTMT) of indicator correlations, and a value of less than 0.9 is required.

Table 18 displays the HTMT Values for the measurement model.  The HTMT values are all below 0.90 demonstrating that discriminant validity for reflective measurements is established.

Table 18: HTMT Matrix

| | **AI** | **BA** | **BI** | **BL** | **PBC** | **GAIPK** | **SAIPK** | **SI** |
|---|---|---|---|---|---|---|---|---|
| **AI** | | | | | | | | |
| **BA** | 0.32 | | | | | | | |
| **BI** | 0.72 | 0.23 | | | | | | |
| **BL** | 0.38 | 0.86 | 0.4 | | | | | |
| **PBC** | 0.3 | 0.34 | 0.3 | 0.45 | | | | |
| **GAIPK** | 0.52 | 0.15 | 0.26 | 0.21 | 0.22 | | | |
| **SAIPK** | 0.52 | 0.22 | 0.3 | 0.23 | 0.3 | 0.72 | | |
| **SI** | 0.86 | 0.39 | 0.66 | 0.39 | 0.37 | 0.43 | 0.45 | |
| **SN** | 0.3 | 0.4 | 0.29 | 0.65 | 0.43 | 0.11 | 0.17 | 0.33 |

### 5.3.3 Common Method Bias Test

In line with the approach described in the methodology chapter, the Kock et al, (2012) test was conducted using a random number variable. The resultant VIF scores are summarised in Table 19. All values fall below 3.3, with the exception of a single item – BL or Brand Loyalty scoring 3.87. This falls comfortably below the wider test of values less than 5 and so no common method bias is assumed. This validates the use of common method bias questions in 4.7.3.

*Table 19: Common Method Bias Test*

| **Path** | **VIF** |
|---|---:|
| AI -> Random | 2.67 |
| BA -> Random | 2.93 |
| BI -> Random | 1.86 |
| BL -> Random | **3.87** |
| PBC -> Random | 1.20 |
| GAIPK -> Random | 1.87 |
| **SAIPK** -> Random | 1.76 |
| SI -> Random | 2.54 |
| SN -> Random | 1.56 |

In line with the above, the measurement model tests were all passed (with reference to attention checks discussed in methodology), and below examination of the structural model is described. Whilst all was done to prevent CMB (see methodology), the attention checks ensured there any CMB was passed before structural model assessments.

### 5.4 Structural Model assessment

In line with the methodology chapter, the structural model is assessed below in 5 stages being collinearity assessment, assess the significance and relevance of the model relationships, assess the level of $R^2$, assess the level of $f^2$ effect size, and assess CVPAT predictive relevance.

#### 5.4.1 Collinearity Assessment

Collinearity assessment involves looking at each latent variable in the model that other latent variables predict, and examining that group of predictors, to ensure they are not too highly correlated with each other. This is achieved using a VIF test to ensure collinearity is not too high (Hair et al, 2022). To assess collinearity the VIF levels need to be below 5.00 (Hair et al, 2022). As can be seen below in Table 20, all VIF scores have a value of less than 3 so this test is met.

*Table 20: Outer Model VIF Scores*

| | **BA** | **BI** | **BL** |
|---|---|---|---|
| **AI** | | 2.51 | |
| **BA** | | | 1.31 |
| **BI** | 1.10 | | 1.18 |
| **BL** | | | |
| **PBC** | | | 1.21 |
| **GAIPK** | 1.66 | 1.82 | 1.79 |
| **SAIPK** | 1.78 | 1.82 | 1.85 |
| **SI** | | 2.46 | |
| **SN** | | | 1.27 |

### 5.4.2 Significance and Relevance of the Model Relationships

Assessing the significance of structural model path coefficients was achieved using Bootstrapping set with 5000 random subsamples. The table below shows the standardised path coefficients and the significance of the model relationships. P values of greater than 0.05 are shown in bold and represent an insignificant relationship at the 5% level.

*Table 21: Path Coefficients and Significance of Relationships*

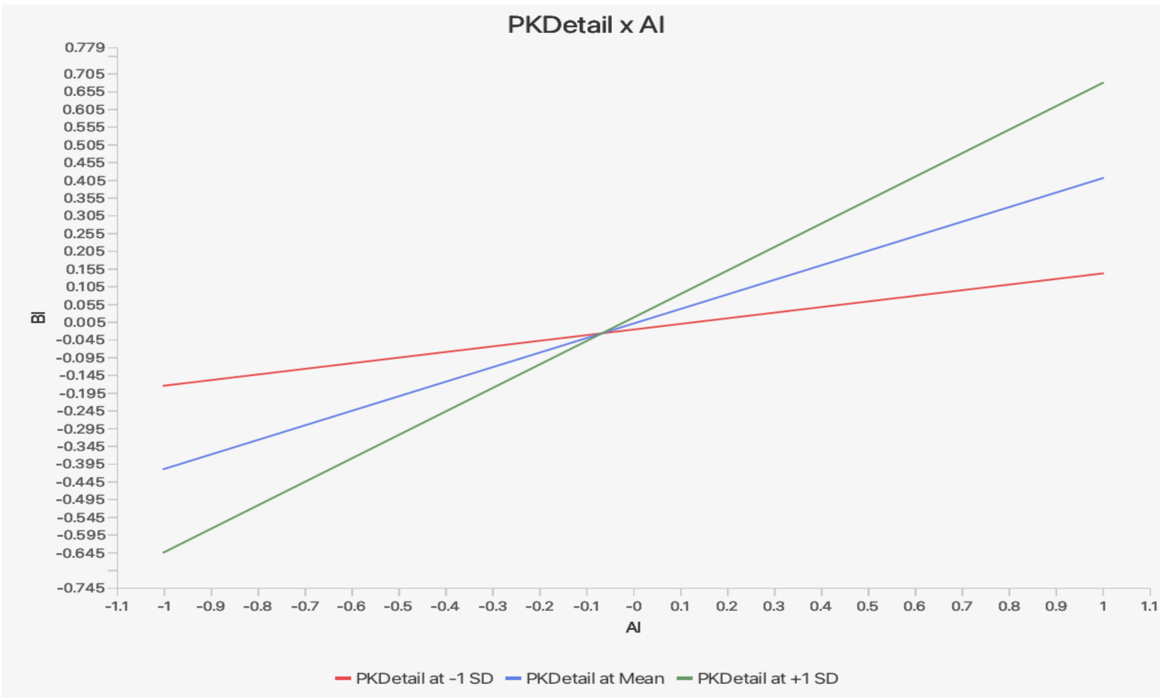
| | Path coefficients | Standard Deviation | T statistics | P values |
|---|---|---|---|---|
| **AI -> BI** | 0.41 | 0.09 | 4.62 | 0.00 |
| **BA -> BL** | 0.62 | 0.06 | 10.42 | 0.00 |
| **BI -> BA** | 0.15 | 0.09 | 1.71 | **0.09** |
| **BI -> BL** | 0.16 | 0.06 | 2.81 | 0.00 |
| **PBC -> BL** | 0.07 | 0.06 | 1.17 | **0.24** |
| **GAIPK -> BA** | 0.04 | 0.10 | 0.41 | **0.68** |
| **GAIPK -> BI** | -0.11 | 0.08 | 1.42 | **0.16** |
| **GAIPK -> BL** | 0.11 | 0.05 | 2.43 | 0.02 |
| **SAIPK -> BA** | 0.13 | 0.11 | 1.11 | **0.27** |
| **SAIPK -> BI** | 0.02 | 0.08 | 0.22 | **0.82** |
| **SAIPK -> BL** | -0.09 | 0.05 | 1.89 | **0.06** |
| **SI -> BI** | 0.31 | 0.08 | 3.68 | 0.00 |
| **SN -> BL** | 0.26 | 0.05 | 5.38 | 0.00 |
| **GAIPK x SI -> BI** | 0.16 | 0.12 | 1.30 | **0.19** |
| **SAIPK x BI -> BA** | 0.00 | 0.13 | 0.01 | **0.99** |
| **SAIPK x BI -> BL** | 0.11 | 0.05 | 2.24 | 0.03 |
| **GAIPK x BA -> BL** | -0.05 | 0.06 | 0.83 | **0.41** |
| **SAIPK x BA -> BL** | -0.03 | 0.05 | 0.74 | **0.46** |
| **SAIPK x SI -> BI** | -0.17 | 0.10 | 1.66 | **0.10** |
| **GAIPK x AI -> BI** | -0.14 | 0.11 | 1.23 | **0.22** |

| | | | | |
|---|---|---|---|---|
| **GAIPK x BI -> BA** | -0.02 | 0.10 | 0.20 | **0.84** |
| **GAIPK x BI -> BL** | -0.02 | 0.05 | 0.37 | **0.71** |
| **SAIPK x AI -> BI** | 0.25 | 0.11 | 2.25 | 0.02 |

As can be seen from the above table, significant relationships exist between all the main variables excluding SAIPK. Surprisingly, no significant relationship is found between BI and BA (p= 0.09), however BI does have a direct significant relationship with BL (p= 0.00). Some significant moderating effects are observed for **SAIPK** in relation to impact on BI's relationship with BL (p= 0.03) and impact on AI's relationship with BI (p=0.02).

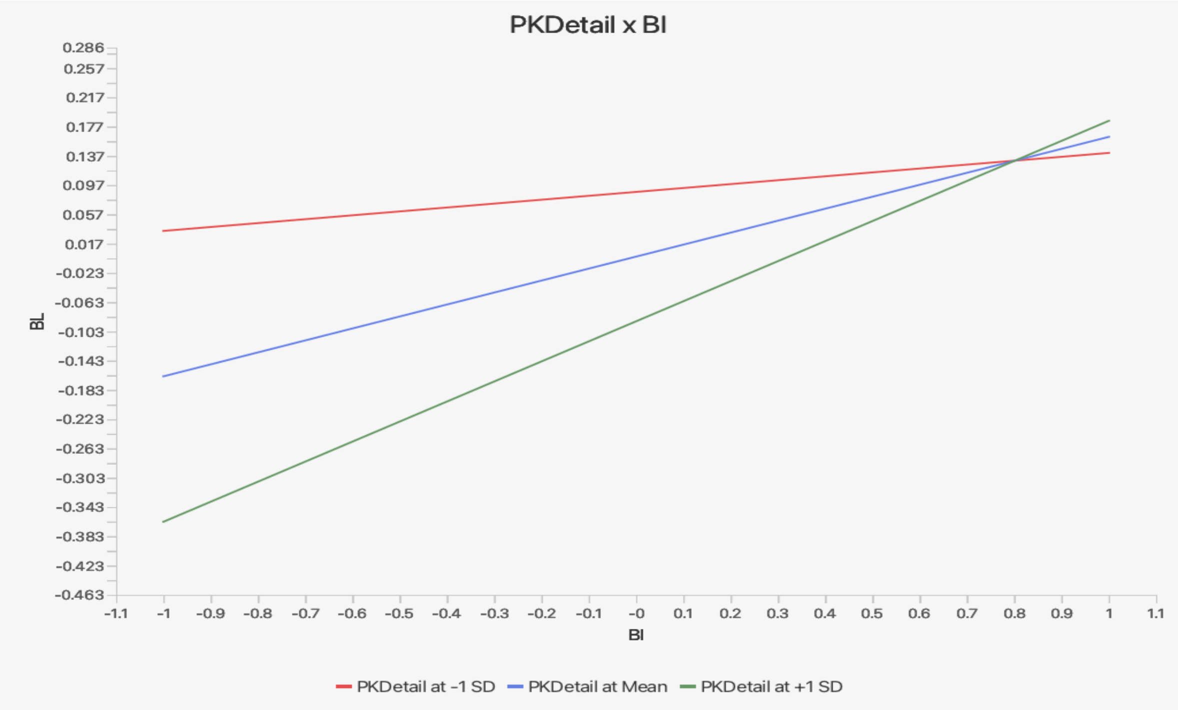
*Figure 24 and 25 below* show the slope of lines to represent the path coefficients. As specific AI product knowledge (SAIPK) levels increase, then the strength of the relationships between AI amplifying innovation (AI) and brand innovativeness (BI), and between brand innovativeness (BI) and brand loyalty (BL) increase.

*Figure 24: Moderating effect of SAIPK on the AI and BI Relationship*




* Note PKDetail here represents SAIPK

*Figure 25: Moderating effect of SAIPK on the AI and BL Relationship*




* Note PKDetail here represents SAIPK

*Figure 26: Moderating effect of SAIPK on the SI and BI Relationship*


* Note PKDetail here represents SAIPK

### 5.4.3 Coefficient of Determination ($R^2$)

According to Hair et al, (2017) the coefficient of determination ($R^2$) explains the variance of the endogenous variable explained by the exogenous variable and is used as a measure of goodness of fit or explanatory power of the model. . $R^2$ values may vary depending on the research discipline, however in consumer behavioural studies values of 0.2 can be considered as high (Hair et al, 2017). Generally Hair et al (2017) suggest that in research focusing on marketing issues $R^2$ above 0.75 are substantial, 0.50 moderate and 0.25 weak.

As can be seen in the table below, the value of 0.06 for Brand Attitude (BA) shows that there is only limited explanatory power of Brand Attitude in the model, consistent with the weak and insignificant path coefficient for BI → BA in the table above. Strong explanatory power is achieved for both Brand Innovativeness and Brand Loyalty with $R^2$ of .43 and .74 respectively, given this a consumer study.

*Table 22: $R^2$ Values*

| | **R-square** | **R-square adjusted** |
|---|---|---|
| **BA** | 0.06 | 0.04 |
| **BI** | 0.43 | 0.40 |
| **BL** | 0.74 | 0.73 |

### 5.4.4 Assessment of Effect Sizes (f²)

Effect sizes assess the change in $R^2$ for an exogenous variable that occurs when a predictor (endogenous) variable is dropped, hence the importance of a predictor variable in the model (Hair et al, 2017). According to Cohen (1998) the f² effect size is 0.02 small, 0.15 medium or 0.35 large effect on an endogenous construct. Effect sizes smaller than 0.02 which are insignificant are shown in bold in the table below.

