EXAMINING USER ADOPTION OF AUGMENTED REALITY TECHNOLOGY- AN EMPIRICAL STUDY

Thesis

Submitted in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

KOMAL ANAND

SCHOOL OF HUMANITIES, SOCIAL SCIENCES AND MANAGEMENT
NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA, SURATHKAL, MANGALORE-575025

AUGUST, 2024

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DECLARATION

I declare that the research thesis entitled, **"EXAMINING USER ADOPTION OF AUGMENTED REALITY TECHNOLOGY- AN EMPIRICAL STUDY"** submitted to the National Institute of Technology Karnataka, Surathkal in partial fulfilment of the requirements for the award of the degree of **Doctor of Philosophy** in Management is a bonafide report of the research work carried out by me. The material contained in this thesis has not been submitted to any University or Institution for the award of any degree.

Signature of the research scholar

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Date:7th August 2024

CERTIFICATE

This is to *certify* that the Research Thesis entitled **"EXAMINING USER ADOPTION OF AUGMENTED REALITY TECHNOLOGY- AN EMPIRICAL STUDY"** submitted by **Komal Anand (Register Number:187078SM001)** as the record of the research work carried out by her, is *accepted as the Research Thesis submission* in partial fulfilment of the requirements for the award of degree of Doctor of Philosophy.

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Our greatest glory is not in never falling

but in rising every time we fall –

Confucius

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ABSTRACT

The development of technology and the internet has pushed the growth of the E-Commerce sector. This growth has urged utilizing technology to offer better products and services. With the rapid growth in online shopping, e-commerce platforms face high product returns and cart abandonment, which increase cost and waste of resources due to a lack of experience with the product before placing the order. Further, to meet the technological advancements and offer a better shopping experience, companies can utilize technologies such as AR (Augmented Reality). AR uses visual technology, which provides a virtual product experience within the users' surroundings, offering an enhanced shopping experience. AR is a novel technology, and there is a dearth of studies in developing countries such as India. Hence, it is essential to understand the customer's perspective towards using AR in online shopping platforms.

This thesis examines the factors influencing users' behavioral intention towards AR in online shopping platforms. Further, the study has also investigated the mediating role of performance expectancy, effort expectancy and trust between the factors and user behavioral intention. The study has adopted the UTAUT 3 theory, extending it with variables, namely privacy risk, trust, and quality factors. The study is quantitative. Data was collected from Tier 1 cities in South India and analysed using SPSS and AMOS. The descriptive statistics, reliability, and validity tests were computed using IBSS SPSS software 25, whereas the SEM technique was computed using IBM SPSS AMOS 23 software. The proposed research model was verified through the measurement model, and the structural model has reported a good model fit.

The research used 1,029 respondents for the empirical analysis. The statistical analysis of the research data revealed that performance expectancy, Trust, social influence, hedonic motivation, personal innovativeness, and information quality are the significant factors influencing user intention. Trust emerged as the most critical factor, and hedonic motivation emerged as a highly influential factor in UTAUT. Meanwhile, effort expectancy, facilitating conditions, system quality, and privacy risk were found to be insignificant predictors. The study has also examined the presence of performance expectancy, effort expectancy and trust as mediators. Except for effort expectancy, the study found the mediating role of performance expectancy and trust among the factors.

Research on user adoption of AR technology in online shopping apps is nascent. Hence, the present study has attempted to contribute to the literature area with empirical results. Furthermore, the research has offered valuable theoretical and practical implications for the benefit of academia and policymakers.

Keywords – Augmented Reality, E-commerce, Online Shopping, India, UTAUT3, Trust, SEM

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LIST OF ABBREVIATIONS

AGFI	: Adjusted Goodness of Fit Index
AMOS	: Analysis of Moment Structures
APP	: Application
AR	: Augmented Reality
AVE	: Average Variance Extracted
BCA	: Bibliometric Coupling Analysis
BI	: Behavioral Intention
CB-SEM	: Covariance-Based Structural Equation Modelling
CCA	: Co-Citation Analysis
CFA	: Confirmatory Factor Analysis
CFI	: Comparative Fit Index
E-Commerce	: Electronic Commerce
E-tailing	: Electronic Retailing
EE	: Effort Expectancy
EFA	: Exploratory Factor Analysis
FC	: Facilitating Conditions
HM	: Hedonic Motivation
IQ	: Information Quality
IT	: Information Technology
KMO	: Kaiser-Meyer-Olkin
PE	: Performance Expectancy
PI	: Personal Innovativeness
PLS-SEM	: Partial Least Squares Structural Equation Modelling
PR	: Privacy Risk
RMSEA	: Root Mean Square Error of Approximation
SEM	: Structural Equation Modelling
SI	: Social Influence

SJR : SCImago Journal Rank

SNIP : Source Normalized Impact per Paper

SPSS : Statistical Package for Social Sciences

SQ : System Quality

SRMR : Standardized Root Mean Squared Residual

TAM : Technology Acceptance Model

TLI : Tucker-Lewis Index.

TPB : Theory of Planned Behavior

TR : Trust

TRA : Theory of Reasoned Action

UTAUT : Unified Theory of Acceptance and Use of Technology

VIF : Variance Inflation Factor

VR : Virtual Reality

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The emergence of technology has dramatically improved the efficiency and efficacy of an individual's daily tasks. People's perspectives have shifted regarding employing technology to do tasks. Since the 1980s, the domain of information technology has experienced substantial progress. Consequently, adopting technology has emerged as a highly investigated domain in the information technology field, leading to the development of theoretical frameworks to examine the relationship between variables and adoption behavior (Salahshour Rad et al. 2018). Exploring the concept of 'Intention' has received consideration in adopting and using information systems (Jeyaraj et al. 2023). 'Intention' has the foundation in theories (such as the theory of reasoned action and the theory of planned behavior) and is considered proximate to the actual behavior (Venkatesh et al. 2003). The omnipresent nature of technology has created opportunities for various stakeholders. Hence, examining the user's behavioral intention towards using an information system is essential as a technology-equipped environment grows (Dubey and Sahu 2022).

The growth of the e-commerce sector has changed users' perception of shopping at brick-and-mortar stores. Though e-commerce offers numerous benefits, it poses several challenges to retailers and customers. These challenges sparked interest among businesses towards adopting advanced technologies to enhance the shopping experience with better customer service. Augmented reality (AR) is one of the interactive technologies receiving immense attention in online retailing (Perannagari and Chakrabarti 2019). AR technologies in online shopping apps give customers a "try-before-you-buy" opportunity, which can reduce the difficulty experienced in online shopping apps due to uncertainty in product features, dimensions and the appearance of the products (Dogra et al. 2023). Indians are curious about new technologies, as 31 percent of Indian consumers are willing to be early users of the latest technologies (PwC India 2023). AR is a novel technology that needs to be explored to investigate its potentiality in online shopping apps in the Indian context, as prior studies call out the need to focus on adopting AR technologies in developed countries (Abed 2021; Dargan et al. 2023). This research has attempted to investigate the factors influencing online shoppers to use AR technologies in online shopping apps.

The chapter commences with a succinct introduction, followed by a brief note on the e-commerce industry. Later, the chapter focuses on the problem statement, research questions and research objectives. The succeeding sections explain the model adopted in the study with construct definitions. The significance and scope of the research study scope are discussed. Finally, the chapter briefly discusses the organisation of the thesis report.

1.2 E-COMMERCE INDUSTRY: AN INDIAN SCENARIO

Businesses develop innovative methods to draw customer's interest towards new products and services. Technological advancements in information technology, smartphones, and gadgets have significantly enhanced consumer brand interactions (Dacko 2017). Companies have started to invest in technologies to attract the target market, which can create more convenient ways of exploring the company's products and services. The rapid growth of information technology has led to the inclusion of modern technologies in the retailing industry. Technological advancements in retailing have led to many discoveries, and e-commerce is considered the pioneer among them (Bansal et al. 2023). E-commerce uses electronic ways and technologies to handle commerce (Manzoor 2010) and is viewed as an innovation in the retail industry (Bertram and Chi 2018). The e-commerce sector has drastically changed customers' shopping behaviour due to the ease and accessibility of technology. Global e-commerce sales (online retailing or e-tailing) are expected to reach USD 8.1 trillion in 2026, and India is one of the fastest-growing countries (Chevalier 2022).

The increase in smartphone users and widespread internet use has exponentially increased the growth of the Indian e-commerce market, with revenue generation of more than USD 63 billion, and it is expected to reach USD 107 billion by 2027 (Minhas 2023b). Though there are vast opportunities, the e-commerce sector faces numerous challenges, such as online shopping cart abandonment and high product return volume (Jayaswal and Parida 2023), creating losses for the companies as well as raising concerns over the negative impact of reverse logistics (Jauhar et al. 2023).