*Table 23: Effect Sizes*

| | **BA** | **BI** | **BL** |
|---|---|---|---|
| **AI** | | 0.12 | |
| **BA** | | | 1.14 |
| **BI** | 0.02 | | 0.09 |
| **BL** | | | |
| **PBC** | | | 0.02 |
| **GAIPK** | **0.00** | **0.01** | 0.03 |
| **SAIPK** | **0.01** | **0.00** | 0.02 |
| **SI** | | 0.07 | |
| **SN** | | | 0.21 |
| **GAIPK x SI** | | **0.01** | |
| **SAIPK x BI** | **0.00** | | 0.03 |
| **GAIPK x BA** | | | **0.00** |
| **SAIPK x BA** | | | **0.00** |
| **SAIPKx SI** | | **0.01** | |
| **GAIPK x AI** | | **0.01** | |
| **GAIPK x BI** | **0.00** | | **0.00** |
| **SAIPK x AI** | | 0.02 | |

The highest $f^2$ effect size tested is for the effect of Brand Attitude (BA) in predicting Brand Loyalty (BL) at 1.14. This concurs with the literature, in addition to this supporting the literature is the second strongest link between Social Norm (SN) and BL 0.21. In general effect sizes correspond with significant loadings in the structural model.

### 5.4.5 Assessment of predictive relevance via CVPAT

As outlined in the methodology chapter average loss difference should be significant at a p value of 0.05 for the model to demonstrate predictive power (Ringle, 2024). The results for the CVPAT test are shown in the table below.

*Table 24: CVPAT*

| | PLS loss | IA loss | Average loss difference | t value | p value |
|---|---|---|---|---|---|
| **BA** | 1.59 | 1.63 | -0.04 | 0.73 | **0.46** |
| **BI** | 1.32 | 1.64 | -0.32 | 3.59 | 0.00 |
| **BL** | 1.30 | 1.63 | -0.33 | 4.34 | 0.00 |
| **Overall** | 1.36 | 1.63 | -0.27 | 5.19 | 0.00 |

The model has significant overall predictive relevance, since the average loss difference has a p value of 0.00 (Ringle, 2024) model predictive relevance is established. As expected, the model fails to have predictive significance for Brand Attitude (consistent with path coefficient and $f^2$ findings above).

### 5.5 Mediation Analysis

Specific Indirect Effects show both SI and AI have significant indirect causal effects on BL mediated by BI. The moderator PKDetail moderating the relationship between AI and BI has a significant indirect causal effect on BL mediated by BI.

*Table 25: Mediation Results: Specific Indirect Effects*

<u>Specific indirect effects</u>

<u>Mean, STDEV, T values, p values</u>

| | Loading | Sample mean | Standard deviation | T statistics | P values |
|---|---|---|---|---|---|
| PKDetail x AI -> BI -> BA -> BL | 0.02 | 0.02 | 0.02 | 1.25 | 0.21 |
| BI -> BA -> BL | 0.10 | 0.10 | 0.06 | 1.65 | 0.10 |
| PK x AI -> BI -> BA -> BL | -0.01 | -0.01 | 0.01 | 0.95 | 0.34 |
| PK -> BA -> BL | 0.03 | 0.03 | 0.06 | 0.41 | 0.68 |
| PKDetail -> BA -> BL | 0.08 | 0.08 | 0.07 | 1.12 | 0.26 |
| PKDetail x BI -> BA -> BL | 0.00 | -0.01 | 0.08 | 0.01 | 0.99 |
| PKDetail -> BI -> BA -> BL | 0.00 | 0.00 | 0.01 | 0.19 | 0.85 |
| PK -> BI -> BA -> BL | -0.01 | -0.01 | 0.01 | 1.01 | 0.31 |
| PK x BI -> BA -> BL | -0.01 | -0.01 | 0.06 | 0.20 | 0.84 |
| AI -> BI -> BA | 0.06 | 0.07 | 0.04 | 1.54 | 0.12 |
| **AI -> BI -> BL** | 0.07 | 0.07 | 0.03 | 2.34 | **0.02** |
| PK -> BI -> BA | -0.02 | -0.02 | 0.02 | 1.02 | 0.31 |
| PKDetail -> BI -> BA | 0.00 | 0.00 | 0.01 | 0.19 | 0.85 |
| PK -> BI -> BL | -0.02 | -0.02 | 0.02 | 1.16 | 0.24 |
| SI -> BI -> BA | 0.05 | 0.05 | 0.03 | 1.56 | 0.12 |
| PKDetail -> BI -> BL | 0.00 | 0.00 | 0.01 | 0.21 | 0.83 |

| | | | | | |
|---|---|---|---|---|---|
| **SI -> BI -> BL** | 0.05 | 0.05 | 0.02 | 2.17 | **0.03** |
| PK x SI -> BI -> BA | 0.02 | 0.02 | 0.02 | 1.04 | 0.30 |
| PK x SI -> BI -> BL | 0.03 | 0.02 | 0.02 | 1.15 | 0.25 |
| AI -> BI -> BA -> BL | 0.04 | 0.04 | 0.03 | 1.48 | 0.14 |
| PKDetail x SI -> BI -> BA | -0.03 | -0.02 | 0.02 | 1.13 | 0.26 |
| PKDetail x SI -> BI -> BA -> BL | -0.02 | -0.02 | 0.01 | 1.10 | 0.27 |
| PK x AI -> BI -> BA | -0.02 | -0.02 | 0.02 | 0.97 | 0.33 |
| PKDetail x SI -> BI -> BL | -0.03 | -0.02 | 0.02 | 1.52 | 0.13 |
| PK x SI -> BI -> BA -> BL | 0.02 | 0.01 | 0.01 | 1.02 | 0.31 |
| PK x AI -> BI -> BL | -0.02 | -0.02 | 0.02 | 1.10 | 0.27 |
| PKDetail x AI -> BI -> BA | 0.04 | 0.04 | 0.03 | 1.29 | 0.20 |
| SI -> BI -> BA -> BL | 0.03 | 0.03 | 0.02 | 1.52 | 0.13 |
| **PKDetail x AI -> BI -> BL** | 0.04 | 0.04 | 0.02 | 1.92 | **0.05** |

**Total Indirect Effects**

The significance of all possible pathways between latent variables that involve mediators can also be examined as per Total Indirect Effects in the PLS outputs. It represents the sum of all path coefficients for pathways to the dependent latent variables (Hair et al, 2017).

The results indicate how both SI and AI have significant total indirect causal effects on BL mediated by both BA and BI, and the moderator PKDetail moderating the relationship between AI and BI has a significant indirect causal effect on BL mediated by both BA and BI.

*Table 26: Mediation Results: Total Indirect Effects*

Mean, STDEV, T values, p values

| | Loading | Sample mean | Standard deviation | T statistics | P values |
|---|---|---|---|---|---|
| AI -> BA | 0.06 | 0.07 | 0.04 | 1.54 | 0.12 |
| **AI -> BL** | 0.11 | 0.11 | 0.04 | 2.61 | **0.01** |
| BI -> BL | 0.10 | 0.10 | 0.06 | 1.65 | 0.10 |
| PK -> BA | -0.02 | -0.02 | 0.02 | 1.02 | 0.31 |
| PK -> BL | 0.00 | 0.00 | 0.06 | 0.04 | 0.97 |
| PKDetail -> BA | 0.00 | 0.00 | 0.01 | 0.19 | 0.85 |
| PKDetail -> BL | 0.08 | 0.08 | 0.07 | 1.19 | 0.23 |
| SI -> BA | 0.05 | 0.05 | 0.03 | 1.56 | 0.12 |
| **SI -> BL** | 0.08 | 0.08 | 0.03 | 2.49 | **0.01** |
| PK x SI -> BA | 0.02 | 0.02 | 0.02 | 1.04 | 0.30 |
| PK x SI -> BL | 0.04 | 0.03 | 0.03 | 1.23 | 0.22 |
| PKDetail x BI -> BL | 0.00 | -0.01 | 0.08 | 0.01 | 0.99 |
| PKDetail x SI -> BA | -0.03 | -0.02 | 0.02 | 1.13 | 0.26 |
| PKDetail x SI -> BL | -0.04 | -0.04 | 0.03 | 1.54 | 0.12 |
| PK x AI -> BA | -0.02 | -0.02 | 0.02 | 0.97 | 0.33 |
| PK x AI -> BL | -0.04 | -0.03 | 0.03 | 1.15 | 0.25 |
| PK x BI -> BL | -0.01 | -0.01 | 0.06 | 0.20 | 0.84 |
| PKDetail x AI -> BA | 0.04 | 0.04 | 0.03 | 1.29 | 0.20 |
| **PKDetail x AI -> BL** | 0.07 | 0.06 | 0.03 | 1.93 | **0.05** |

**Total Effects**

Finally, the significance total of both direct and direct effects can be examined via Total Effects output in PLS -– see Hair et al, (2017). The results demonstrate direct relationships and indirect relationships are all shown as highlighted below:

*Table 27: Mediation Results: Total Effects*

Total effects

Mean, STDEV, T values, p values

| | **Loading** | **Sample mean** | **Standard deviation** | **T statistics** | **P values** |
|---|---|---|---|---|---|
| AI -> BA | 0.06 | 0.07 | 0.04 | 1.54 | 0.12 |
| **AI -> BI** | 0.41 | 0.41 | 0.09 | 4.62 | **0.00** |
| **AI -> BL** | 0.11 | 0.11 | 0.04 | 2.61 | **0.01** |
| BA -> BL | 0.62 | 0.61 | 0.06 | 10.42 | **0.00** |
| BI -> BA | 0.15 | 0.16 | 0.09 | 1.71 | 0.09 |
| **BI -> BL** | 0.26 | 0.26 | 0.08 | 3.41 | **0.00** |
| PBC -> BL | 0.07 | 0.07 | 0.06 | 1.17 | 0.24 |
| PK -> BA | 0.03 | 0.03 | 0.10 | 0.25 | 0.80 |
| PK -> BI | -0.11 | -0.11 | 0.08 | 1.42 | 0.16 |
| PK -> BL | 0.11 | 0.11 | 0.08 | 1.43 | 0.15 |
| PKDetail -> BA | 0.13 | 0.13 | 0.11 | 1.16 | 0.25 |
| PKDetail -> BI | 0.02 | 0.02 | 0.08 | 0.22 | 0.82 |
| PKDetail -> BL | -0.01 | 0.00 | 0.08 | 0.08 | 0.94 |
| SI -> BA | 0.05 | 0.05 | 0.03 | 1.56 | 0.12 |
| **SI -> BI** | 0.31 | 0.30 | 0.08 | 3.68 | **0.00** |
| **SI -> BL** | 0.08 | 0.08 | 0.03 | 2.49 | **0.01** |
| **SN -> BL** | 0.26 | 0.26 | 0.05 | 5.38 | **0.00** |
| PK x SI -> BA | 0.02 | 0.02 | 0.02 | 1.04 | 0.30 |
| PK x SI -> BI | 0.16 | 0.14 | 0.12 | 1.30 | 0.19 |
| PK x SI -> BL | 0.04 | 0.03 | 0.03 | 1.23 | 0.22 |
| PKDetail x BI -> BA | 0.00 | -0.02 | 0.13 | 0.01 | 0.99 |
| PKDetail x BI -> BL | 0.11 | 0.09 | 0.10 | 1.10 | 0.27 |
| PK x BA -> BL | -0.05 | -0.05 | 0.06 | 0.83 | 0.41 |
| PKDetail x BA -> BL | -0.03 | -0.04 | 0.05 | 0.74 | 0.46 |

| | | | | | |
|---|---|---|---|---|---|
| PKDetail x SI -> BA | -0.03 | -0.02 | 0.02 | 1.13 | 0.26 |
| PKDetail x SI -> BI | -0.17 | -0.16 | 0.10 | 1.66 | 0.10 |
| PKDetail x SI -> BL | -0.04 | -0.04 | 0.03 | 1.54 | 0.12 |
| PK x AI -> BA | -0.02 | -0.02 | 0.02 | 0.97 | 0.33 |
| PK x AI -> BI | -0.14 | -0.11 | 0.11 | 1.23 | 0.22 |
| PK x AI -> BL | -0.04 | -0.03 | 0.03 | 1.15 | 0.25 |
| PK x BI -> BA | -0.02 | -0.02 | 0.10 | 0.20 | 0.84 |
| PK x BI -> BL | -0.03 | -0.03 | 0.09 | 0.36 | 0.72 |
| PKDetail x AI -> BA | 0.04 | 0.04 | 0.03 | 1.29 | 0.20 |
| **PKDetail x AI -> BI** | 0.25 | 0.24 | 0.11 | 2.25 | **0.02** |
| **PKDetail x AI -> BL** | 0.07 | 0.06 | 0.03 | 1.93 | **0.05** |

### 5.6 PLS-SEM Multigroup Analysis (PLS-MGA) by Age Group

Group analysis in relation to the younger and older groups were observed. As stated in the literature review, attitudes from differing age groups differ, due to two age groups having a differing lens towards AI. The age literature suggests the younger groups experiences and perceptions towards AI are engaging. Older groups are more resistant to AI and in some cases only use it when other areas are exhaustive. Age has been used in group analysis, which is justified as it has been used as a moderator in recent studies, (Gentina and Kratzer, 2020, and Hwang et al, 2019). These studies have tested the implication of dividing the respondents into two age groups. There is an apparent significance when moderating with age using technology, where Yoo et al, (2021) used and applied a median age of 35 to define respondents as younger or older than this age. Hurst et al, 2007 used age 38 as a mean, whereas many scholars have divided age by generations. However, it may be contended that age may not play a factor in consumer satisfaction or even customer loyalty (Kim et al, 2016 and Walsh et al, 2008. Adding to this argument, Kuppelwieser, and Klaus (2020) advise to being less rigid about the age measurement concept to enhance marketing theory, warranting the research age division for under 35 (younger) and over 35 (mature) users.

## Age Group Analysis and MICOM

### Multigroup analysis (MGA)

To evaluate investigate whether there are differences in the model relationships between age groups, a multigroup analysis was performed. According to Henseler et al (2016), before proceeding to perform the multigroup analysis, it is necessary to perform a MICOM analysis. As the objective of the MICOM analysis is to confirm that any differences between the two groups are, in fact, due to differences between the structural model and not due to differences in the measurement model (Henseler et al, 2016). The testing of MICOM is a three-stage process that includes: (1) configuration invariance (Step 1); (2) compositional invariance (Step 2); (3) the equality of composite mean values and variances (Steps 3a and 3b) (Henseler et al, 2016).

### Configural invariance

Configural invariance consists of a qualitative assessment of the composites' (constructs) specification across all the groups (Henseler et al, 2016).

Results:

Identical indicators were retained. and data treatment and algorithm settings were identical. Therefore, configurational invariance is confirmed.

### Compositional Invariance

Compositional invariance is established when the scores of a composite variable using the weights of one group do not differ from those created using the weights of another group. Therefore, to verify composite invariance, it is necessary to examine the correlation between scores of each latent variable, using permutation approach and testing that correlation between groups is not significantly different from 1 using permutation analysis (similar to bootstrapping). This is the case when the p value is insignificant (greater than 0.05) (Hair et al, 2024)

The results show no significant configurational invariance was seen.

*Table 28: MICOM Compositional Invariance*

| | Original correlation | Correlation permutation mean | 5.0% | Permutation p value |
|---|---|---|---|---|
| AI | 1.00 | 1.00 | 0.99 | 0.55 |
| BA | 1.00 | 1.00 | 1.00 | 0.94 |
| BI | 0.99 | 0.99 | 0.96 | 0.39 |
| BL | 1.00 | 1.00 | 1.00 | 0.25 |
| PBC | 0.85 | 0.90 | 0.66 | 0.19 |
| PK | 1.00 | 0.95 | 0.72 | 0.92 |
| PKDetail | 0.99 | 0.97 | 0.89 | 0.34 |
| SI | 1.00 | 1.00 | 0.99 | 0.26 |
| SN | 0.99 | 0.99 | 0.97 | 0.25 |

**Equality of means and variances**

Examination of the equality of means, and, subsequently, the equality of variances of latent variables, is the final test It should be noted that failure of this test does not prevent multi-group analysis, but means that pooled data analysis is not possible. Again, meeting this test requires the p value to be insignificant (greater than 0.05).

Results: Equality of means and variances is established.

*Table 29: Equality of Means and Variances*

| **Step 3a (mean)** | | | | | |
|---|---|---|---|---|---|
| | **Original difference** | **Permutation mean difference** | **2.5%** | **97.5%** | **Permutation p value** |
| AI | 0.17 | -0.01 | -0.34 | 0.34 | 0.31 |
| BA | 0.06 | 0.00 | -0.34 | 0.31 | 0.72 |
| BI | -0.11 | 0.00 | -0.34 | 0.32 | 0.50 |
| BL | -0.04 | 0.00 | -0.35 | 0.33 | 0.81 |
| PBC | -0.32 | 0.00 | -0.33 | 0.33 | 0.06 |
| PK | 0.17 | 0.00 | -0.31 | 0.33 | 0.32 |
| PKDetail | -0.23 | -0.01 | -0.31 | 0.29 | 0.15 |
| SI | -0.06 | 0.00 | -0.32 | 0.33 | 0.73 |
| SN | -0.20 | 0.00 | -0.32 | 0.30 | 0.22 |
| **Step 3b (variance)** | | | | | |
| | Original difference | Permutation mean difference | 2.5% | 97.5% | Permutation p value |
| AI | -0.15 | -0.04 | -0.51 | 0.44 | 0.57 |
| BA | -0.37 | -0.05 | -0.87 | 0.61 | 0.31 |
| BI | 0.55 | -0.05 | -0.63 | 0.58 | 0.08 |
| BL | -0.14 | -0.04 | -0.72 | 0.60 | 0.68 |
| PBC | -0.05 | -0.03 | -0.49 | 0.44 | 0.85 |

| | | | | | |
|---|---|---|---|---|---|
| PK | -0.17 | -0.04 | -0.44 | 0.34 | 0.39 |
| PKDetail | -0.09 | -0.02 | -0.38 | 0.31 | 0.60 |
| SI | 0.24 | -0.04 | -0.64 | 0.55 | 0.46 |
| SN | -0.01 | -0.05 | -0.68 | 0.54 | 0.97 |

**Multi-Group Analysis**

An analysis of any differences between the path coefficients for the two groups being compared (Young and Old Respondents) can be performed once the above steps have been completed. Any significant difference in paths will result in a significant p value using permutation analysis.

Results:

As can be seen below all p values are insignificant, suggesting no differences between age groups.

*Table 30: Multi-Group Analysis*

| | **Original (Age O)** | **Original (Age Y)** | **Original difference** | **Permutation mean difference** | **2.5%** | **97.5%** | **Permutation p value** |
|---|---|---|---|---|---|---|---|
| AI -> BI | 0.36 | 0.45 | -0.09 | -0.01 | -0.49 | 0.43 | 0.70 |
| BA -> BL | 0.75 | 0.61 | 0.13 | -0.01 | -0.35 | 0.25 | 0.43 |
| BI -> BA | 0.10 | 0.19 | -0.09 | 0.03 | -0.42 | 0.47 | 0.69 |
| BI -> BL | 0.26 | 0.13 | 0.12 | -0.01 | -0.26 | 0.30 | 0.41 |
| PBC -> BL | -0.07 | 0.11 | -0.17 | 0.01 | -0.25 | 0.34 | 0.25 |
| PK -> BA | 0.09 | 0.00 | 0.08 | -0.01 | -0.51 | 0.47 | 0.74 |
| PK -> BI | -0.05 | -0.09 | 0.04 | 0.01 | -0.40 | 0.39 | 0.83 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| PK -> BL | 0.27 | 0.06 | 0.20 | 0.00 | -0.25 | 0.24 | 0.11 |
| PKDetail -> BA | 0.49 | 0.07 | 0.42 | 0.03 | -0.56 | 0.52 | 0.13 |
| PKDetail -> BI | -0.11 | 0.04 | -0.15 | 0.01 | -0.40 | 0.38 | 0.46 |
| PKDetail -> BL | -0.16 | -0.06 | -0.10 | 0.02 | -0.24 | 0.27 | 0.47 |
| SI -> BI | 0.41 | 0.25 | 0.15 | -0.01 | -0.48 | 0.45 | 0.50 |
| SN -> BL | 0.22 | 0.28 | -0.05 | -0.01 | -0.25 | 0.25 | 0.68 |
| PK x SI -> BI | 0.24 | 0.06 | 0.18 | -0.06 | -0.71 | 0.56 | 0.57 |
| PKDetail x BI -> BA | -0.26 | 0.03 | -0.28 | -0.05 | -0.69 | 0.57 | 0.40 |
| PKDetail x BI -> BL | 0.13 | 0.07 | 0.06 | -0.02 | -0.32 | 0.25 | 0.62 |
| PK x BA -> BL | -0.19 | -0.05 | -0.15 | -0.01 | -0.31 | 0.34 | 0.33 |
| PKDetail x BA -> BL | 0.23 | -0.05 | 0.28 | 0.00 | -0.30 | 0.31 | 0.07 |
| PKDetail x SI -> BI | -0.06 | -0.20 | 0.14 | 0.05 | -0.48 | 0.64 | 0.62 |
| PK x AI -> BI | -0.35 | -0.09 | -0.26 | 0.07 | -0.47 | 0.71 | 0.39 |
| PK x BI -> BA | -0.06 | -0.01 | -0.05 | 0.02 | -0.44 | 0.56 | 0.83 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| PK x BI -> BL | -0.06 | 0.01 | -0.07 | 0.02 | -0.25 | 0.32 | 0.60 |
| PKDetail x AI -> BI | 0.37 | 0.27 | 0.10 | -0.05 | -0.76 | 0.49 | 0.74 |

### 5.7 Chapter Summary

This chapter has presented the quantitative results from the data collection process. The chapter followed the systematic procedure for PLS-SEM by Hair et al (2014). First, the descriptive statistics provided a brief overview of the sample's characteristics. Then, the validity and reliability robustness checks were carried out for the reflective measurement model. Once the model was verified, the assessment of the model took place. This involved assessing the collinearity of the model, which checks the relationships between the constructs, then measuring the effect size, path coefficients and overall predictive relevance which substantial. Finally, the PLS-MGA results showed there was no difference between the younger and older group comparisons. Overall, PLS-SEM shows many hypotheses were supported with exceptions for the relationship between Brand Innovativeness and Brand Attitude and for Perceived Behavioural Control with Brand Loyalty, and for many of the hypothesised moderations. However, two specific moderating effects of specific AI product knowledge were supported, with SAIPK moderating relationships between amplifying innovations and brand innovativeness, and between brand innovativeness and brand loyalty. The next chapter discusses the findings in further detail.

## Chapter 6

## Discussion

### 6.1 Introduction

This chapter provides a discussion of the key findings reported in Chapter 5, exploring the hypotheses derived from the conceptual framework to identify key findings, and linking back to the three research questions under examination. The findings are linked to key contributions the research makes to new knowledge surrounding the AI and Brand literature. The chapter begins with a table summarising the results of testing the hypotheses and discussion of the main findings. The discussion is developed around the three research questions set and discusses each the implications of the significance or non-significance of each hypothesis in detail. Finally, a summary of the chapter concludes the discussion.

### 6.2 Overall Findings

This study aimed to explore three research questions set out again below empirically, using the context of the Amazon UK Shopping App and AI innovations related to it.

The three research questions were as follows:

1. Do AI enabled simplifying innovations and AI enabled amplifying innovations increase perceived brand innovativeness?
2. Does increased brand innovativeness lead to increased brand loyalty and is this relationship (partially) mediated by brand attitude?
3. Does product knowledge have a moderating effect on the relationships described in Research Questions 1 and 2 above?

In examining research question 3, two sub-questions exist: a. does knowledge of specific AI enabled features have a moderating effect (Specific AI Product Knowledge) and b. does knowledge more generally of the existence AI enabled features (General AI Product Knowledge) act as a moderator?

*Table 31: Hypotheses Results*

| **Hypotheses** | **P Values** | **Conclusion** |
|---|---|---|
| H1 AI Simplifying Innovation is positively related to Brand Innovativeness | **0.00** | Supported |
| H2 AI Amplifying Innovation is positively related to Brand Innovativeness | **0.00** | Supported |
| H3 Brand innovativeness is positively related to Brand Loyalty | **0.00** | Supported |
| H4a Brand Innovativeness is positively related to Brand Attitude | 0.09 | Unsupported |
| H4b Brand Attitude is positively related to Brand Loyalty | **0.00** | Supported |
| H5 Social Norms are positively related to Brand Loyalty | **0.00** | Supported |
| H6 Perceived Behavioural Control is positively related to Brand Loyalty | 0.24 | Unsupported |
| H7A General AI Product Knowledge moderates the relationship between AI Simplifying Innovation and Brand Innovativeness | 0.29 | Unsupported |
| H7B General AI Product knowledge moderates the relationship between AI Amplifying innovation and Brand innovativeness | 0.22 | Unsupported |
| H7C General AI Product knowledge moderates the relationship between Brand Innovativeness and Brand Loyalty | 0.71 | Unsupported |
| H7D General AI Product knowledge moderates the relationship between Brand Attitude and Brand Loyalty | 0.41 | Unsupported |
| H7E General AI Product knowledge moderates the relationship between Brand innovativeness and Brand Attitude | 0.84 | Unsupported |
| H7F Specific AI Product knowledge moderates the relationship between AI Simplifying innovation and Brand innovativeness | 0.10 | Unsupported |
| H7G Specific AI Product knowledge moderates the relationship between AI Amplifying innovation and Brand innovativeness | 0.02 | Supported |
| H7H Specific AI Product knowledge moderates the relationship between Brand Innovativeness and Brand Loyalty | 0.03 | Supported |
| H7I Specific AI Product knowledge moderates the relationship between Brand Attitude and Brand Loyalty | 0.46 | Unsupported |
| H7J Specific AI Product knowledge moderates the relationship between Brand innovativeness and Brand Attitude | 0.99 | Unsupported |
| H8 Group Analysis – does Age change any of the proposed relationships? | >0.20 | Unsupported |

Source: Table 21 and Figure 12

Empirical findings of this study confirm the overall relationship between AI innovations and brand innovativeness, and between brand innovativeness and brand loyalty. It identifies that some moderating effects of product knowledge exist, relating solely to specific AI product knowledge. No significant relationship between brand innovativeness and brand attitude is found, but brand attitude has an independent significant relationship with brand loyalty. The results for each of the related hypotheses are summarised in Table 27.

The remaining discussion is structured by research question.

### 6.3 Exploration of Research Question 1

Research question 1 asks: Do AI enabled simplifying innovations and AI enabled amplifying innovations increase perceived brand innovativeness? These two questions are examined via hypotheses H1 and H2, and as can be seen from Table 27 above both hypotheses are supported by the empirical testing in the context of the Amazon App. The Amazon App was chosen together with the Amazon brand because this App has recently seen a number of both amplifying and simplifying innovations enabled by AI.

A previous study has demonstrated the existence of a link between product level innovation and Brand innovativeness (Shams et al, 2015). However, no study can be found that examines specifically AI enabled product innovations and their impact on brand innovativeness. Further, no study has empirically examined the impact of the two product innovation types of Amplifying Innovation and Simplifying Innovation on brand innovativeness. The impact of amplifying and simplifying innovation on product affect and ultimately intention to purchase (a form of brand loyalty) has been examined, without a focus on AI enablement (Hardie et al, 2016). In addition, it is by no means certain AI enabled product innovations are universally positively experienced by consumers. Fears and concerns related to AI can outweigh the advantages of new features and functions in the minds of some consumers – see for example Puntoni et al (2021) and Pantano and Scarpi (2022). The finding of a positive relationship between AI simplifying and AI amplifying innovations and brand innovativeness, together with the identified positive relationship between brand innovativeness and brand loyalty, therefore provides support for the advantages of well executed AI enabled product innovations for brands.