Though e-commerce portals offer convenience in shopping, they lack in providing sensory shopping cues (touch and feel of the products), which prevents the consumers from finally placing the order, leading to cart abandonment or placing the order with

the idea of returning or exchanging the products multiple times (Goel et al. 2023; Jayaswal and Parida 2023). Retailers incur immense losses of 30 percent in revenue when customers undertake excessive product returns, exchanges or cart abandonment (Benson 2020). In addition to financial losses, the increasing online product returns can negatively influence the environment. It was found that e-commerce companies dispose of 25 percent of the product returned, and around 6 billion pounds worth of products are dumped in landfills annually (Selyukh 2022). Furthermore, the rise in online product returns directly impacts the carbon footprint. As per the study (Halldorsson and Kovacs 2010), shipping the products to the customer's doorstep is considered the most energy-consuming process; likewise, the logistics involved in online product returns negatively impact the environment, creating carbon emissions. Including technologies can help companies reduce these problems in the e-commerce sector. The primary reason for the excessive product returns in e-commerce is the gap between physical and online experiences, which can be effectively connected with the inclusion of AR technologies (Jayaswal and Parida 2023).

AR technology augments the real world with virtual elements that appear to concur in the same space as the real world (Azuma 1997). The deployment of AR technologies in e-commerce aids the users in experiencing the virtual representation of the products in their present environment, which gives an enhanced experience compared to the 2D product images in the e-commerce portals (Hilken et al. 2017; Smink et al. 2020). AR offers sensory cues in online shopping, which helps in efficient decision-making. It provides valuable product information and gives more clarity in the visualization of the products, overcoming the uncertainty among consumers regarding product purchases (Jayaswal and Parida 2023). As a result, customers will be more confident in placing online orders, which reduces product returns and exchanges, benefiting e-commerce retailers (Deloitte Digital and Snap Inc 2021).

AR technology is expected to attain USD 88.4 billion in 2026, with a CAGR of 31.5 percent from 2021 to 2026 (Markets and Markets 2021). Indians are highly interested towards adopting AR technologies in shopping (Indian Retailer Bureau 2021), and the number of users in the AR and VR (virtual reality) market in India is anticipated to reach 742.3 million users by 2028 with a user penetration rate expected to increase to 49.8 percent by 2028 (Statista 2023). These reports indicate the potentiality of AR

technologies in future scenarios. As AR is a new technology, exploring and understanding the user's perception towards adopting AR technologies in e-commerce platforms is essential. This calls out the need for research studies examining the factors influencing AR technologies in online shopping apps in the Indian context.

1.3 PROBLEM STATEMENT

The Indian e-commerce market is rapidly growing with increased competition among companies (IBEF 2017). Though e-commerce has offered profits to the industry, it faces the central issue of product returns creating losses for the companies (Sun et al. 2020; Tupikovskaja-Omovie and Tyler 2021). When customers receive an online order, they may return or exchange the product because of the post-purchase dissonance feeling caused by ignoring the product characteristics, absence of physical presence of the product, etc. (Jauhar et al. 2023; Jayaswal and Parida 2023). These high product returns create significant losses for e-commerce companies and environmental damage due to the wastage of products (Jauhar et al. 2023; Zhang et al. 2023). The consumer's uncertainty towards product choices and problems of product returns can be reduced using AR technologies. AR technologies in online shopping apps offer product information with a virtual presentation of the products in the user's preferred space (Smink et al. 2020). Further, AR technologies also help online shopping customers inspect the products before placing the order, which will help reduce excessive product returns and exchanges.

With the wide penetration of online shopping, the Indian e-commerce market is predicted to be the second-largest e-commerce industry by 2034 (Krishna 2023). Despite these optimistic predictions, the Indian e-commerce industry faces the issue of online return product volume. Nearly 15.8 percent of online product orders are returned in the Indian e-commerce industry (Minhas 2023a), increasing product returns by 25-40 percent during holidays and sales events. When a product is returned, it forms a reverse supply chain, creating huge company losses and impacting the environment. India is the third largest country producing greenhouse gas emissions (Tiseo 2023) and the top country where users have returned the products ordered online during the past 12 months, negatively impacting the industry's growth (Armstrong 2022). Online product returns lead to unnecessary packaging and shipping speed and reverse logistics

accelerate the environment's waste and carbon footprint (Bertram and Chi 2018). Immersive technologies such as AR technologies will help to reduce product returns and eliminate the need to experience the physical product when placing online orders. AR technologies in online shopping platforms will help solve these issues somewhat. Hence, this study aims to examine the factors that will motivate users to use AR technologies before placing the final order to reduce the uncertainties in product characteristics.

1.4 RESEARCH QUESTIONS

The research investigation aims to seek answers to the underlying research questions.

1. What factors influence the user's behavioural intention to adopt AR technologies in online shopping apps?
2. How do factors such as privacy risk, quality, and trust affect the user's behavioural intention to adopt AR technologies in online shopping apps?
3. What contribution do performance expectancy, effort expectancy and trust play in mediating the link between factors and the user's behavioural intention to adopt AR technologies in online shopping apps?

1.5 RESEARCH OBJECTIVES

Research objectives explain what the researcher aims to attain through the research investigation process. The formulation of research objectives is a critical process as it gives direction for the research study. This research examines the key factors influencing user's behavioural intention towards using AR technologies in online shopping apps. The following objectives are formulated in this research.

1. To explore and identify the significant factors influencing user's behavioural intention to adopt AR technologies in online shopping apps.
2. To examine the impact of these factors on using AR technologies in online shopping apps among users.
3. To analyse the influence of performance expectancy as a mediator between factors and intention to use AR technologies in online shopping apps.

4. To examine the mediating role of effort expectancy between factors and users' behavioural intention to use AR technologies.
5. To investigate the mediating role of trust among factors and users' behavioural intention to use AR technologies in online shopping apps.

1.6 MODEL OF THE STUDY

Technology adoption is the most widely researched area in the information system. It is the acceptance of emerging technologies or products (Khasawneh 2008). Research on technology adoption attempts to know, predict and discuss factors inducing user adoption behavior at individual and organisation levels in the acceptance and use of technologies (Salahshour Rad et al. 2018). The model adopted in this study is the Unified Theory of Acceptance and Use of Technology (UTAUT3) proposed by Farooq et al. (2017), which was substantiated in the acceptance and use of the lecture capture systems among business students in foreign universities in Malaysia. The constructs of UTAUT3, namely performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and personal innovativeness, are adopted in the study. The study has extended the model with information quality, system quality, privacy risk and trust. Meanwhile, the study has not incorporated the constructs such as price value (Enaizan et al. 2020), habit (Vimalkumar et al. 2021) and actual usage behavior (Wang 2010) for the research investigation. The following discusses the definition of the key constructs adopted in the study.

1.7 DEFINITION OF KEY CONSTRUCTS

The research model developed in this study consists of eleven constructs taken from prior scholarly work. The definitions of the constructs used in the study are mentioned below.

- *Performance Expectancy* – Performance expectancy indicates an individual's perception that using AR technologies in online shopping apps will help attain the relevant goals (Venkatesh et al. 2003).
- *Effort Expectancy* - Effort expectancy refers to the extent to which users can easily use AR technologies in online shopping apps (Venkatesh et al. 2003).

- *Social influence* – Social influence indicates how an individual views other's opinions and perceptions that they should use AR technologies in online shopping apps (Venkatesh et al. 2003).
- *Facilitating Conditions* – Facilitating conditions indicate how an individual feels that organizational support and technical setup are available to support the use of AR technologies in online shopping apps (Venkatesh et al. 2003).
- *Hedonic Motivation* – Hedonic motivation indicates the extent of fun or pleasure experienced by users in using AR technologies in online shopping apps (Venkatesh et al. 2003).
- *Personal Innovativeness* – Personal innovativeness is an individual's stable personality trait that creates the propensity to try AR technologies in online shopping apps (Farooq et al. 2017).
- *Information quality* – Information quality indicates the availability of valid, trustworthy, personalized, and reliable virtual information to users of online shopping apps by AR technologies (Poushneh 2018).
- *System quality* – System quality refers to the capacity of the AR technologies system in the online shopping apps to perform most reliably and accurately, offering demanded services with a minimum processing speed (Kowalczuk et al. 2021).
- *Privacy risk* – Privacy risk states the possible risks and losses arising from disclosing personal information while using AR technologies in online shopping apps (Vimalkumar et al. 2021).
- *Trust* – Trust indicates the degree to which users perceive that the AR technologies in online shopping apps are trustworthy and function as per prescribed terms and conditions (Saprikis et al. 2021).
- *Behavioral intention* – Behavioral intention is stated as an individual tendency and willingness to adopt AR technologies in online shopping apps (Davis 1989).