The standardised path coefficient between Amplifying Innovation and Brand Innovativeness at +0.41 is higher than that between Simplifying Innovation and Brand Innovativeness at +0.31 (see Table 21). Consistent with this the effect size of amplified innovation on brand innovativeness was higher (0.12) than simplified innovation, which was weaker (.07) (see Table 23). This suggests that amplifying innovations may have a stronger impact on brand innovativeness than simplifying ones – probably due to the increased novelty of being able to do new things within the app (as opposed to achieve similar tasks more easily in the case of simplifying innovation). Both AI enabled amplifying and simplifying innovations appear to have significant predictive value in relation to brand innovativeness (see Table 24) and explain around 43% of the variance in Brand Innovativeness (see Table 22 $R^2$ value).

Technology driven features of AI convey innovativeness. Implications of this finding means businesses are required to assist consumers to increase their understanding of the features of AI innovations, in order to manifest a perception of brand innovativeness. The increased confidence of users has been linked to increased positive perceptions (Berger et al, 1994). Brand innovativeness studies have assessed brands through associations of offering new technologies, whereas the present study pushes the boundaries by using amplified innovation to test if consumers of Amazon agreed with Amazon introducing new functionalities and AI innovations to increase productivity through reinvention. The primary implication is to improve the customers image of the business; companies may invest in firstly enhancing the experience through using AI innovations to manifest a positive perception. Secondly, efficiency and productivity are increased by using AI technologies, this creating a better perception of innovativeness for customers. In order to remain competitive, businesses must reinvent their AI innovations to demonstrate their ability to integrate AI innovations advancing rapidly.

In summary, research question 1 can be answered “Yes, AI enabled simplifying innovations and AI enabled amplifying innovations increase perceived brand innovativeness” in the context of this study.

### 6.4 Exploration of Research Question 2

Research question 2 asks: Does increased brand innovativeness lead to increased brand loyalty and is this relationship (partially) mediated by brand attitude? This question is examined via hypotheses H3, H4a and H4b. As can be seen from table 27, both H3 (brand innovativeness is positively related to brand loyalty) and H4b (brand attitude is positively related to brand loyalty) are supported. However, H4a (brand innovativeness is positively related to brand attitude) is not supported at the 5% significance level with a p value of 0.09 and a path coefficient of 0.15 (see Table 21). It is worth noting however that the standardised path coefficient between Brand Innovativeness and Brand Loyalty is only very slightly larger at 0.16, and this has a p value of 0.00 (see Table 21). The reason for this is that the standard deviation of the path coefficient between Brand Innovativeness and Brand Attitude is much larger than that between Brand Innovativeness and Brand Loyalty, resulting in the latter having a higher t value and lower probability (see Table 21). On this basis there is some tentative evidence for a relationship between Brand Innovativeness and Brand Attitude, but the null hypothesis, that no relationship exists cannot be dismissed at the 5% probability level. From the mediation analysis, there is no significant mediation of Brand Attitude between Brand Innovativeness and Brand Loyalty with a p value of 0.10. Although there is no partial mediation in this study, this may be worthy of an in-depth investigation for future studies.

The findings for H3 and H4b are in line with expectations and previous studies which have shown positive relationships between brand innovativeness and brand loyalty (Eisingerich and Rubera, 2010) and brand attitude and brand loyalty (Liu et al, 2012). Established literature in the field has always linked the brand attitude and brand loyalty constructs (Boisvert and Khan, 2020; Malhotra, 2005). Consistent with previous studies, Hubert et al (2017) demonstrated the importance of brand attitudes and how purchase intention is a result of perceived brand innovativeness. Tentative evidence of a relationship between brand innovativeness and brand attitude is in line with the findings of Sanavei et al, (2013). In exploring the relationship between brand innovativeness and brand attitude further, it is worth noting that brand attitudes represent "general brand evaluations, based on beliefs or automatic affective reactions" that are contingent personal evaluations (He et al, 2016:792). For this reason, a consumer's belief about brand innovativeness is only one of many beliefs about the brand that forms an overall brand attitude, with many others being relevant including attitudes towards globalisation (Riefler, 2012), the influence of views of others or subjective norms (Kim et al, 2009) and brand satisfaction (Hwang et al, 2021). This explains its modest and contingent relationship with brand attitude.

In summary, research question 2 can be answered "Yes, increased brand innovativeness does lead to increased brand loyalty, but only tentative evidence of this relationship being partially mediated by brand attitude is found" in the context of this study.

### 6.5 Exploration of Research Question 3

Research question 3 asks: Does Product knowledge have a moderating effect on the relationships described in Research Questions 1 and 2. This is explored through hypotheses for two types of product knowledge being general AI product knowledge (tested with hypotheses H7A-H7E), and specific AI product knowledge (H7F-H7J).

#### 6.5.1 General AI product knowledge as a moderator

As can be seen in Table 27, none of the hypothesised moderating relationships for general AI product knowledge are supported, with probabilities exceeding 0.2 in all cases. General AI product knowledge is operationalised in the study with the questions set out in Table 9, one example being "On a scale of 1-7 How knowledgeable are you about Amazon's Artificial Intelligence features on the Amazon App?". One potential explanation of the lack of moderation effect is that knowledge of AI features is too remote from beliefs about simplifying and amplifying innovations, and brand innovativeness, to create additional confidence in the individual evaluation of those beliefs. For confidence to be increased in the judgements made, knowledge must be specific and relevant to that judgement (Peterson and Pitz, 1988).

An alternative explanation relates to the nature of the empirical model tested, particularly in relation to moderation of relationships between simplifying and amplifying innovation and brand innovativeness. Examples of the measures of simplifying innovation and amplifying innovation from Table 9 above are as follows:

1. SI01 Please state the extent to which you agree with the following: "Amazon has been able to use artificial intelligence to help make it easier to use its digital shopping services".
2. AI01 Please state the extent to which you agree with the following: "Amazon introduces Innovations powered by artificial intelligence that let me do things I couldn't do before".

As can be seen, there is significant conceptual overlap between the wording of General AI product knowledge measures and the questions above, meaning much of the level of AI 'knowledge' captured in general AI product knowledge is already captured in the simplifying and amplifying innovation questions, and therefore already accounted for in the relationships between simplifying / amplifying innovation and brand innovativeness.

### 6.5.2 Specific AI product knowledge as a moderator

As can be seen in Table 25, two of the hypothesised moderating relationships for specific AI product knowledge are supported, being H7G (Specific AI product knowledge moderates the relationship between AI amplifying innovation and brand innovativeness) and H7H (Specific AI product knowledge moderates the relationship between brand innovativeness and brand loyalty). Both have positive moderating effects with path coefficients of +0.25 and +0.11 respectively (see Table 21). This means that as specific AI product knowledge (SAIPK) levels increase, then the strength of the relationships between AI amplifying innovation (AI) and brand innovativeness (BI), and between brand innovativeness (BI) and brand loyalty (BL) increase. This is illustrated in the figures 24 and 25 where the slope of lines represents the path coefficients (steeper slope equals a larger path coefficient).

These relationships can be explained by the contrast of SAIPK with general AI product knowledge, in that SAIPK asks questions about knowledge of specific AI features and functionality, which may give increased confidence in the judgements in the beliefs being formed (Peterson and Pitz, 1988).

H7F is not significant at the 5% probability level cut-off but has a p value of 10% and a negative path coefficient of -.17. This is some tentative evidence for a moderating effect, where increased knowledge of the specific features used in the SAIPK questions decreased confidence in a belief that simplifying innovations are associated with brand innovativeness (possibly because the specific AI features shown did not link to successful simplifications of functionality – only to successful amplifications of functionality) see figure 26.

The remaining two hypotheses (H7I and H7J) concern relationships with very little evidence supporting a moderating effect on the relationships between brand attitude and brand loyalty, or brand innovativeness and brand attitude with small path coefficients close to zero and large probabilities (see Table 21). The latter is potentially explained by the weak relationship between brand innovativeness and brand attitude. Having prior knowledge about the features of a brand have been researched to promote positive brand attitudes (Kim and Hwang, 2020). It is believed that brand attitudes are formed by feeling and emotions, which could be influenced by the amount of product knowledge a consumer has (Li, 2019). The findings did not correlate with the literature and AI product knowledge was not significant with attitude.

This is more surprising, but consistent with an argument that brand attitude evaluation is only marginally based on innovations at the product level, and so limited impact on confidence in brand attitudes and therefore brand loyalty may be achieved by increased product knowledge. This has contributed to the gap addressed in the literature, as Moreau et al, (2018) stated the area is under-researched.

### 6.5.3 Overall implications for research question 3

Overall, the answer to research question 3: Does Product knowledge have a moderating effect on the relationships described in Research Questions 1 and 2. Is yes, in the case of knowledge of specific features enabled by AI as innovations I the Amazon app, and no in the case of general knowledge of the use of AI enabled approaches in the Amazon app.

Strong moderating effects were found as described above in relation to specific AI product knowledge relevant to relationships in both research question 1 (amplifying innovation and brand innovativeness) and research question 2 (brand innovativeness and brand loyalty).

A final observation is that general AI product knowledge was found to have a positive relationship with brand loyalty (examined as a part of moderation testing) with a p value of 0.02 (see Table 21). This is suggestive of general awareness of use of AI in relation to brands leading to brand loyalty directly rather than being wholly mediated by brand innovativeness – but this would need to be further examined in future studies. The antecedent to innovation is the capacity to innovate, thus consumer perceives Amazon to have large capacity for research and development from being a billion-dollar/pound company. The literature adds, perceived brand innovativeness has a positive effect on new product launches and is moderated by social consumer innovativeness (Hetet et al, 2020). In addition to this, the perception of brand innovativeness impacts customer satisfaction levels, where it has been proved to develop repurchasing intentions. Furthermore, the findings presented from the results demonstrate the predictive accuracy of the conceptual model is high. The findings indicate the respondents were and anticipated to be brand loyal. Drawing on the work of Leckie et al (2018), the practical implication for marketers indicates focusing marketing activities to produce brand information to influence attitude and increase the value of the brand. Eisingerich and Rubera (2010) support emphasising the innovativeness of brands is an effective method to drive loyalty. Marketers should focus on brand innovative strategies to build brand loyalty, as this link is verified within the study. This implication plays a key role in incorporating differentiation in marketing strategies, to convey innovativeness to consumers (Shams et al, 2015).

### 6.6 Other elements of the analysis

Below are comments on findings in relation to some of the control variables in the study, specifically age, and social norm and perceived behavioural controls.

#### 6.5.1 Significance of age

Age has been seen to have a moderating or group effect in relation to some studies concerning technology and brand intentions – see for example Yee et al, (2019), Kim et al, (2020) and Hwang et al, (2019). For this reason, H8 explores whether there is any significant difference between responses in the theoretical model between a younger and older age group using the SMARTPLS multi-group analysis procedure. There were no significant differences between path coefficients in the models for the younger and older age groups (see Table 24), so the hypothesis that there is a difference is unsupported, and age appears to have no bearing on the answer to the three research questions. This finding suggests that people from all age groups are accepting of the Amazon app. The main reason for an app to be developed is to make life easier for consumers, offering a smooth and easy user interface to encourage shopping. The work correlates with the concept of a consumer that is interested, will be willing to try new products and undertake their own research. Ease of use and convenience are reported as adoption characteristics of age groups. The context of the actual technology reigns as important for comparing older and younger age groups. If the AI technology were more complex or unfamiliar, such as in XR, the information sought from social groups are perceived to be higher. This is a consideration for future research. A review of perceived behavioural control for various age groups has signalled the strength of the intentions and knowledge of the product and its features. Marketers have long used segmentation to target the differing needs of target groups. The social position of a consumer and who and how they spend is determined by their interests as well as socio-economic status and culture around this (Shavitt et al, 2016).

### 6.6.2 Social Norms and Perceived Behavioural Control

Social norms and PBC were tested as control variables in the model in line with the Theory of Planned Behaviour (Ajzen, 1980). Social norms were found to have a positive and significant relationship with brand loyalty as expected, and therefore H5 is supported (see Table 27). This is consistent with previous research which has found the social norm and intention relationship to be positive and significant (Maruping et al, 2017; Venkatesh et al, 2012). Previous studies by Fu and Elliot (2013) evaluated the construct to measure whether social norms had an impact on perceived product innovativeness and on product adoption. They found social norms to be a strong predictor of intention. The present study found the social norms to have a good effect size. This correlates with the previous research in this area, of the social norm and intentions relationship to be significant (Maruping et al, 2017; Venkatesh et al, 2012). Innovativeness research postulates adoption of new technologies to be impacted by social influence of adoption rates. Consumers value their reference groups, where they often seek social support when using technology and making purchase decisions. They have beliefs of their social groups option to be true. Consumers in this study would encourage their friends and family to use the app. This influence of their social groups consisting of friends and family, allows them to feel reassured as they start to create positive associations with the brand, in turn, developing in brand loyalty. The influence of a person's social norms and confidence also impact PBC.

The relationship between perceived behavioural control and brand loyalty was insignificant and therefore H6 is unsupported. This is unsurprising, as use of the Amazon app is free, and all respondents are existing app users with Amazon accounts so there is limited scope for perceptions of an inability to continue to shop with Amazon. Nevertheless, the data must be interpreted with caution as there are several explanations for this. First, the assessment of a user not to be using the app to a higher level with AI, the belief of not being able to use the AI innovations were low. Adding to this, consumers did not feel they had the decision to use the app freely. These findings stipulate whether the consumer is interested in using the app or are not inclined to use such facilities due to unawareness. Perceived Behavioural

Control is context specific and has been found by other researchers to be insignificant the findings align with Crespo and del Bosque (2008) who found perceived behavioural control to have no relevant effects on intentions. The results of the study can be explained by the context, when there is no challenge to the consumers, according to flow theory (Csikszentmihalyi, 1997), the consumers becomes bored. Accordingly, the Amazon App is not considered a challenge for consumers to use, or goes beyond the minimum limit of flow, therefore, this theory is acceptable under the context of the present study. The relationship from social norms to intention is theorised as high, in addition to this, the results are regarded as acceptable. The Amazon app in general is regarded as innovative. There are less barriers to control when using the AI features within the App. Technological advancements using mobiles have ensured consumers use their mobiles even more, and developers are constantly updating AI technology. The societal changes in consumer behaviour caused by the upheaval of the global pandemic in 2020, further research in this area is required (Sheth, 2020). For example, since 2020, it has become the new norm as society has adapted to order food in a restaurant using a QR code reader on a mobile phone, now most new phones have a built in QR reader. AI innovations within a phone are discovered by consumers or their social groups to enable users to develop their skills on an app. Factors concerning the shopping habits were not apparent. However, Amazon is not a fashion brand. If this were tested on ASOS, the hypothesised relationship is higher due to being a visual brand, with consumers willing to learn how to use the AI innovations, to draw on the visuals before purchase. However, the results generated are acceptable.

To conclude, AI simplified and amplified innovations in this study imply general marketing is required to inform consumers of AI is within a technology to boost brand innovativeness. To increase brand innovativeness, a strategy of communications promoting the AI within the product as a general technology are required to be communicated to consumers. In addition to this, using marketing communications to promote the specific new functionalities strengthens consumer relationships with a brand.

## 6.7 Chapter Summary

This chapter provides a broader discussion of the key findings of the study, linking the results back to the three research questions being explored and examining the relationships hypothesised in the conceptual model.  In general, each of the research questions were addressed and as such the contribution to knowledge of this thesis is established.  The next chapter looks specifically at the contribution of this study, managerial implications and addresses the limitations of the study.

# Chapter 7

## Conclusions, Limitations and Future Research

### 7.1 Introduction

This chapter begins a summary of the findings in this study, with reference to the three research questions discussed throughout. Next the contributions to knowledge resulting from this study are outlined.  Then implications for managers and for practice are presented to enable organisations to consider implications for marketing in relation to AI enabled innovations in the context of branding.  Next, the limitations of the study are discussed.  These include time and geographic constraints.

Finally, the chapter ends with a look to future research suggested by the findings in this study.   This includes adaptations of the methodology, as well as widening the generalisability of study by using an alternative brand and product combination, widening the geographic location of the study, and use of other models and variables to extend or modify the theoretical framework.

### 7.2 Summary of the findings

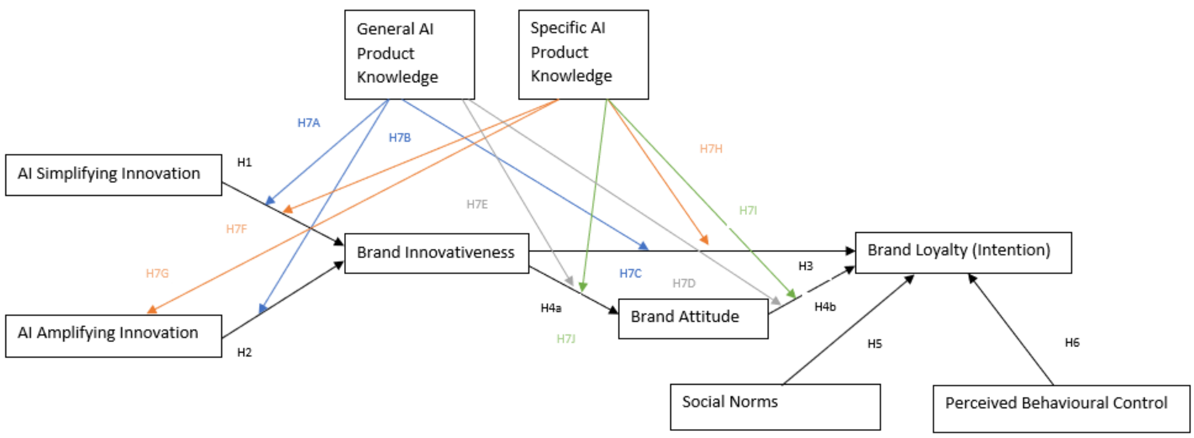
A theoretical model was derived from the literature in relation to brand innovativeness and brand loyalty, in order to explore research questions related to the impact of introducing AI enabled product innovations on brands. The model was empirically tested based on a measurement model which was operationalised around Amazon UK shopping and the Amazon app. Amazon, and the Amazon App were chosen as an established consumer brand and a key brand product which had introduced both AI enabled simplifying and amplifying innovations.  An online survey was sent to a purposive sample of Amazon app users, gathering 209 usable responses. Users were from two age categories, 18 to 35 years of age and over 35s.

A central assertion of the model is that AI enabled product innovations (both simplifying and amplifying) can lead to increased perceived brand innovativeness which in turn can lead to brand loyalty. In more detail, the following research questions were derived from the literature and addressed:

- *Research Question 1:* Do AI Simplifying Innovations and AI Amplifying Innovations increase perceived Brand Innovativeness?
- *Research Question 2:* Does increased Brand Innovativeness lead to increased Brand Loyalty and is this relationship (partially) mediated by Brand Attitude?
- Research Question 3: Does Product knowledge have a moderating effect on the relationships described in Research Questions 1 and 2 above?

A conceptual model relating to the three research questions was created, and hypotheses developed to enable exploration of each of the research questions empirically. A total of 18 hypotheses were examined utilising PLS-SEM (covariance based structural equation modelling) and either accepted or rejected. The conceptual model and hypotheses (with the exception of H8 – age acts as a moderator of the model relationships) are repeated below for ease of reference.

*Figure 27: Conceptual model*




### 7.2.1 Research Question 1

The two hypotheses relating to research question 1 were strongly supported by the analysis, with relationships being positive and statistically significant. On this basis AI enabled simplifying innovations and AI enabled amplifying innovations do increase perceived brand innovativeness in the context of this study. The relationship between amplifying innovation and brand innovativeness appeared to be significantly stronger than that between simplifying innovation and brand innovativeness.

### 7.2.2 Research Question 2

Of the three hypotheses forming the basis of research question 2, two were strongly supported, and weak evidence for the third hypothesis was seen. Brand innovativeness had a significant positive relationship with brand loyalty, as did brand attitude. Only tentative evidence of a positive relationship between brand innovativeness and brand loyalty was found – so only weak evidence that the relationship between brand innovativeness and brand loyalty is partially mediated by brand attitude is found.

### 7.2.3 Research Question 3

Eight tentative hypotheses were developed to explore potential moderating effects of two types of knowledge of AI innovations at the product level on relationships described in the other research questions were explored. Support was found for knowledge of specific AI enabled new product features in the Amazon app having a moderating effect on the relationship between AI enabled product innovations and brand innovativeness, and brand innovativeness and brand loyalty. No moderating effect for general knowledge of the use of AI in the Amazon app was observed, however an interesting direct effect of general knowledge on brand loyalty was noted.

### 7.2.4 Other Hypotheses Relating to Control Variables

No age-related moderation was identified by the study. Social norms have a positive and significant relationship with brand loyalty, but perceived behavioural control did not. These results are not necessarily surprising.

## 7.3 Theoretical Contributions of this Research

In addressing research question 1 we make a first contribution to knowledge, as no study can be found empirically examining the impact of AI enabled product innovations on brand innovativeness along the two innovation dimensions of Amplifying Innovation and Simplifying Innovation, comparing the impact of each type. Our study demonstrates that both AI enabled simplifying innovations and AI enabled amplifying innovations when implemented effectively can have a positive impact on perceived brand innovativeness and suggest that AI enabled amplifying innovations have a much stronger impact than simplifying ones based on our examination of standardises path coefficients.

In relation to research question 2, the study finds tentative evidence for the partial mediation by brand attitude of the relationship between brand innovativeness and brand loyalty. No prior study can be identified that empirically examines the impact of Brand Attitude as a partial moderator of the relationship between Brand Innovativeness and Brand Loyalty. Whilst individual relationships can be found in between brand innovativeness and brand loyalty, (Eisingerich and Rubera, 2010), brand innovativeness and brand attitude, (Sanayei et al, 2013) and brand attitude and brand loyalty (Liu et al, 2012), no model has tested all three relationships simultaneously to date. However, further studies will be required to confirm more substantially brand attitude as a partial moderator given the limited sample size in this study and lack of statistical significance of the relationship between brand innovativeness and brand attitude in this study.

Finally, with regards to research question 3, it has been identified that attitude confidence can act as a moderator between attitude and behavioural intention (Berger, 1992; Berger et al,1994) found that product knowledge through the mechanism of increased confidence, had a moderating effect on the relationship between attitude to a product and intention to buy it. In general, it can be argued, by extension, different types of subjective product knowledge may have moderating effects on the relationship between any belief or perception that is an antecedent to another belief or perception if product knowledge might improve confidence in those beliefs, or indeed reduce confidence in those beliefs. Judgments based on more knowledge are made with greater confidence (Peterson and Pitz, 1988). However, no prior study can be found that examines the moderating effects of the degree of product knowledge on relationships between AI enabled product innovations and Brand Innovativeness, and on relationships between Brand Innovativeness and Brand Loyalty. In relation to research question 3 we find evidence of moderation by specific AI product knowledge, being knowledge of specific features and functions in the Amazon app introduced as AI enabled innovations. This knowledge appears to moderate the relationship between AI enabled amplifying product innovations and brand innovativeness, and brand innovativeness and brand loyalty. This is a new contribution to the literature.

### 7.3.1 Research Extends Theory

Although previous studies have explored the BVC and TPB model, no study has combined the specific variables in one model. The study extends the applications of the BVC model, in particular to understand the customer mindset theme by proposing a conceptual framework which reaches beyond the scope of the traditional brand value chain. The study responds to the call by Mariani et al, (2022) to investigate combining behavioural research with other theory such as BVC and product innovation.

The study extends understanding of the influence of AI innovations in particular on the perception of brand innovativeness by demonstrating that increasing specific AI product knowledge (knowledge of specific AI enabled applications) can increase the effectiveness of AI enabled product innovations in boosting perceptions of brand innovativeness. This extension of the framework offers a perspective for researchers and managers to create apps for consumers and to ensure they educate consumers to increase brand loyalty.

The conceptual framework highlights the critical role of specific AI product knowledge to increase competitiveness as well as a novel contribution. The expanded framework takes into account the broader context of AI innovations, in doing so providing a comprehensive understanding of overseeing the process linking brand development to social influence and ability to extend consumer tasks further. Furthermore, the marketing activities which take place within the consumer mindset create brand equity by adding value through specific AI product knowledge and a sense of perceived brand innovativeness through amplification of tasks.

The current literature shows an apparent gap of knowledge around the influence of AI, which has often been overlooked when applying these models. The study prompts a re-evaluation of these models by challenging and extending these existing frameworks. The study introduces brand attitude as a partial moderator, of the link between brand innovativeness to brand attitude, and loyalty to brand attitude in the literature. The exploration of whether brand attitude moderates these relationships further extends and challenges the present literature in this area. The study offers fresh insights into the influence of AI product knowledge as a moderator, as specific AI product knowledge further extends the knowledge in this area.

As there is no current literature around AI product knowledge, separating specific from general AI product knowledge proposes additional value to knowledge for future study in this area. The study advances the dialogue on brand loyalty by deepening the comprehension of the factors that contribute to brand innovativeness through examination of AI amplifying and simplifying innovations for consumers as distinct constructs. It further shows that AI innovations creating new functions and features (amplifying) as opposed to making existing functionality easier to use (simplifying) have stronger effect on perceptions of brand innovativeness.

### 7.3.2 Brand innovativeness and Brand Loyalty

The study advances the dialogue on brand loyalty by deepening the comprehension of the factors that contribute to brand loyalty. The present study provides valuable insight into how brand loyalty is cultivated through increased brand innovativeness and is further enlarged through the moderating role of specific AI product knowledge. The study build on the TAM Model (Venkatesh et al, 2000) by offering important insights into the factors the influence purchase intentions. The discovery of acknowledging consumers with specific AI product knowledge moderating the relationship of AI amplifying innovation and brand innovativeness highlights the dimension of increased AI power to do more with the innovations, influencing the perception of brand innovativeness to play a crucial role in creating a strong relationship with brand loyalty to increase purchase intentions. Brand loyalty is cultivated through AI amplifying and simplifying innovations for consumers, by increasing perceived brand innovativeness. Purchase intentions are formed through trust, confidence, usefulness and ease of use. The research further develops the understanding of the necessary requirements to increase consumers product knowledge of specific AI innovations, to increase trust, confidence and usefulness in order to enhance the perception of brand innovativeness. Brand loyalty is developed through an increase of brand innovativeness, by increasing confidence through the amplification of tasks resulting in positive impressions developing an innovative brand association. As AI mobile applications use a variety of mechanisms to retain customers such as offering personalised experiences through recommendations, tailored content and interacting through an individual interface. This enhances consumer satisfaction and engagement as the consumer feels connected to the brand. The findings indicated that consumers associated a higher level of brand innovativeness with increased capabilities offered by AI innovations, the more they perceived the brand to be innovative, thus resulting in a higher level of brand loyalty. This improves the user experience and reinforces brand commitment to ensuring consumer expectations are met. The result of amplified innovations means consumers are more knowledgeable and favour the brand. This increases brand innovativeness as perceptions towards the brand become useful and offer productive solutions. Brand innovativeness helps to make a brand stay relevant, as well as increase the quality and reliability of a brand. New features are trusted, making expansion of features easier – for example adding music on Instagram carousel posts, which was a direct transition of posts. Furthermore, according to the findings of the study, a high level of brand innovativeness implies an increased amount of brand loyalty. This example can be employed for global companies such as Apple, Google, Nike, Amazon, and Microsoft who have spent billions of dollars on marketing by claiming a core value is innovation at the heart of their research and development in order to increase their perceived brand innovativeness to enhance the loyalty of their customers (Pappu and Quester, 2016: Henard and Dacin, 2010). The results speak for themselves, as these businesses are classed in the top 20 of the worlds iconic and innovative brands. A high level of brand attitude and social norms, which are already well-established links to brand loyalty are also confirmed in the study. With reference to Sham's (2015) framework, the investigation proved that brand loyalty and brand innovativeness are related in the context of AI innovations within an App. In the case of Amazon, reviews and testimonials have been employed to build credibility and brand recognition. This social influence strengthens the brands reputation by encouraging non-users to use Amazon, as well as build a loyal customer base. Although no PBC were established, the reason may be the ease of use of using the App.  Overall, the findings indicate a favourable relationship between brand innovativeness to brand loyalty as a result of specific product knowledge and amplified AI innovations, representing a significant theoretical advancement in the area of knowledge in AI, marketing, consumer behaviour, brand innovativeness, product knowledge and brand loyalty.