1.8 SIGNIFICANCE OF THE STUDY

AR is an innovative technology offering numerous benefits to the e-tailing industry. The use of AR technologies in online shopping apps will help to reduce the problems of online product returns to a certain extent as it gives the virtual experience of the product before placing the online product order. This study empirically examines the factors influencing users to adopt AR technologies in online shopping apps. The findings help uncover users' perceptions of AR technologies in online shopping. Further, it helps identify the highly significant and insignificant factors influencing the user behavioral intention. The results of this study support the policymakers and academic practitioners for the successful implementation of AR technologies and the better use of technologies by online shopping customers, leading to the reduction of cart abandonment, product returns and wastage of secondary products due to product returns.

1.9 SCOPE OF THE STUDY

The scope of the study elucidates the coverage of the research. It explains the degree to which the research will explore the study area. The scope or delimitation of the study is the boundaries that the researcher sets to make the study easy and more focused (Akanle et al. 2020). The present study emphasises identifying the factors influencing the user's behavioral intention towards using AR technologies in online shopping apps in India. The cities in India are classified into Tier I, Tier II and Tier III. The population of tier 1 cities consist of upper-middle-class consumers with good knowledge of information technology (Jamwal et al. 2023). Tier 1 cities are highly populated with the growth of information technology, and IT-enabled services result in good connectivity, creating the desire among people to use new technologies. Further, it was also found that tier-1 cities are preferred for introducing new technologies (Sinha et al. 2019). These findings indicated that tier 1 cities are ideal for exploring user's behavioral intention towards accepting new technology. South India consists of three tier 1 cities, namely Bangalore, Chennai, and Hyderabad, and is found to have the highest online retail spending from 2020 to 2021 (Browntape 2014; Minhas 2022). Hence, this research was conducted in three tier 1 cities in South India. The study's target population consists of users who are aware of AR technologies and willing to use AR technologies

in online shopping apps. The study has focused only on tier 1 cities in south India; however, the study's results can be generalised to other tier 1 cities in other regions as the population groups comprise individuals from different locations and backgrounds.

1.10 ORGANISATION OF THESIS

This thesis comprises five chapters:

Chapter One: This chapter briefly introduces the research study, followed by an overview of the e-commerce industry with the prospects of AR technologies in e-commerce platforms. It then highlights the problem statement based on the review of the e-commerce industry's challenges. The chapter also presented the framed research questions, research objectives and model adopted in the study, with definitions of the key constructs considered in the research. Later, the study's significance and the research scope are highlighted. The chapter is wrapped up with a description of the structure and organisation of the thesis report.

Chapter Two: This chapter presents a literature review with an overview of AR. Later, this chapter reviews the concept of behavioral intention, which was further explored in AR through Scopus metric analysis and bibliometric analysis.

Chapter Three: This chapter presents the study's theoretical background with the research gaps identified in AR research. It then deliberates on the research model developed in the study with the proposed research hypothesis. A detailed review of literature connected to the research hypothesis is discussed, which provides a foundation for the research hypothesis. Finally, the chapter presents the study's conceptual framework and lists the hypothesis defined in the research study.

Chapter Four: This chapter discusses the research methodology followed in the study. It presents the 'research onion' proposed by Saunders et al. (2009) as the foundation for the research methodology. The research onion comprises six layers, which explain the philosophy, approach, strategy, choices, time frame, techniques and processes emphasised in detail.

Chapter Five: This chapter gives an overview of the data analysis with the results of the research investigation. It explains the data screening process utilized in the study, and the descriptive analysis of the demographic data and latent variables were

evaluated. The process involved in the computation of exploratory factor analysis was presented in detail. Later, the chapter discusses the assessment of the measurement model, wherein the reliability and validity measures are discussed in detail. Then, it deliberates the structural model assessment wherein the proposed hypothesis was tested through path analysis to test the direct path and the mediation analysis to test the indirect path. The chapter concludes with the results of the direct and indirect effects with supporting literature studies.

Chapter Six: This is the study's final chapter, which discusses the results obtained in the data analysis. The findings section converses socio-demographic information, the proposed hypothesis examining the direct effect and the proposed hypothesis investigating the indirect effect. The proposed research hypothesis is presented with the results obtained and previous scholarly works. This comprehensive discussion of the results with the other research studies gave insights into the relevance of the results obtained in the research investigation. The theoretical implications of the study, which aid in the growth of the literature area, have also been mentioned. Further, the chapter discusses the practical implications that can be valuable to policymakers and companies in successfully implementing AR technologies in online shopping apps. The chapter concludes by presenting the limitations of the research study with future research directions indicating the opportunities for research scholars to expand the research study for an in-depth investigation of the AR research area.

CHAPTER 2

REVIEW OF LITERATURE

2.1 INTRODUCTION

Conducting good research and bridging the same with existing research studies is the foundation of a research process. The current research studies are reviewed through the process termed a literature review. A literature review is a systematic way of collecting and presenting previous research studies on the research area (Snyder 2019). It gives an overview of the research areas in various disciplines. A literature review is performed through an in-depth investigation of scholarly publications, conference proceedings, books, etc. Conducting a deep investigation of the research area through a literature survey gives a comprehensive view of the area, aiding the researcher in validating the research question and hypothesis. This chapter, 'Review of Literature', outlines how the research study has undertaken the literature survey in the research area related to AR. The chapter deliberates on the overview of AR, details the technology's functioning and emphasises the online product presentation through AR. The chapter also explains the use of Scopus metric analysis and bibliometric analysis in the area of AR examining behavioral intention, which has aided in identifying highly cited papers, prominent authors, classification of research documents based on country, year, subject area, etc. Using the bibliometric analysis, the study will determine the prominent work in the area of AR through the co-citation analysis and bibliometric coupling analysis of documents. Further, the chapter also summarises an overview of the highly cited research work in AR. The chapter concludes with a summary of the various phases of the literature review process undertaken in this research study.

2.2 AUGMENTED REALITY-AN OVERVIEW

Technological growth has led business organisations to shift from traditional operations towards adopting specialised tools that aid their development. When a business organisation includes a new technology, it has always been considered a sophisticated process. However, over time, the business organisation and the stakeholders get accustomed to the latest technologies, and as a result, companies attain efficiency and effectiveness in their business activities. Hence, companies must adopt new technologies to meet the fast-growing contemporary business world. A business organisation is highly competitive when technology can benefit both present and

prospective markets (Sharma et al. 2017). This reflects the need to thoroughly examine the pros and cons of technology before its adoption in the business setup. E-commerce was one technological outcome drastically changing traditional shopping behaviour among customers and companies. Though e-commerce offered numerous benefits, customers were initially sceptical towards using online shopping due to lack of trust, limited internet access, refund and return policies, and lack of awareness about the process involved in online shopping (Lafond and Sinha 2005; Vaithianathan 2010). But with time, the growth of the internet, the availability of smartphones and other gadgets, and the technological aspects of e-commerce have greatly improved, making e-commerce an inevitable tool in people's daily lives. The e-commerce business is proliferating with the advancement of technology, offering convenience and comfort in the shopping experience. Though it provides convenience, it lacks in giving the consumers the experience of the products before placing the order (Barta et al. 2023), which hinders the shopping experience. AR is one technology that can offer customers a product experience by merging virtual elements into the customer's physical environment, facilitating the decision-making process (Dacko 2017).

AR is a medium wherein virtual elements are overlaid with the user's physical environment, offering interactive experiences to the users (Craig 2013). The concept of AR was conceived in 1965 by Morton Heilig, a cinematographer who created Sensorama, which was not controlled by computer systems but supplemented the experience with additional data. Following the invention of Morton Heilig, Ivan Sutherland developed a head-mounted display, "The Sword of Damocles", which was considered the first head-mounted display. However, Morton Heilig pioneered the concept of AR. Though the idea of AR was brought forward, the term "Augmented Reality" was coined by Tom Caudell in 1990. Later, in 1992, Thomas P. Caudell and David W. Mizell's research reflected the growth of this innovative technology (Sudharshan 2020). With the development of devices and the upgradation of information systems, AR technology started to gain momentum with varied applications in diverse fields.

2.2.1 Functioning of Augmented Reality

The AR system comprises a camera, tracking mechanism and user interface. The camera is the primary sensor of the device, which connects the real world and virtual representation. It captures the surroundings and represents the virtual elements on the user's screen. Based on capturing the physical surroundings, the tracking mechanisms precisely place the obtained virtual objects in the user's desired position. The user interface is the screen that acts as a two-way communication platform wherein the users give input to the system, and the system gives results back to the user. Therefore, the proper functioning of the camera, tracking system, and user interface aids in the adequate functioning of AR technology (Sharma et al. 2022). Figure 2.1 illustrates the basic functioning of AR.

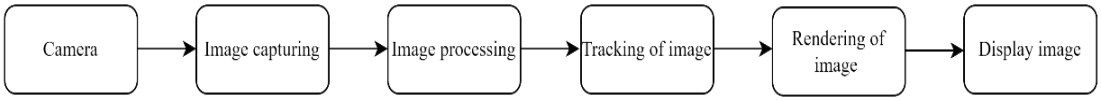

Figure 2.1: Working of AR
Source: Secondary data

As per Figure 2.1, AR functions with the camera operation wherein the physical surroundings are scanned and captured. The image captured is processed to assess the space wherein the virtual object must be projected. The fourth box represents tracking of the image, which is done either by marker-based or using spatial mapping to determine where the virtual object will be placed in the captured spot. Once the location is fixed, the virtual object is shown in the area. Finally, a three-dimensional virtual object is displayed on the specified location, which will be visible on the screen. When a customer uses the AR feature, the virtual product is projected in the physical environment, which gives a perception of how the product will look in the projected context. In the case of online shopping, the customers must depend on the product images and descriptions mentioned on the online shopping apps, making it difficult to assess the product like in physical stores. Furthermore, it creates uncertainty regarding the product's dimensions in the physical space based on the description in the online shopping portals, decreasing the order placement (Lu and Smith 2007). AR technology can remove this difficulty, which gives the user a virtual product experience (Hilken et al. 2017). For instance, using an AR feature, a consumer can see the look of a desired

product (e.g. a printer) at a designated place in the user's surroundings. Figure 2.2 illustrates how the AR view of the printer is projected on a table.

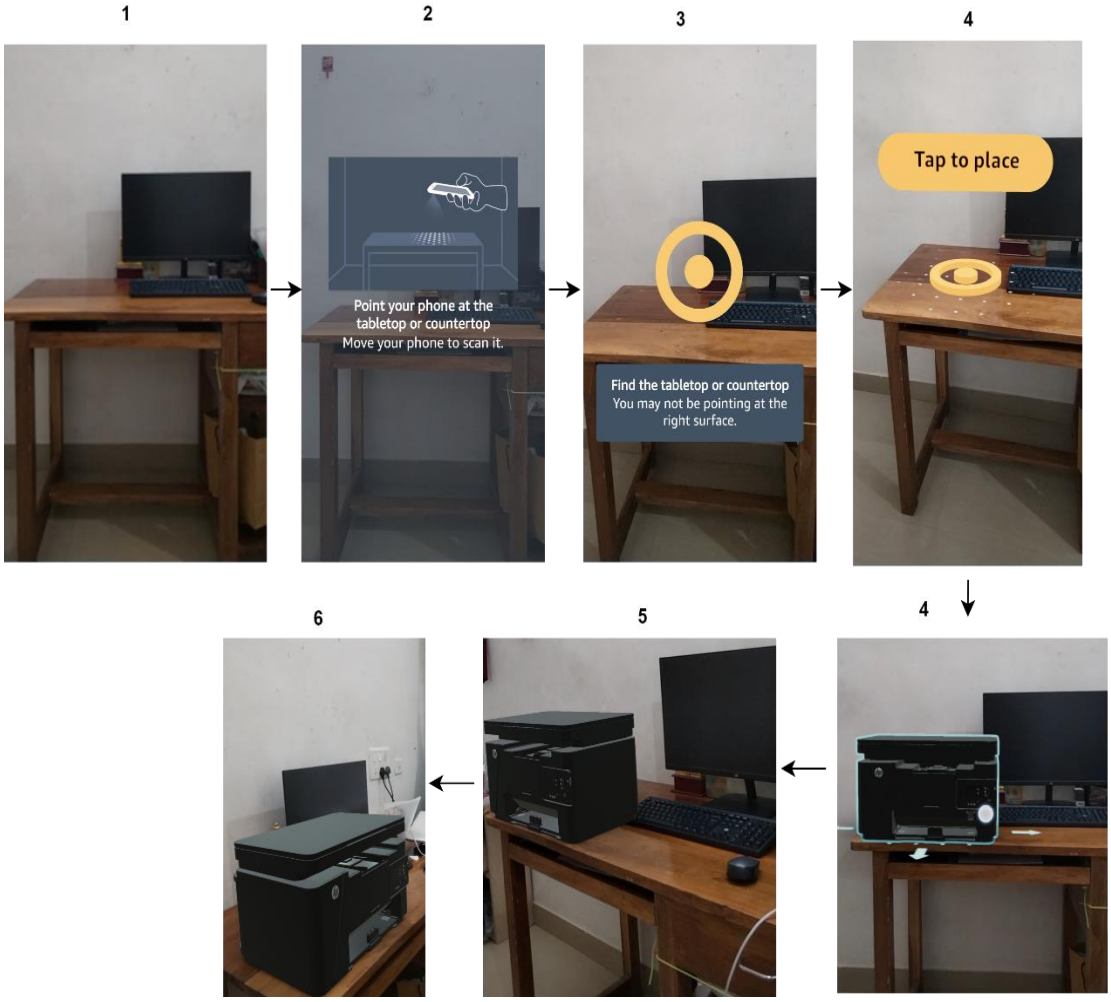

Figure 2.2: AR view of the product
Source: Author

The figure mentioned above represents the AR view of the printer. This three-dimensional interactive view gives the customer a view of the printer in the current surroundings, offering the presence of the product in front of the user. Furthermore, it helps the user decide among several options in their space that a physical store cannot provide. Thus, users can evaluate the product using the AR feature before purchasing the product. AR technology offers customers a "try before you buy" experience before purchasing the products (Smink et al. 2019). AR comprises features combining virtual elements into the physical world, interactivity, and a three-dimensional view of the virtual products. These benefits offered by AR features can directly influence the customer's decision to purchase the product rather than depending on the product

description and images from the e-commerce app (Kowalczuk et al. 2021). With the immense benefits offered by AR technologies, there has been a surge in the installation of AR mobile apps. It is also estimated that 75 percent of customers expect retailers to incorporate AR technologies and offer enriched AR experiences (Gartner 2020). Though AR is in the infancy stage, the potential benefits provided by the technology have sparked interest among academicians and practitioners, leading to the gradual inclusion of AR technology in online shopping apps

2.2.2 Augmented Reality in Online Product Presentation

Online shopping offers convenience to consumers and is continuing to grow to a large extent. However, online shopping platforms face problems such as high product returns, online shopping cart abandonment, and web rooming (Dacko 2017; Hilken et al. 2018). E-commerce platforms offer customers product images, descriptions and video demonstrations of the products showcased in the portals. These help customers evaluate the products but fail to provide real experience. This results in a gap in experiencing the product between online and offline shopping, which is abridged through AR (Baek et al. 2018). AR helps consumers have a virtual experience on a real-time basis, delivering an actual product experience (Hilken et al. 2017). As AR gives a virtual product experience, it benefits online retailers by improving conversion rates, reducing product returns, and lowering tendencies for web rooming (Smink et al. 2019).

The conventional product presentation in online shopping apps and product presentation through AR are significantly different. Firstly, AR combines the real and virtual worlds by projecting virtual elements onto the physical surroundings, giving the users an authentic experience of the products (Scholz and Smith 2016). Second, the virtual elements projected through AR in real-time are highly interactive as the surroundings are captured through a webcam or camera in smartphones or tablets (Azuma 1997). Third, the virtual object projected through the AR feature has a fixed position in space, enabling the evaluation of the projected product from various angles and creating interaction between the projected virtual elements and the real world (Azuma 1997). These features of AR offer a real product experience in the actual surroundings of the users. AR offers a more realistic product presentation with user interaction, providing an enhanced customer experience. The virtual presentation of the

products through AR features offers high conversion rates, from whether to buy the product to finally placing the order (Billewar et al. 2021). With the increasing demand for virtual product experiences among customers, AR features are emerging as a tool aiding customers in online shopping (Rauschnabel et al. 2022a). Compared to traditional shopping portals, AR features in online shopping apps offer immense benefits by influencing consumer behavior. As a result, companies such as Flipkart and Amazon have recently launched AR-based product visualizers that give virtual experience across a wide range of products (Tarafdar et al. 2024). The AR market is estimated to be valued at 35 billion dollars by 2025, and in future, the AR adoption rate will be at the same level as smartphone adoption (Park and Yoo 2020). The study by Dogra et al. (2023) indicated that abundant research had been undertaken in developed countries such as the USA (Rauschnabel et al. 2016) and Germany (Rauschnabel et al. 2022b; Rauschnabel and Ro 2016); however, the application of AR in Indian context needs to be investigated. Furthermore, Indians are highly curious about implementing modern technology (Indian Retailer Bureau 2021), a positive sign of adopting novel technologies such as AR. Henceforth, considering the relevance of the technology, this research aims to examine the adoption of AR technology in online shopping apps in the Indian context.