### 7.4 Implications for Managers

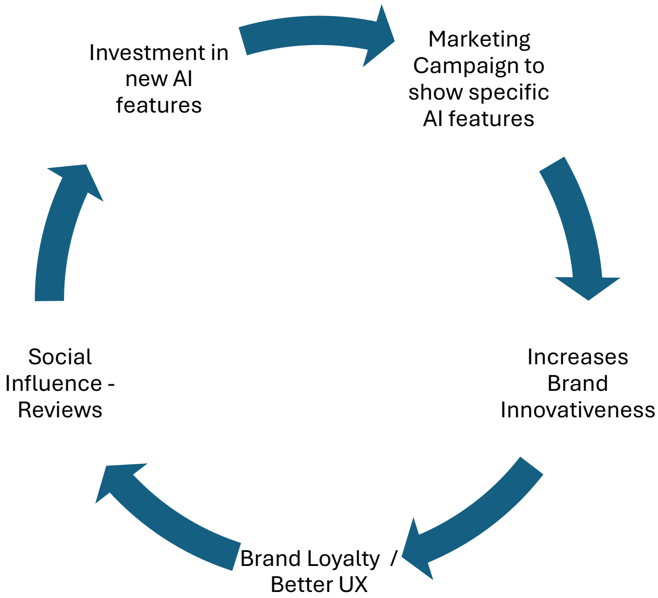
This research poses practical relevance for marketing managers who are searching to improve their marketing strategies for AI innovative products.  Businesses invest heavily in research and development in AI innovations, yet risk unable to create a robust marketing strategy which understands the influence of AI innovations and how to build brand innovativeness perceptions.  Brand innovativeness is important for attracting consumers (Lafferty and Goldsmith, 2004).  The importance for managers to understand the significance of the impact of brand innovativeness, and the investment in AI is required to increase consumer perception, as behaviours are rapidly evolving (Mustak et al, 2021), competitors are investing in AI, it is essential to remain competitive.  Managers are able to use AI to frame and innovate their strategy (Mariani et al, 2023).

First, Managers need to understand a consumer's perception of Brand Innovativeness is enhanced when an app is made easier or amplifies their production of tasks.  To build a successful innovative image of a brand, consumers evaluate their experiences with the information they are given.  Consumers with specific AI product knowledge leads to brand innovativeness.  When consumers have low product knowledge, managers should use influential strategies to focus on using the social groups to influence those consumers.  An influential form of communication will increase interest and knowledge.  By incorporating influencers (reference groups) to advise their peers, to increase awareness, intention and brand loyalty.

Another important practical implication for managers is to focus their strategies to enhance brand innovativeness which will have many consequences. Greater efforts by managers are needed to question their current communications with a focus on the development of strategies to lead to Brand Innovativeness.  Furthermore, the literature states “Consumers are not aware of all of a brand’s innovations, they do not keep track of all innovations” (Hubert et al, 2017:157). The findings showed perceived brand innovativeness could be increased through targeted communications about the functionalities and features to consumers. On one hand, promotions on the actual features and functionalities of AI innovations will create stronger brand relationships (Shams et al, 2015). This ensures the specific features are used and understood by consumers. By understanding and using the new functions, they increase productivity, whilst manifesting positive associations with the brand. The general promotions of AI should be used within the communications to increase decision-making behaviours. When consumers have specific or knowledge that AI is in the function, they are inclined to manifest positive perceptions of the brands ability to be innovative. By incorporating brand theory and principles, such as positive associations of newness or extrinsic clues via image association, innovation is likely to be cost effective (Shams et al, 2015).

The study’s main practical implication for actual design of the App is to remain simple and easy to use. As the findings demonstrate, both groups of specific and general AI product knowledge users crave a convenient, accessible, easy and useful app. By providing a simple and useful app, this ensures customers are satisfied and hold positive perceptions of the brand. If they are able to do more within the app, which makes it easier to use, their perception of Brand innovativeness increases. Specific product knowledge significantly contributes to building and nurturing brand loyalty amongst consumers. Enabling a comprehensive understanding of the AI features that resonates with their target audience, as well as the development of tailored marketing campaigns, can be used to effectively communicate these advantages. Ensuring brand marketing campaigns specifically accentuate the new features will firstly enhance brand innovativeness, as well as ensure the specific features impress their consumers. By enabling the specific features in the marketing communications by conveying the benefits of the AI enhancements, a stronger connection with consumers is built (building brand loyalty), as they are able to establish an amplified use of this, leading to customer retention and repeat purchase. Furthermore, managers are encouraged to invest heavily in robust marketing to develop specific knowledge of the AI features to increase brand innovativeness. The education of consumers enhances their understanding of the specific features, which as the research demonstrates leads to satisfaction and increased levels of loyalty. Knowledgeable consumers are able to make informed purchasing decisions, which also increases perceived brand innovativeness as it empowers consumers to use AI feature more effectively, which maximises the value of the brand, leading to repeat purchase. Overall, communicating the specific AI features to a consumer leads the consumer to believe the brand is innovative, as they feel they can “do more” with the knowledge they have from AI. Ultimately with reference to the BVC model, where brand building investments influence customer perceptions and translate to value creation. These efforts result in enhancing market performance as well as lead to increased shareholder value enabling a tangible economic value to investments in AI features (see model below). A consumer with positive Brand Innovativeness forms a brand attitude which in turn stimulates brand loyalty. The importance of brand loyalty for managers is also crucial for positively influencing brand equity (Lang et al, 2022). Furthermore, Brand Loyalty in business is seen as a measurement of marketing efforts. The BVC postulates that from understanding the consumer mindset, it affects the brand performance reflects in the shareholder value. For businesses, the value created by moving through the chain, brings monetary success to the organisation (Keller and Lehmann, 2003). Investments in AI innovations (both amplified and simplified) will benefit the business. Marketing activity informing consumers of the AI functions and features, using both amplified and simplified AI innovations presents a positive brand perception. To add to this, forming a positive brand attitude through the marketing communications will enhance perceptions of innovativeness. The loyalty of current customer can be used to create brand ambassadors for the business, as part of the influential form of communication referred to earlier. This cycle will ensure a loop of long-term success of retention and sustainability for marketers.

*Figure 28: Model to Demonstrate Practical Implications*




The model above demonstrates the continuous flow from Investment to a tailored marketing campaign to demonstrate the specific AI feature will increase brand innovativeness, brand loyalty and enhance the customer experience will enabling obtain positive social reviews whilst increasing the value of the brand. This practical model is to be used by marketing practitioners to increase brand loyalty by using specific marketing communications to increase brand awareness as well as socially influence users' perceptions to build a brand perception of innovativeness.

### 7.5 Limitations of this research

The scope of the study has offered a number of contributions to the field of AI in marketing, however, there are a number of uncontrollable factors. First, the UK was chosen as the target location, as the researcher is based in the UK and has access to UK participants and Amazon UK data. While an unavoidable limitation is proposed through the geographic location chosen, it was not possible to plan to venture further geographically due to the exceptional factors and uncertainties of covid restrictions, during the planning stage of this research. Furthermore, if the location was cast further, additional environmental aspects such as cultural differences, or technology readiness of a country will have impacted the results. Moreover, attitudes and access to technology globally vary. It was not possible to extend the questionnaire to obtain further questions, though this may have addressed supplementary possibilities, the length of a questionnaires can detract respondents. It is unfortunate that the researcher was unable to conduct longitudinal studies due to the project deadlines. Conducting a longitudinal study may have revealed the extent to which consumers are loyal. Additionally, although the minimum sample size was met, future studies to expand the sample size for a longer period will increase the participation rate, as well as the age range, extending the contribution to the study. Additionally a small sample size can cause significant relationships between constructs to be missed, due limitations on statistical power achieved (Hair et al, (2022). There was an imbalance of sample size between the age groups of respondents, which may affect generalisability of the study and accuracy of the group analysis conducted. Future studies may choose to address these issues.

The frequency of updates from the Amazon brand and technology updating rapidly, the depth of tracking consumers for a study over a long period of time may reveal additional patterns and trends as attitudes and product knowledge adapts. The present study used the BVC model, whilst this was carefully applied, this set the boundaries of the brand research. Other theoretical models may have widened the scope of the study. Despite the limitations, the research provided valuable insights from the present study.

### 7.6 Directions for Future Research

This study has several directions for future research. As this research used a single cross-sectional quantitative design to test the proposed model. First, future studies can experiment with methods by adding a qualitative or mixed methods approach to layer interviews and focus groups to add further responses, additionally longitudinal studies may be considered to allow for deeper insights. This could validate the findings further. In-depth interviews with users could have provided insight into why and how they use the app further. As the survey was online, a face-to-face interview or focus groups may have verified the findings further through triangulation, through interpretation of body language and gestures. With the emphasis on testing the conceptual model and hypothesised relationships, this was not feasible. Secondly, as AI innovations are rapidly evolving, future research should test various AI functions, such as AR, VR, XR, chatbots, voice assistants or generative AI within alternative innovative (IT /car) sectors (Google or Tesla) could be beneficial, as this research has developed the rise in interest from consumers and businesses has developed. New AI innovations on Chat-GPT, are popular amongst consumers which would enhance the understanding of the broader perspectives of AI innovations. Moreover, testing an upcoming AI innovation which has not gained any traction would be feasible to test the market, though longitudinal research is required, to test brand loyalty. Additionally, extending the present study from online consumer retails to other industries such as travel. This may provide a different viewpoint, as consumer perceptions are varied. Third, the research was based in the UK, this could be expanded to a comparative study to test the model from a geographical basis by users from other countries who shop via the Amazon App, benefitting from a difference in perceptions due to social norms, PBC and technology readiness. Fourth, other research directions could be to test “emotions” into the model. Such a study would provide a deeper analysis into brand attitudes. Within the findings chapter, a lack of frequency and time tested on the app was not recoded. Researching the behaviours on usage of the AI innovations for frequency and time may results in a higher perception of the brand. The present study used three AI-functions to test the AI product knowledge variable; other AI innovative functions can be tested such as the voice function within the Amazon App. This will widen the scope of understanding AI innovations which facilitate product knowledge. Fifth, as general awareness of AI product knowledge had a positive relationship to brand loyalty, future studies may delve into researching the reasons behind having a general awareness of brands leading to loyalty (rather than exclusively brand innovativeness).

## 7.7 Chapter Summary

This final chapter summarised the findings of the study. The contributions of the study were outlined in the form of contribution to the extant literature on AI innovations, and existing body of knowledge in this area. Next, several implications for managers were set out. The study had few limitations, with a look to the future direction this research could expand into.

Acknowledging the limitations of the present study, the research expands the body of knowledge to the AI literature. It has offered valuable insights and implications or managers. This investigation answers the research question of the influence of AI product knowledge, using AI innovations on brand innovativeness and brand loyalty. Future studies will add to the depth of this comprehensive research. The study bought together different disciplines by developing practical relevance for research and practice. Moreover, the study contributes to further develop the understanding of AI innovations and their influence on consumer perceived brand innovativeness.

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# Appendix

Appendix A **-** Table of Companies with Amplified and Simplified elements in their App.

| **Company** | **Amplification** | **Simplification** |
|---|---|---|
| Amazon | Echo integrates home devices | Alexa Voice commands |
| Amazon | StyleSnap/Barcode/Images from the APP – take a photo and find the product | Product Recommendations |
| Microsoft | Excel - Insights or Cortana – reminders in outlook | word- grammar assistant |
| Google | Google assistant, Cortana | text suggestions / Smart reply GMAIL |
| Apple | Hotel bookings – when you open your Map | Siri |
| LinkedIn | Helps recruiters sift through candidates | Connect suitable candidates with recruiters |
| Pinterest | Lens | Pinterest search and recommendations |
| Spotify | AI bot to roast fans (about their music tastes) | Recommendations |
| Netflix | Auto-Generation and Personalization of Thumbnails / Artwork | Recommendations |
| Uber | Map to show car location | Chatbot (to the driver) |
| Social media | Recognise bullying online | Recognise your face, recommendations, filters, chatbots, sentiment analysis, monitor topics, rank topics, |
| Asos | Style Match - is a visual search tool, where you can find products on our app with one quick tap. | FIT assistant |
| Loreal | Modiface – Virtual make-up try on | See lipstick colours on consumer - AR |
| Estee lauder | App for Visually impaired users – feedback on make-up | Advice on how to put make up on via voice-enabled AI |
| Banking | Fraud Prevention | Chatbots |
| Tesla | Self-driving cars | Driver support features, driver biometrics |
| Healthcare | identify patterns within patient data to determine their probability of getting a specific disease or illness | AI Symptom checkers/ streamline processes |

Appendix B – Recruitment Post

Manchester
Metropolitan
University

- Hi, I'm Monica, a PhD Student at Manchester Metropolitan University, researching AI and Marketing.

- If you have an Amazon App, I'd like to learn more about whether the AI within it affects your attitude towards the Brand.

- It's short and will take less than 4 minutes.
- It will mean the world to me and my PhD study.
- Please feel free to share!

Appendix C - Questionnaire

qualtrics XM

# Survey

Start of Block: Information and Consent

Q1a Do you have the Amazon App on your smart devices?

○ Yes (1)

○ No (2)

*Skip To: End of Survey If Do you have the Amazon App on your smart devices? = No*

Q1b Are you over the age of 18?

○ Yes (1)

○ No (2)

*Skip To: End of Survey If Are you over the age of 18? = No*

Q1c Can you confirm you have no learning impairment or disability? (say Yes, if you do not, No, if you do have)

○ Yes (1)

○ No (2)

*Skip To: End of Survey If Can you confirm you have no learning impairment or disability? (say Yes, if you do not, No, if yo... = No*

Q1d Can you confirm you have no problems understanding verbal or written English?