2.3 BEHAVIORAL INTENTION - AN OVERVIEW

'Behavioral Intention' comprises 'Behavior' and 'Intention'. Behavior indicates an organism's activities while interacting with the environment. Intention suggests the quantity of resources an individual is willing to invest in performing a behaviour (Hall 2013). Behavioral intention shows the likelihood of an individual performing or not performing a particular behaviour. Intention points to the motivational factors that influence an individual to perform a behavior and how much they are willing to put their efforts into achieving a particular behaviour (Ajzen 1991). Researchers must explore the underlying factors influencing behavioral intention to understand what makes an individual perform a specific behaviour. There are several theories which have examined the factors influencing the behavioral intention of individuals. The theory of reasoned action (TRA) proposes that subjective norms and attitudes influence behavioral intention (Fishbein and Ajzen 1975). According to the theory of planned

behaviour (TPB) proposed by Ajzen (1985), the behavioral intention of individuals is caused by the influence of subjective norms, attitudes and perceived behavioral control. Though TRA and TPB models can predict behavioral intention, they were found inadequate in implementing these theories in the context of information systems. As a result, Davis (1989) proposed the technology acceptance model (TAM) theory for better prediction. The TAM model explains that perceived usefulness and perceived ease of use influence attitudes towards using, leading to behavioral intention. However, the attitude was found to be irrelevant and hence was dropped from the TAM model (Davis 1989).

The Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003) consist of four factors: performance expectancy, effort expectancy, social influence, and facilitating conditions influencing the behavioral intention towards using technology. Owing to the limitations of the theory, it was revised as UTAUT 2, focusing on consumer context. It included additional constructs such as price value, hedonic motivation and habit influencing behavioral intention (Venkatesh et al. 2012). Later, researchers found that personal innovativeness in information technology plays a significant role in user behavioral intention. As a result, Farooq et al. (2017) proposed UTAUT3 and found that user behavioral intention towards accepting technology is influenced by factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit and personal innovativeness. Understanding user behavioral intention is significant, which sparked the interest to examine the role of behavioral intention in various fields such as open government data (Rizun et al. 2024), mobile payments (Lisana 2024), mobile commerce applications (Siyal et al. 2024), space tourism (Kim et al. 2024) etc. This research study has adopted the UTAUT3 theory, further extended by including other variables in the study context.

2.4 EXPLORING BEHAVIORAL INTENTION THROUGH SCOPUS METRIC ANALYSIS & BIBLIOMETRICS ANALYSIS

It is essential to consider scientific tools and techniques towards exploring research papers during the literature review process. Examining scopus metric analysis and

bibliometric analysis helps to include and exclude research documents in the literature review, which gives a comprehensive list of research studies on the subject's interest. The scopus database is comprehensive, with a wide range of journals, conference proceedings, books and other publications, ensuring accurate validation and making it suitable for analysis (Demir et al. 2024). This study has used the scopus database to explore the contribution of studies in AR. The following section discusses the scopus metric analysis and bibliometric analysis with the results obtained.

2.4.1 Scopus Metric Analysis

Scopus metrics help evaluate the impact of research studies through citations, cite score, source normalized impact per paper (SNIP), and SCImago Journal Rank (SJR). The study used the scopus database to extract research studies in AR examining user behavioral intention. Hence, the following search protocol was used. Initially, this search query was used in September 2019 to get insight into the research area examining behavioral intention in AR research. Later, a refined search was performed in December 2023 for better results.

Search query:

TITLE-ABS-KEY ("Augmented Reality" OR "AR" OR "Augmented Reality Technology" OR "AR Technology" OR "Mobile Augmented Reality" OR "Mobile AR" AND "Behavioral Intention" OR "Behavioural Intention" OR "Use Acceptance" OR "Intention To Use" OR "Technology Acceptance") AND (LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "PSYC")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English"))

The keyword extracts the relevant documents as per the search query. Only journal articles in English were extracted from the scopus database as they are more reliable (Linan and Fayolle 2015). Further, the extraction process has also excluded books, chapters and conference paper proceedings as each has a varied peer review process, resulting in less reliability (Jones et al. 2011). The search query resulted in 282 documents. After searching the documents based on the search query, the details of the

articles were extracted as a dot csv file. The dot csv file contains author details, the name of the research paper, references, citations, journal details, etc. Each research paper was further evaluated to check whether it met the search criteria, and further exclusion was performed, resulting in 195 documents. The following section explains the various scopus metrics used.

- Cite Score: The cite score indicates the average citation obtained by a journal. It is computed by taking the average of the citations received by the documents in a journal in three years. Cite score and impact factor are similar. However, the impact factor is calculated based on all document types for two years (Kim and Chung 2018).
- SCImago Journal Rank (SJR): The SJR is an indicator that measures the popularity of the journal based on the citations received by the paper of its journal and the prestige of the journals from where the paper has received the citation during three years ("Elsevier" 2024).
- Source Normalized Impact per Paper (SNIP): The SNIP indicator considers the field-specific citation differences. The SNIP is the ratio of the journal citation per publication with the possibility of citation to its field ("Elsevier" 2024). This indicator adjusts the citation patterns over different academic areas. They are more relevant and can be used instead of an impact factor (Kim and Chung 2018).

The above methods help researchers obtain high-quality research studies in relevant academic fields. The journals obtained from these indicators are the most preferred ones by the researchers for scholarly activities such as referring, publishing work and citing for their scholarly work. Figure 2.3 represents the cite score publications by year. The SNIP per paper by year is illustrated in Figure 2.4. According to the results of the cite score publication by year and SNIP per paper by year, the journal "Computers in Human Behavior" was recognized as a prestigious journal with a cite score of 17.8 and SNIP of 3.223 followed by "Journal of Retailing and Consumer Services" with cite score 11.4 and SNIP 2.651. The results indicated that "Computers in Human Behavior" is a prevalent journal in AR research.

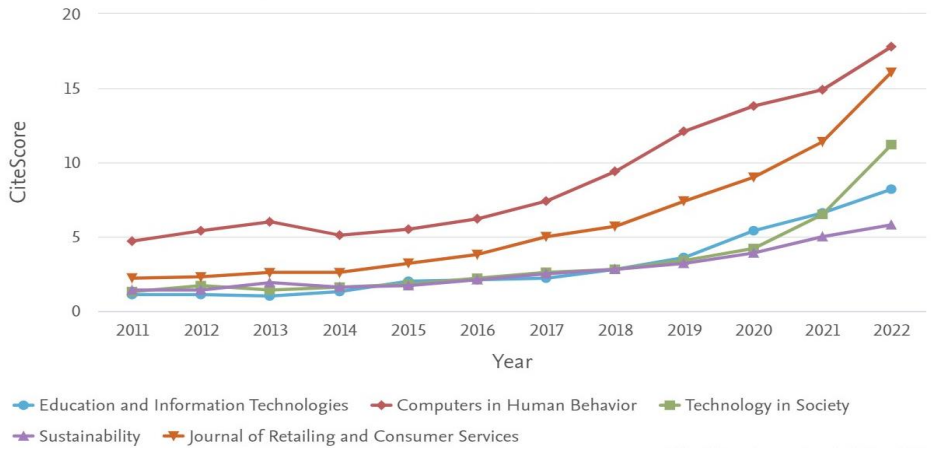

Figure 2.3: Cite score publication by year
Source: Scopus database

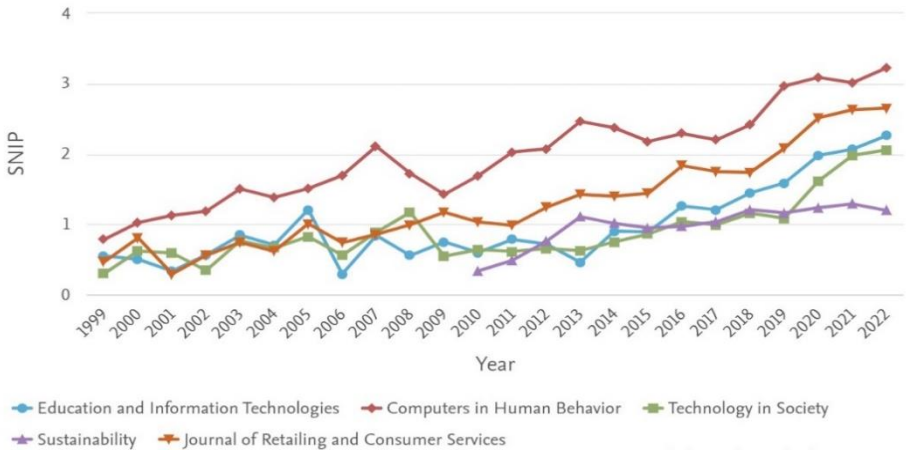

Figure 2.4: SNIP per paper by year
Source: Scopus database

The present study has also evaluated the research documents year-wise and country-wise in the area of AR towards exploring user behavioral intention. The results of documents by country indicate that the United States has the highest contribution towards AR research, followed by Taiwan, whereas Indonesia holds the last position with fewer research studies. The number of research studies from India is lower than that of the United States, Taiwan, South Korea, United Kingdom, China, Malaysia and Germany. The following figure 2.5 illustrates documents by country.

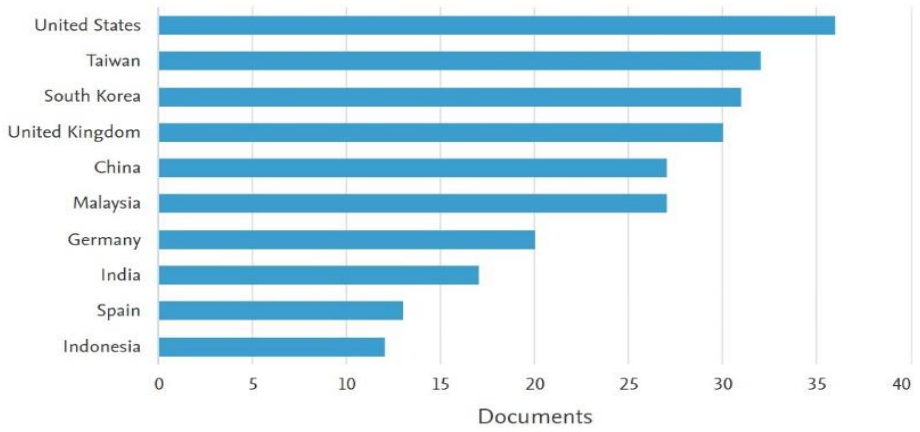

Figure 2.5: Documents by country
Source: Scopus database

Examining the number of research documents year-wise gives an insight into the growth of the research area. Figure 2.6 represents the number of documents generated year-wise in the scopus database from 2009 to 2024. The figure illustrates that research studies in AR started in 2009. The research in AR was accelerated in the year of 2013 to 2016. However, there has been a decline in the number of documents in 2017, but it gained thrust in 2018 and has seen a significant increase in the contribution of research studies. This indicates that there has been considerable demand to examine user behavioral intention in AR. Furthermore, the results of the metric analysis also revealed the lack of studies in the Indian context. Hence, the present study will be highly significant as it aims to contribute to the research area by investigating the user's behavioral intention towards using AR technologies in online shopping apps in the Indian context.

Figure 2.7 indicates the research studies based on the subject area. Though the research in behavioral intention is more towards the business management domain, there has been a significant shift towards other domains, reflecting it as a multidisciplinary topic. During the initial stage, there has been extensive research in AR in the technology domain examining the technical aspects of the technology. With the increase in the application of AR, researchers in diverse areas showed keen interest towards exploring the benefits of implementing AR in other areas. The results indicate that social sciences comprise 116 research documents (20.5 percent), and business management and accounting comprise 104 research documents (18.4 percent). The area of computer

science has made the most contributions, with 139 research documents (24.6 percent) to AR research, as the foundation of AR lies in this subject area. As a result, computer science and technology researchers know more about its application level and potential benefits than researchers in other fields. Moreover, research funding agencies and industries may be interested in investing in computer science AR projects due to their technology upgrade. Despite the growth of research in computer science, the results indicate prospective growth in AR research in business management and social sciences.

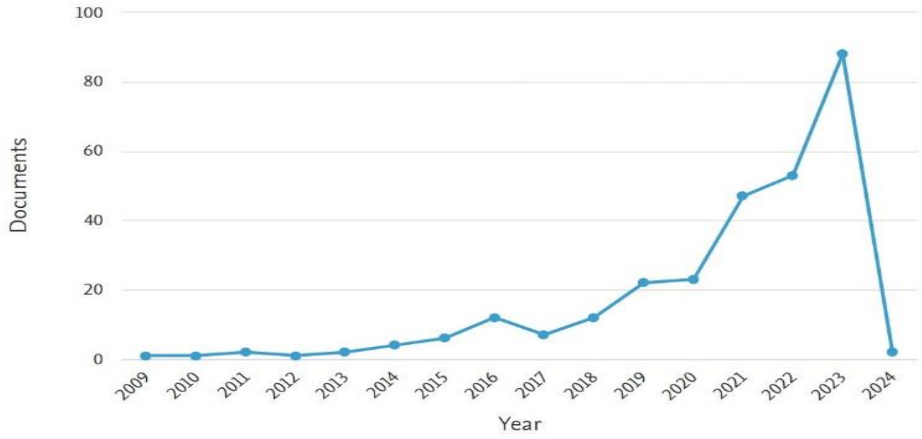

Figure 2.6: Documents by year
Source: Scopus database

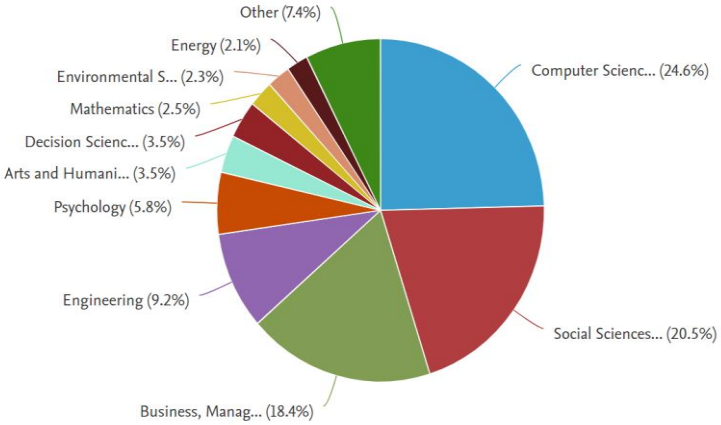

Figure 2.7: Documents by subject area
Source: Scopus database

2.4.2 Bibliometric Analysis

A thorough literature review is essential for having a good direction in the research process. The research study used bibliometric analysis to examine the relevant literature in the study area. Bibliometric analysis is used to quantitatively analyse the research studies (Ellegaard and Wallin 2015). It helps researchers explore the trends in the research area, the performance index of journals and collaboration patterns among researchers (Donthu et al. 2021). Bibliometric analysis gives a systematic overview of the research area using software. Researchers cited that prior studies indicated the relevance of bibliometrics in the early 1950s (Wallin 2005). Yet, it has only recently gained prominence in business management, economics, and social sciences (Donthu et al. 2021). The growth of research databases such as scopus and web of science with the emergence of bibliometrics software packages such as VOS Viewer, Gephi, etc., has sparked researcher's interest in exploring bibliometric analysis.

Scopus represents a scientific publication platform with comprehensive disciplinary coverage of research studies; thus, it is considered suitable for accessing research documents (Tibana-Herrera et al. 2018). Hence, this research study has used the Scopus database to explore studies investigating users' behavioral intentions towards using AR technologies. The study used the following methodology to extract documents from the scopus database about investigating user behavioral intention in AR. The study used the following search query in September 2019. However, a refinement in the search was made to extract documents from the scopus database in December 2023.

- Search query:

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TITLE-ABS-KEY ( "Augmented Reality" OR "AR" OR "Augmented Reality Technology" OR "AR Technology" OR "Mobile Augmented Reality" OR "Mobile AR" AND "Behavioral Intention" OR "Behavioural Intention" OR "Use Acceptance" OR "Intention To Use" OR "Technology Acceptance" ) AND ( LIMIT-TO ( SUBJAREA , "SOCI" ) OR LIMIT-TO ( SUBJAREA , "COMP" ) OR LIMIT-TO ( SUBJAREA , "BUSI" ) OR LIMIT-TO ( SUBJAREA , "ENGI" ) OR LIMIT-TO ( SUBJAREA , "PSYC" ) ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) ) AND ( LIMIT-TO ( SRCTYPE , "j" ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) )
```

- Based on the search query, a total of 517 documents were retrieved. However, the study has considered only research articles published in journals. Therefore, document types such as conference papers, reviews, book chapters, conference reviews, book reviews, etc. and source types such as conference proceedings, book series, books, trade journals, etc., were excluded, resulting in 282 documents. The search query has extracted only English research. Though specified keywords are mentioned in search queries, research papers from other areas may be included. Hence, it is essential to thoroughly evaluate each research article from the extracted list to exclude research papers unrelated to the subject area. After examining the research papers, the final list consists of 195 articles sorted and arranged.

The study used VOS viewer software version 1.6.20 for the bibliometric analysis (van Eck and Waltman 2010). It is free software for creating and evaluating bibliometric maps to obtain insights into research studies in AR. The study used co-citation analysis (CCA) and bibliometric coupling analysis of documents (BCA). The following section discusses the techniques used in the study.

Co-citation analysis (CCA): Co-citation analysis is a widely used technique in bibliometric analysis. This technique reveals the various authors, theoretical frameworks, and adopted methodologies in the research area. Co-citation indicates the frequency with which two documents are cited together (Small 1973). When two papers are cited together, it is assumed that they share related content in the research area (Zupic and Cater 2015). For instance, there are three documents: X, Y and Z. These three documents have cited documents A and B. Here, we can say that document A and document B are related as both are cited together in doc x, doc y and doc z indicating co-citation strength or co-citation index. Figure 2.8 illustrates the concept of co-citation analysis. Hence, to say that two documents are co-cited, both documents must be listed in the reference list of the third, fourth or nth document (Surwase et al. 2011). The results of the co-citation index indicate the initial research papers and the authors who have contributed significant work in the research area. This research study has evaluated the co-citation of cited authors and the co-citation of cited references.

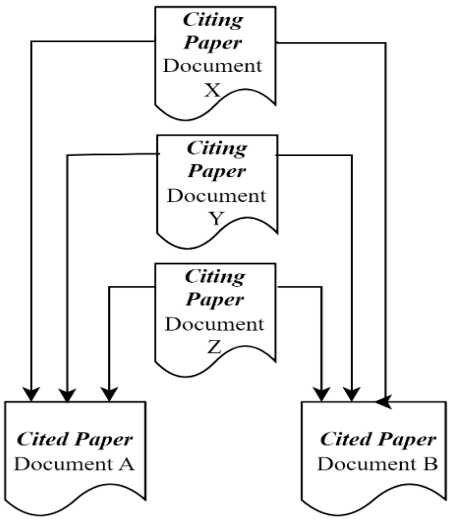

Figure 2.8: Co-citation coupling analysis
Source: Secondary data

a. **Co-citation of cited authors:** The Co-citation of cited authors categorizes the most distinguished authors in the research area. It is performed to identify authors who obtained significant citations in the research area. The analysis was executed through the fractional counting method, and the minimum threshold for citations was fixed as 5 (Okaiyeto and Oguntibeju 2021). Thus, out of 18427 authors, only 1243 have met the set threshold levels. Only the top 20 authors were selected through co-citation analysis of cited authors. The size of the node indicates the relevance of the item. The distance between the nodes indicates the connection between the items. Hence, when the distance between the nodes is small, it suggests the relatedness between the items (van Eck and Waltman 2010). Figure 2.9 illustrates the top 20 authors.

   The analysis demonstrated that Fred D. Davis attained the highest citation (285), followed by Viswanath Venkatesh, Timothy Jung, Marko Sarstedt, Namho Chung, M. Claudia tom Dieck, Philipp A. Rauschnabel, Icek Ajzen, Joseph F. Hair and Christian M. Ringle. The results of the co-citation of cited references based on extracting the top 20 authors revealed the presence of three clusters, namely "Cluster 1 (8 items) Red", "Cluster 2 (7 items) Green", and "Cluster 3 (5 items) Blue". Figure 2.10 illustrates the top five authors contributing to the research, namely Fred D. Davis (citation 285) followed by Viswanath Venkatesh (citation

250), Timothy Jung (citation 192), Marko Sarstedt (citation 155), Namho Chung (citation 154).

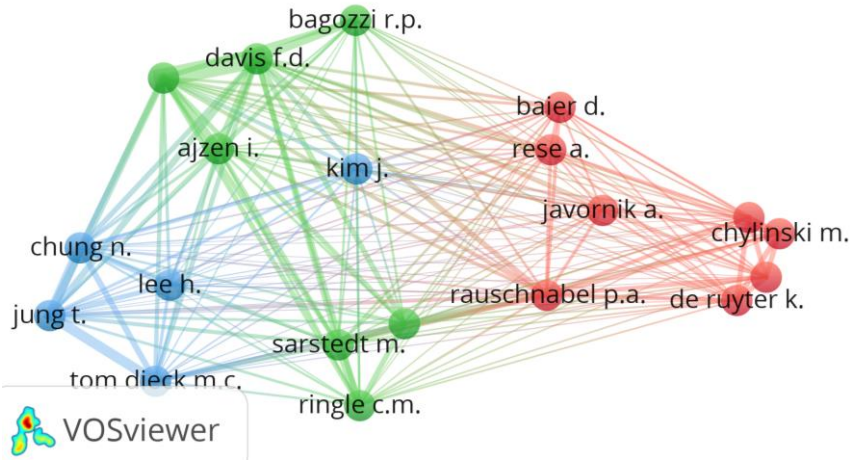

Figure 2.9: Top 20 authors as per co-citation of cited authors
Source: VOS viewer

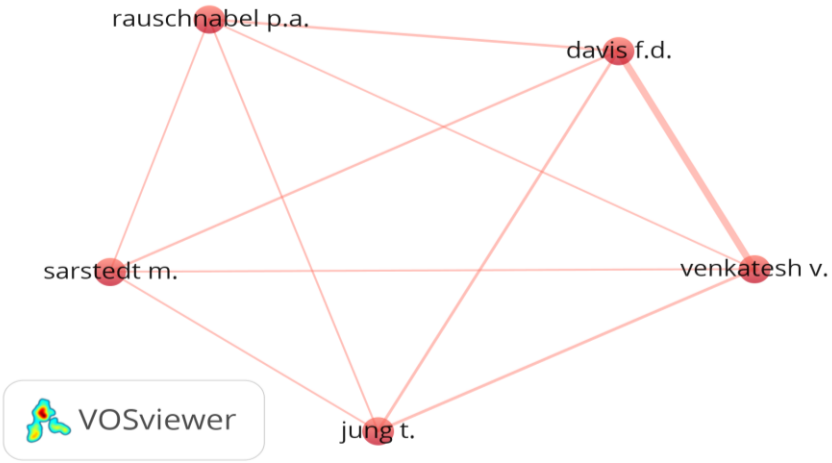

Figure 2.10: Top 5 authors as per co-citation of cited authors
Source: VOS viewer

b. **Co-citation of cited references**: The co-citation of cited references represents the highly cited literature in the research area, which has immense significance to researchers and other practitioners. The co-citation of cited references was performed with fractional counting as the counting method, and the minimum number of cited references was set as 5 (Okaiyeto and Oguntibeju 2021). It was observed that 12,457 cited references were found, of which only 130 met the mentioned threshold levels. The final number of cited references to be selected

was fixed at 130, which was further analysed. The analysis of the co-citation of cited references revealed that 130 items were classified into four clusters, namely "Cluster 1 (41 items) Red", "Cluster 2 (39 items) Green", "Cluster 3 (31 items) Blue" and "Cluster 4 (19 items) Yellow". The results of the co-citation of cited references are presented in Figure 2.11.

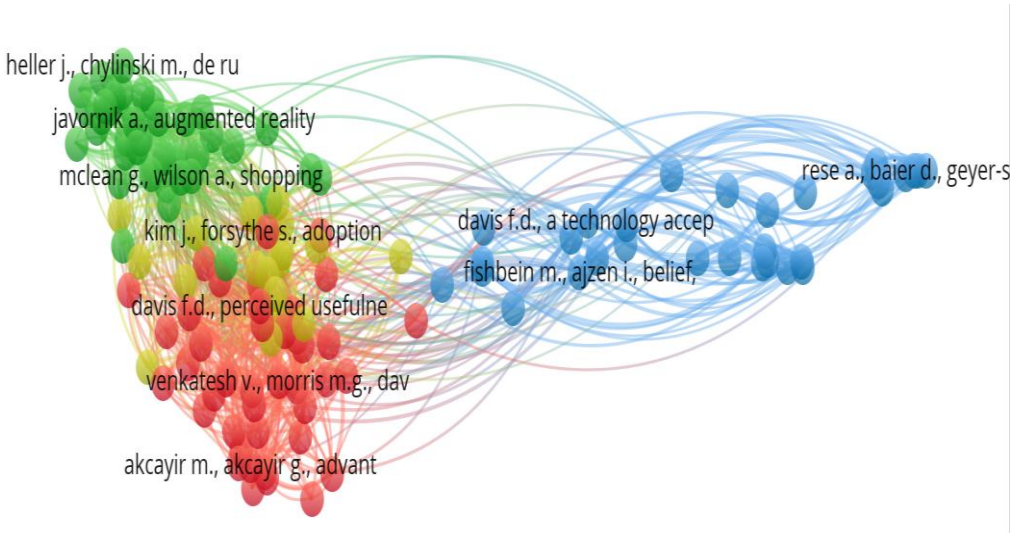

Figure 2.11: Co-citation of cited references
Source: VOS viewer

Bibliometric Coupling Analysis of Documents (BCA): Bibliometric coupling analysis evaluates the references mentioned in the bibliography of research documents. A bibliographic couple is created when two documents cite two or more common references (Kessler 1963). Bibliographic coupling depends on references mentioned in the reference list of research articles. The degree of relatedness among the cited documents reveals the research areas in the research domain. The bibliographic coupling indices indicate the number of references similar to the bibliographies of two documents (Walsh and Rowe 2023). For example, if two documents, A and B, have cited documents X, Y and Z and are duly listed in the reference list of A and B, then A and B are said to be bibliographically coupled (Figure 2.12).

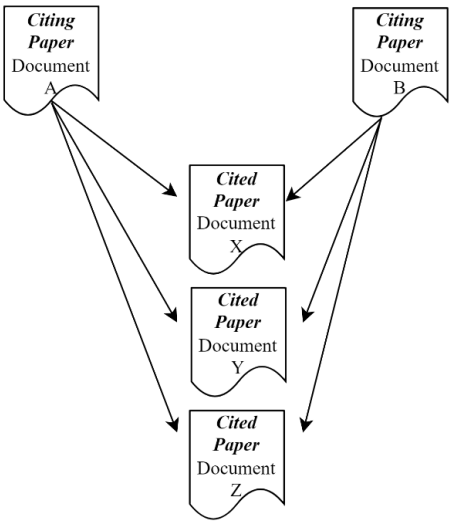

Figure 2.12: Bibliometric coupling analysis
Source: Secondary data