◯ Yes (1)

◯ No (2)

*Skip To: End of Survey If Can you confirm you have no problems understanding verbal or written English? = No*

Q1

**Participant Information Sheet**

**1. Invitation to research.**
I would like to invite you to take part in a research project based on brand attitudes, and what this means for brand loyalty. My name is Monica Chauhan, and I am a PhD researcher at Manchester Metropolitan University (MMU), UK, working with academic supervisors at MMU on the project. Our research project is exploring the influence of product and service improvements.

**2. Why have I been invited?**
You have been chosen because you are over 18, and are familiar with Amazon consumer products and services, and so meet our selection criteria for the study.

**3. Do I have to take part?**
It is up to you to decide. We will describe the study and go through this information sheet, which we will give to you. We will then ask you give consent via the online questionnaire you will be asked to complete to show you agreed to take part in a survey. You are free to withdraw at any time before completion of the questionnaire or within 24 hours of completing any survey, without giving a reason. If you do withdraw, the data you have given so far will be securely deleted and not used in the study. If you withdraw from the survey, and it is not possible to identify the information you have already given, because of the nature of the data capture, it may not be possible to delete the data. If you choose to withdraw at anytime, it also cannot be guaranteed to withdraw information once it has been analysed or aggregated with other data. Hence, you need to contact Monica Chauhan within 24 hours of the study data capture.

**4. What will I be asked to do?**
You will be asked to either participate in an online questionnaire answering questions for about 8-10 minutes. The questions do not collect sensitive data other than the following - age group, nationality, gender and income level. You can decline to give gender and income level information as an option within the questionnaire. All data is anonymised and stored securely. The questionnaire data will be used in a statistical analysis to test theories about how AI (Artificial Intelligence) affects brand loyalty. In this study we define Artificial intelligence (AI) as a technology, or machine, that can perform a task which if conducted by a human would

require intelligence to complete.

**5. Are there any risks if I participate?**
There are no risks to participation we are aware of.

**6. Are there any advantages if I participate?**
There are no direct advantages or rewards available for participating, but you will be helping research that ultimately may lead to products like Amazon web offerings being better targeted at the right individuals, potentially leading to benefits for all purchasers.

**7. What will happen with the data I provide?**
When you agree to participate in this research, we will collect from you personally-identifiable information. The Manchester Metropolitan University ('the University') is the Data Controller in respect of this research and any personal data that you provide as a research participant. The University is registered with the Information Commissioner's Office (ICO) and manages personal data in accordance with the General Data Protection Regulation (GDPR) and the University's Data Protection Policy. We collect personal data as part of this research in the form of gender, income level, age range and nationality. As a public authority acting in the public interest, we rely upon the 'public task' lawful basis. When we collect special category data (such as medical information or ethnicity) we rely upon the research and archiving purposes in the public interest lawful basis. All data will remain anonymous. Your rights to access, change or move your information are limited, as we need to manage your information in specific ways in order for the research to be reliable and accurate. If you withdraw from the study, your data will be securely deleted and not used in the research. We will not share your personal data collected in this form with any third parties. It is the University's policy to only publish anonymised data unless you have given your explicit written consent to be identified in the research. The University never sells personal data to third parties. We will only retain your personal data for as long as is necessary to achieve the research purpose. Data is held on secure encrypted hard drives in the UK and can only be accessed by authorised individuals involved in the research. For further information about use of your personal data and your data protection rights please see the University's Data Protection Pages.

**8. What will happen to the results of the research study?**
The results will be published in peer reviewed academic journals, in an internal report, and in conference presentations.

**9. Who has reviewed this research project?**
The research project has been reviewed by the MMU Faculty ethics team.

**10. Who do I contact if I have concerns about this study or I wish to complain?**
For general questions contact: Professor Paul Smith via email: psmith@mmu.ac.uk or telephone +44 161 247 6053 If you have any concerns or complaints about the project, please contact Professor Kevin Albertson, head of ethics for Manchester Metropolitan University Business School, by email: k.albertson@mmu.ac.uk. If you have any concerns regarding the personal data collected from you, our Data Protection Officer can be contacted using the legal@mmu.ac.uk e-mail address, by calling 0161 247 3331 or in writing to: Data Protection Officer, Legal Services, All Saints Building, Manchester Metropolitan University, Manchester, M15 6BH.

You also have a right to lodge a complaint in respect of the processing of your personal data with the Information Commissioner's Office as the supervisory authority. Please see: https://ico.org.uk/global/contact-us/

**THANK YOU FOR CONSIDERING PARTICIPATING IN THIS PROJECT**

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Q29 Please select Yes to all of the items below to show that you agree with the statements and consent to participating in the study (or No if you do not consent).

| | Yes (1) | No (2) |
|---|---|---|
| I confirm that I have read the participant information above, for the study (1) | ○ | ○ |
| I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily (2) | ○ | ○ |
| I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason, without my legal rights being affected. Withdrawal can be achieved simply through non-completion or only partial completion of the questionnaire. (3) | ○ | ○ |
| I agree to participate in the project to the extent of the activities described to me in the above participant information. (4) | ○ | ○ |
| By clicking YES, I give permission for the data I enter on this questionnaire to be used for research purposes outlined in the participant information (5) | ○ | ○ |

*Skip To: End of Survey If Please select Yes to all of the items below to show that you agree with the statements and consen... = No*

*Skip To: End of Survey If Please select Yes to all of the items below to show that you agree with the statements and consen... = No*

*Skip To: End of Survey If Please select Yes to all of the items below to show that you agree with the statements and consen... = No*

*Skip To: End of Survey If Please select Yes to all of the items below to show that you agree with the statements and consen... = No*

*Skip To: End of Survey If Please select Yes to all of the items below to show that you agree with the statements and consen... = No*

Page Break

Q2 What is your age?

○ 18-35 (1)

○ 36-55 (2)

○ 55+ (3)

**End of Block: Information and Consent**

**Start of Block: Product Knowledge**

Q3 On a scale of 1-7, how knowledgeable are you about Amazon's Artificial Intelligence features on the Amazon App?
(1 = very weak knowledge, to 7 = very knowledgeable.)

Remember: Artificial intelligence (AI) is defined as a technology, or machine, that can perform a task which if conducted by a human would require intelligence to complete.

- ◯ Very weak level of knowledge (1)
- ◯ Weak level of knowledge (2)
- ◯ Somewhat weak level of knowledge (3)
- ◯ Neither strong nor weak level of knowledge (4)
- ◯ Somewhat strong level of knowledge (5)
- ◯ Strong level of knowledge (6)
- ◯ Very knowledgeable (7)

---

Q4 On a scale of 1-7, how familiar are you with Amazon's Artificial Intelligence features on the Amazon App?
(1 being completely unfamiliar, 7 being very familiar)

- ◯ Completely unfamiliar (1)
- ◯ Weak level of familiarity (2)
- ◯ Somewhat weak level of familiarity (3)
- ◯ Neither strong nor weak level of familiarity (4)
- ◯ Somewhat strong level of familiarity (5)
- ◯ Strong level of familiarity (6)
- ◯ Very familiar (7)

---

Q5 Please rate the relative strength of your knowledge of Amazon's AI features compared to the average consumer from 1-7.
(1 being relatively very weak knowledge, 7 being relatively strong weak knowledge).

- ○ Relatively very weak (1)
- ○ Relatively weak (2)
- ○ Relatively somewhat weak (3)
- ○ Neither strong nor weak (4)
- ○ Relatively somewhat strong (5)
- ○ Relatively strong (6)
- ○ Relatively very strong (7)

---

Q6 On a scale of 1-7, rate the strength of your awareness of the StyleSnap feature on the Amazon app.
(1 being very weak or no awareness, 7 being very strong awareness)

- ○ Very weak or no awareness (1)
- ○ Weak awareness (2)
- ○ Somewhat weak awareness (3)
- ○ Neither strong or weak awareness (4)
- ○ Somewhat strong awareness (5)
- ○ Strong awareness (6)
- ○ Very strong awareness (7)

---

Q7 On a scale of 1-7, rate the strength of your awareness of the Barcode Search feature on the Amazon app.
(1 being very weak or no awareness, 7 being very strong awareness)

- Very weak or no awareness (1)
- Weak awareness (2)
- Somewhat weak awareness (3)
- Neither strong or weak awareness (4)
- Somewhat strong awareness (5)
- Strong awareness (6)
- Very strong awareness (7)

---

Q8 On a scale of 1-7, rate the strength of your awareness of the Image Search feature on the Amazon app.
(1 being very weak or no awareness, 7 being very strong awareness)

- Very weak or no awareness (1)
- Weak awareness (2)
- Somewhat weak awareness (3)
- Neither strong or weak awareness (4)
- Somewhat strong awareness (5)
- Strong awareness (6)
- Very strong awareness (7)

**End of Block: Product Knowledge**

---

Start of Block: BI

Q9 Please state the extent to which you agree with the following: "Amazon have introduced technologies that have never been used in online shopping before." (1 being strongly disagree, 7 being strongly agree)

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

---

Q10 Please state the extent to which you agree with the following: " Amazon has caused changes to the whole online shopping industry."
(1 being strongly disagree, 7 being strongly agree)

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q11 Please state the extent to which you agree with the following: "Amazon is highly innovative bringing totally new technologies to the market."
(1 being strongly disagree, 7 being strongly agree)

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

**End of Block: BI**

**Start of Block: AI**

Q12 Please state the extent to which you agree with the following: “Amazon introduces Innovations powered by artificial intelligence that let me do things I couldn't do before”. (1 being strongly disagree, 7 being strongly agree)

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

---

Q13 Please state the extent to which you agree with the following: "Amazon has created new functionality using artificial intelligence bringing new features and services that previously were unavailable".
(1 being strongly disagree, 7 being strongly agree)

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

---

Q13 Please state the extent to which you agree with the following: "Amazon have managed to reinvent their services and deliver different benefits and solutions to me by utilising artificial intelligence".
(1 being strongly disagree, 7 being strongly agree)

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

**End of Block: AI**

---

**Start of Block: SI**

Q14 Please state the extent to which you agree with the following: "Amazon has been able to use artificial intelligence to help make it easier to use its digital shopping services".
(1 being strongly disagree, 7 being strongly agree)

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

---

Q15 Please state the extent to which you agree with the following: "Amazon constantly simplifies its website and app to make it easier to shop using artificial intelligence enabled innovations".
(1 being strongly disagree, 7 being strongly agree)

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

---

Q16 Please state the extent to which you agree with the following: "The technology innovations introduced by Amazon and powered by artificial intelligence make it ever easier to work with their apps and websites when shopping and browsing for products".
(1 being strongly disagree, 7 being strongly agree)

- ○ Strongly disagree (1)
- ○ Disagree (2)
- ○ Somewhat disagree (3)
- ○ Neither agree nor disagree (4)
- ○ Somewhat agree (5)
- ○ Agree (6)
- ○ Strongly agree (7)

End of Block: SI

---

Start of Block: BA

Q17 Rate on a 7 point scale your feelings about Amazon - do you like or dislike Amazon?

- ○ Extremely dislike (1)
- ○ Dislike (2)
- ○ Somewhat dislike (3)
- ○ Neither like nor dislike (4)
- ○ Somewhat like (5)
- ○ Like (6)
- ○ Strongly like (7)

Q18 Please carefully read and carry out the following instruction:  Please select "Disagree" below

○ Strongly disagree  (1)

○ Disagree  (2)

○ Somewhat disagree  (3)

○ Neither agree nor disagree  (4)

○ Somewhat agree  (5)

○ Agree  (6)

○ Strongly agree  (7)

---

Q19 Rate on a 7 point scale your attitude towards Amazon -  is it favourable or unfavourable?

○ Extremely unfavourable  (1)

○ Unfavourable  (2)

○ Somewhat unfavourable  (3)

○ Neither favourable nor unfavourable  (4)

○ Somewhat favourable  (5)

○ Favourable  (6)

○ Strongly favourable  (7)

**End of Block: BA**

---

**Start of Block: BL**

Q20 Please indicate to what extent you agree with the following statements about Amazon

| | Strongly disagree (1) | Disagree (2) | Somewhat disagree (3) | Neither agree nor disagree (4) | Somewhat agree (5) | Agree (6) | Strongly agree (7) |
|---|---|---|---|---|---|---|---|
| I encourage friends and relatives to shop with Amazon (1) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I say positive things about Amazon to other people (2) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I intend to shop with Amazon in the next few years (3) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I would recommend Amazon to someone who seeks my advice (4) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I intend to keep purchasing products from Amazon. (5) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I intend to buy from Amazon the next time I buy online again (6) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Q21 Carefully read and carry out the following instruction:  Please select "Agree" below

- Strongly disagree  (1)
- Disagree  (2)
- Somewhat disagree  (3)
- Neither agree nor disagree  (4)
- Somewhat agree  (5)
- Agree  (6)
- Strongly agree  (7)

**End of Block: BL**

---

**Start of Block: SN**

Q22 Please indicate to what extent you agree with the following statements about Amazon:

| | Strongly disagree (1) | Disagree (2) | Somewhat disagree (3) | Neither agree nor disagree (4) | Somewhat agree (5) | Agree (6) | Strongly agree (7) |
|---|---|---|---|---|---|---|---|
| I believe people important to me would be using Amazon. (1) | o | o | o | o | o | o | o |
| People I look up to would encourage me to use Amazon. (2) | o | o | o | o | o | o | o |
| My friends would encourage me to use Amazon (3) | o | o | o | o | o | o | o |

End of Block: SN

Start of Block: PBC

Q23 Please indicate to what extent you agree with the following statements about Amazon:

| | Strongly disagree (1) | Disagree (2) | Somewhat disagree (3) | Neither agree nor disagree (4) | Somewhat agree (5) | Agree (6) | Strongly agree (7) |
|---|---|---|---|---|---|---|---|
| Whether I use the Amazon AI is entirely up to me (1) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Nothing will prevent me from using the Amazon app and its features if I choose to do so (2) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I believe I have the ability to use the AI Innovation by amazon (StyleSnap, Barcode and Image) (3) | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

**End of Block: PBC**

**Start of Block: Personal**

Q24 Would like to add any other comments about the Amazon App?

________________________________________________________________

Q25 Optional Questions: What is your annual income level?

- Less than £30,000 (1)
- £30,000 - £50,000 (2)
- £50,000 - £70,000 (3)
- More than £70,000 (4)
- Prefer not to say (5)

Q26 Ethnicity: How would you best describe your ethnicity?

________________________________________________________________

Q27 Education: What is your highest level of Education?

- School (1)
- Undergraduate (2)
- Postgraduate (3)
- PhD (4)
- Prefer not to say (5)

Q28 What is your Employment Status?

- ○ Unemployed (1)
- ○ Homemaker (2)
- ○ Student (3)
- ○ Employed full-time (4)
- ○ Employed part-time (5)
- ○ Self-employed (6)
- ○ Other (7)
- ○ Prefer not to say (8)

**End of Block: Personal**

Appendix D – Fornell-Larker Criterion and Cross-Loadings

Fornell-Larcker criterion

| | AI | BA | BI | BL | PBC | PK | PKDetail | SI | SN |
|---|---|---|---|---|---|---|---|---|---|
| AI | **0.87** | | | | | | | | |
| BA | 0.28 | **0.95** | | | | | | | |
| BI | 0.60 | 0.20 | **0.80** | | | | | | |
| BL | 0.34 | 0.78 | 0.36 | **0.82** | | | | | |
| PBC | 0.17 | 0.26 | 0.17 | 0.33 | **0.74** | | | | |
| PK | 0.46 | 0.15 | 0.22 | 0.21 | 0.01 | **0.93** | | | |
| PKDetail | 0.43 | 0.19 | 0.26 | 0.20 | 0.13 | 0.62 | **0.86** | | |
| SI | 0.73 | 0.34 | 0.58 | 0.34 | 0.24 | 0.38 | 0.38 | **0.88** | |
| SN | 0.25 | 0.36 | 0.25 | 0.56 | 0.30 | 0.09 | 0.12 | 0.28 | **0.85** |

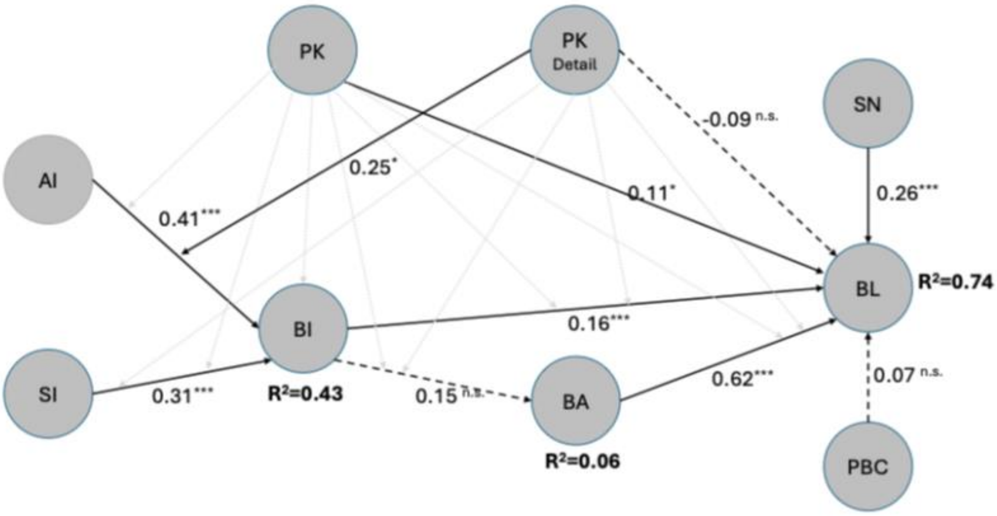
Cross Loadings

| | AI | BA | BI | BL | PBC | PK | PKDetail | SI | SN | PK x SI | PKDetail x BI | PK x BA | PKDetail x BA | PKDetail x SI | PK x AI | PK x BI | PKDetail x AI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **AI1** | 0.87 | 0.31 | 0.51 | 0.30 | 0.17 | 0.45 | 0.42 | 0.59 | 0.17 | 0.02 | 0.12 | 0.09 | 0.06 | -0.05 | -0.05 | 0.06 | -0.03 |
| **AI2** | 0.90 | 0.23 | 0.52 | 0.30 | 0.14 | 0.41 | 0.37 | 0.62 | 0.23 | -0.03 | 0.02 | 0.15 | 0.09 | -0.03 | -0.07 | 0.00 | -0.04 |
| **AI3** | 0.84 | 0.19 | 0.52 | 0.28 | 0.14 | 0.34 | 0.33 | 0.70 | 0.25 | -0.02 | -0.05 | 0.07 | 0.00 | -0.16 | -0.05 | 0.04 | -0.14 |
| **BA1** | 0.28 | 0.95 | 0.20 | 0.76 | 0.25 | 0.15 | 0.20 | 0.31 | 0.35 | 0.05 | 0.04 | -0.19 | -0.18 | -0.03 | 0.10 | 0.01 | 0.07 |
| **BA2** | 0.26 | 0.95 | 0.18 | 0.73 | 0.25 | 0.13 | 0.15 | 0.34 | 0.32 | 0.01 | -0.01 | -0.23 | -0.16 | -0.04 | 0.07 | -0.01 | 0.05 |
| **BI1** | 0.50 | 0.07 | 0.79 | 0.20 | 0.03 | 0.22 | 0.21 | 0.41 | 0.16 | 0.02 | 0.00 | 0.03 | 0.06 | -0.04 | 0.01 | -0.07 | 0.05 |
| **BI2** | 0.29 | -0.07 | 0.67 | 0.13 | 0.13 | 0.09 | 0.09 | 0.26 | 0.05 | 0.10 | -0.04 | 0.06 | 0.05 | 0.05 | 0.01 | -0.03 | 0.05 |
| **BI3** | 0.56 | 0.31 | 0.91 | 0.42 | 0.21 | 0.18 | 0.27 | 0.60 | 0.29 | 0.02 | -0.06 | -0.04 | -0.03 | -0.10 | 0.05 | 0.00 | 0.01 |
| **BL1** | 0.29 | 0.75 | 0.19 | 0.84 | 0.32 | 0.23 | 0.24 | 0.33 | 0.49 | 0.04 | 0.15 | -0.14 | -0.12 | 0.05 | 0.12 | 0.05 | 0.15 |
| **BL2** | 0.35 | 0.73 | 0.27 | 0.85 | 0.21 | 0.24 | 0.19 | 0.29 | 0.45 | -0.03 | 0.04 | -0.21 | -0.09 | -0.03 | 0.00 | 0.02 | 0.04 |
| **BL3** | 0.20 | 0.43 | 0.35 | 0.71 | 0.24 | 0.09 | 0.10 | 0.22 | 0.45 | 0.00 | -0.02 | -0.19 | -0.23 | -0.03 | 0.01 | -0.03 | 0.00 |
| **BL4** | 0.28 | 0.73 | 0.32 | 0.89 | 0.29 | 0.15 | 0.18 | 0.31 | 0.47 | 0.01 | 0.07 | -0.18 | -0.15 | -0.03 | 0.08 | 0.00 | 0.08 |
| **BL5** | 0.25 | 0.59 | 0.36 | 0.85 | 0.24 | 0.14 | 0.09 | 0.26 | 0.42 | 0.08 | 0.11 | -0.15 | -0.12 | 0.04 | 0.10 | 0.08 | 0.10 |
| **BL6** | 0.27 | 0.57 | 0.33 | 0.79 | 0.31 | 0.17 | 0.18 | 0.27 | 0.48 | 0.10 | 0.14 | -0.04 | -0.01 | 0.10 | 0.14 | 0.06 | 0.17 |
| **PBC1** | 0.15 | 0.28 | 0.13 | 0.29 | 0.84 | -0.01 | 0.13 | 0.12 | 0.28 | -0.04 | 0.04 | 0.04 | -0.02 | 0.05 | -0.01 | -0.03 | 0.08 |
| **PBC2** | 0.01 | 0.17 | 0.09 | 0.24 | 0.75 | -0.11 | -0.06 | 0.16 | 0.18 | 0.07 | 0.05 | 0.09 | 0.05 | 0.08 | 0.09 | 0.11 | 0.12 |
| **PBC3** | 0.25 | 0.09 | 0.16 | 0.18 | 0.61 | 0.19 | 0.27 | 0.31 | 0.20 | 0.01 | 0.01 | 0.09 | -0.01 | -0.05 | -0.04 | 0.04 | -0.06 |
| **PK1** | 0.47 | 0.20 | 0.19 | 0.25 | 0.02 | 0.95 | 0.57 | 0.35 | 0.13 | 0.14 | 0.18 | 0.20 | 0.09 | 0.12 | 0.13 | 0.16 | 0.10 |
| **PK2** | 0.40 | 0.16 | 0.18 | 0.20 | -0.01 | 0.95 | 0.61 | 0.36 | 0.06 | 0.17 | 0.18 | 0.24 | 0.13 | 0.15 | 0.16 | 0.17 | 0.12 |
| **PK3** | 0.41 | 0.00 | 0.25 | 0.09 | 0.00 | 0.87 | 0.56 | 0.35 | 0.04 | 0.16 | 0.13 | 0.24 | 0.11 | 0.17 | 0.08 | 0.12 | 0.09 |
| **PK4** | 0.43 | 0.20 | 0.23 | 0.20 | 0.12 | 0.55 | 0.84 | 0.38 | 0.21 | 0.15 | 0.29 | 0.11 | 0.07 | 0.25 | 0.09 | 0.15 | 0.23 |
| **PK5** | 0.36 | 0.14 | 0.26 | 0.14 | 0.09 | 0.54 | 0.88 | 0.29 | -0.02 | 0.13 | 0.21 | 0.16 | 0.03 | 0.13 | 0.11 | 0.16 | 0.12 |
| **PK6** | 0.31 | 0.14 | 0.18 | 0.17 | 0.14 | 0.50 | 0.84 | 0.28 | 0.08 | 0.09 | 0.18 | 0.07 | -0.06 | 0.10 | 0.04 | 0.12 | 0.07 |
| **SI1** | 0.73 | 0.27 | 0.55 | 0.29 | 0.24 | 0.38 | 0.32 | 0.87 | 0.23 | -0.06 | -0.07 | 0.07 | 0.02 | -0.16 | -0.06 | 0.03 | -0.13 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **SI2** | 0.58 | 0.32 | 0.46 | 0.32 | 0.15 | 0.29 | 0.33 | 0.86 | 0.27 | -0.08 | -0.06 | -0.06 | -0.14 | -0.22 | -0.01 | 0.02 | -0.10 |
| **SI3** | 0.61 | 0.32 | 0.50 | 0.30 | 0.23 | 0.33 | 0.35 | 0.91 | 0.23 | -0.04 | -0.04 | 0.07 | 0.00 | -0.16 | 0.05 | 0.06 | -0.02 |
| **SN1** | 0.18 | 0.15 | 0.21 | 0.36 | 0.20 | 0.09 | 0.04 | 0.16 | 0.74 | -0.01 | 0.04 | -0.07 | 0.00 | 0.03 | 0.00 | 0.01 | 0.03 |
| **SN2** | 0.24 | 0.35 | 0.23 | 0.51 | 0.29 | 0.12 | 0.17 | 0.30 | 0.91 | -0.05 | 0.05 | -0.07 | -0.04 | -0.05 | 0.00 | -0.01 | 0.03 |
| **SN3** | 0.22 | 0.37 | 0.21 | 0.53 | 0.27 | 0.03 | 0.07 | 0.22 | 0.90 | -0.04 | 0.07 | -0.10 | -0.03 | -0.03 | 0.01 | -0.02 | 0.08 |
| **PKDetail x BA** | 0.06 | -0.18 | 0.02 | -0.14 | 0.01 | 0.12 | 0.02 | -0.04 | -0.03 | 0.27 | 0.28 | 0.63 | 1.00 | 0.41 | 0.22 | 0.19 | 0.35 |
| **PK x BA** | 0.12 | -0.22 | 0.00 | -0.18 | 0.10 | 0.24 | 0.13 | 0.03 | -0.09 | 0.39 | 0.22 | 1.00 | 0.63 | 0.34 | 0.34 | 0.28 | 0.31 |
| **PKDetail x BI** | 0.04 | 0.02 | -0.04 | 0.10 | 0.05 | 0.18 | 0.27 | -0.06 | 0.06 | 0.48 | 1.00 | 0.22 | 0.28 | 0.65 | 0.46 | 0.67 | 0.66 |
| **PK x BI** | 0.04 | 0.00 | -0.03 | 0.04 | 0.05 | 0.17 | 0.17 | 0.04 | -0.01 | 0.70 | 0.67 | 0.28 | 0.19 | 0.49 | 0.68 | 1.00 | 0.52 |
| **PK x AI** | -0.07 | 0.09 | 0.03 | 0.09 | 0.02 | 0.14 | 0.10 | -0.01 | 0.01 | 0.81 | 0.46 | 0.34 | 0.22 | 0.54 | 1.00 | 0.68 | 0.75 |
| **PKDetail x SI** | -0.09 | -0.04 | -0.06 | 0.02 | 0.04 | 0.15 | 0.20 | -0.21 | -0.03 | 0.65 | 0.65 | 0.34 | 0.41 | 1.00 | 0.54 | 0.49 | 0.77 |
| **PK x SI** | -0.01 | 0.03 | 0.04 | 0.04 | 0.02 | 0.16 | 0.15 | -0.07 | -0.04 | 1.00 | 0.48 | 0.39 | 0.27 | 0.65 | 0.81 | 0.70 | 0.60 |
| **PKDetail x AI** | -0.08 | 0.06 | 0.04 | 0.11 | 0.08 | 0.11 | 0.17 | -0.09 | 0.06 | 0.60 | 0.66 | 0.31 | 0.35 | 0.77 | 0.75 | 0.52 | 1.00 |

Appendix E

Final SEM model (with path coefficients)




*p < = .05, **p < = .01, ***p < = .001 n.s. – not significant