The bibliographic coupling technique indicates the relevant studies conducted in the area and helps to identify the research themes in the research areas (Kessler 1963). When the number of references is similar, the bibliographic coupling strength increases. The current study has used bibliometric coupling of documents using fractional counting with a minimum of five citations for a document (Okaiyeto and Oguntibeju 2021). Out of the 195 documents, only 125 have met the threshold. Hence, all 125 documents were considered. The scrutiny of bibliographic coupling analysis of documents indicated that 125 items were classified into eight clusters namely “Cluster 1 (36 items) Red”, “Cluster 2 (25 items) Green”, “Cluster 3 (23 items) Blue”, “Cluster 4 (18 items) Yellow”, “Cluster 5 (8 items) Violet”, “Cluster 6 (7 items) Turquoise blue”, “Cluster 7 (4 Items) Orange” and “Cluster 8 (4 items) Brown”. The size of the node and the label in the diagram indicate the relevance of the item. Hence, the label and node sizes will be big when the item's weight is high. Further, the items are highly related when the distance between nodes is less (van Eck and Waltman 2010). Figure 2.13 illustrates the bibliographical coupling analysis based on documents.

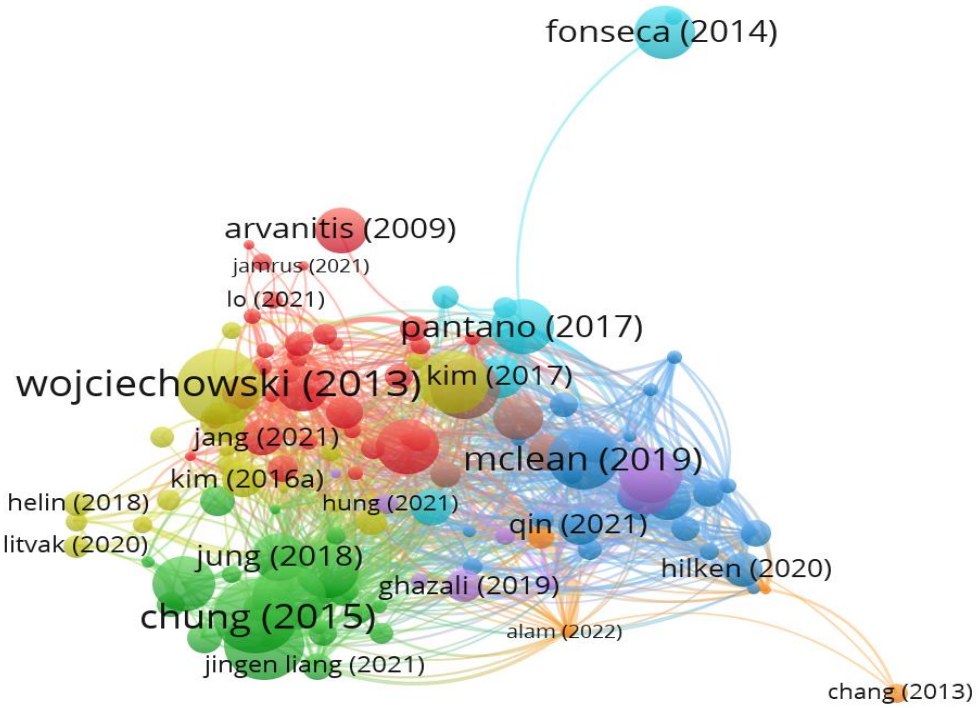

Figure 2.13: Bibliographical coupling analysis based on documents
Source: VOS viewer

The review of the top 25 highly cited papers as per the bibliographic coupling is presented in Table 2.1. This literature review table consists of details of the research paper, citations, methodology adopted, theory or constructs used and a summary of the research paper.

Table 2.1: Review of highly cited papers as per bibliographic coupling of documents

1. Evaluation of learners' attitude toward learning in ARIES augmented reality environments - (Wojciechowski and Cellary 2013) **Journal: Computers & Education (Citation:358)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study of 42 students in the age group of 14-16 years belonging to second grade of lower secondary school was selected. Participants must complete the questionnaire after the experiment is successful. The items were measured on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The construct attitude toward using was measured on a reversed five-point Likert scale ranging from strongly agree (1) to strongly disagree (5).	Model used: TAM Constructs: Interface style, perceived usefulness, perceived ease of use, perceived enjoyment, attitude toward using, intention to use	The paper evaluated the students' attitudes towards experiential learning through AR learning environments. Perceived usefulness and perceived enjoyment are significant predictors of student's attitudes towards using the technology except for perceived ease of use of the system. Perceived enjoyment and attitude significantly influence the student's intention to use the system. However, the system's perceived usefulness was an insignificant predictor of student's intention to use the system. Perceived ease of use and Interface style were significant factors in enhancing the system's perceived enjoyment. Interface style significantly predicted the system's perceived usefulness and ease of use.
2. Tourists' intention to visit a destination: The role of augmented reality (AR) application for a heritage site - (Chung et al. 2015) **Journal: Computers & Education (Citation:348)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study was considered on 145 visitors who have used the AR apps at a heritage location in South Korea (Deoksugung Palace). The items were	Model used: TAM Constructs: Perceived usefulness, Perceived ease of use, Attitudes towards	This research investigated the various factors influencing the tourists' intention to use AR at heritage destination points and how it affects the attitudes, beliefs and intentions to visit destination spots by tourists. All factors were found to be significant predictors except technology readiness, which was an insignificant

measured on a seven-point Likert scale ranging from strongly disagree (1) to strongly agree (7).	AR, Technology readiness consisting of optimism and innovativeness, Visual appeal, facilitating conditions, AR usage intention and Destination visit intention.	factor in the perceived use of the AR app. Perceived usefulness was the strongest predictor of tourists' AR attitude. The strong effect of visual appeal and facilitating conditions on the perceived ease of use of the system might be the reason for the insignificant role of technology readiness.
3. The determinants of recommendations to use augmented reality technologies: The case of a Korean theme park - (Jung et al. 2015) **Journal: Tourism Management (Citation:312)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The data was collected from 241 visitors at Characworld Theme Park in South Korea with a cross-sectional research design. The study participants were theme park visitors who used the marker-based AR book that exhibited 3D characters on a TV screen, which responded to the movement of the book. The items were measured on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5).	Theory: Process theory Constructs: Content quality, system quality, personalized service quality, AR satisfaction, Intention to recommend marker-based AR app.	This study investigated user satisfaction and intention to recommend marker-based AR book applications. Further, the research has also measured the moderating role of personal innovativeness (high innovators and low innovators) on the quality factors and user satisfaction towards marker-based AR books. All the quality factors were found to be significant towards AR satisfaction. The content and system quality of marker-based AR books statistically differed between high and low innovators. In contrast, it was found to be contrary in the case of personalized service quality. The study has also reported the presence of full mediation of AR satisfaction on content quality and personalised service quality on the intention to recommend AR as well it was also found that AR satisfaction partially mediated the relationship between AR system quality and the intention to recommend AR book. The study showed that a highly satisfied customer tends to give a positive word of mouth about the destination and the AR book.

4. A theoretical model of mobile augmented reality acceptance in urban heritage tourism - (tom Dieck and Jung 2018) **Journal: Current Issues in Tourism (Citation:268)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a qualitative approach using thematic analysis on 44 British female travellers in Dublin using the Dublin AR application, which is marker and GPS-based. Five focus group interviews were conducted on the 44 participants of the study to obtain in-depth information.	Thematic analysis Theme 1 External dimensions: Information quality, System quality, Costs of use, Recommendations, Personal Innovativeness, Risk, Facilitating conditions Theme 2: Perceptions: Perceived usefulness, Perceived ease of use Theme 3: Attitude: Attitude Theme 4: Behavioral Intention: Intention to use	The study investigated the acceptance of AR applications in Dublin by British female travellers through thematic analysis. AR acceptance is influenced by external dimensions such as information quality, system quality, costs of use, recommendations, personal innovativeness, risk, and facilitating conditions in a tourism context.
5. A model of acceptance of augmented-reality interactive technology: the moderating role of cognitive innovativeness - (Huang and Liao 2015) **Journal: Electronic Commerce Research (Citation:253)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional survey of 220 graduate and undergraduate students of a university in Taiwan. First, the	Model used: TAM Perceived ease of use, Perceived usefulness, Perceived aesthetics,	This research investigated the various factors influencing sustainable relationship behaviour towards AR interactive technology. It was found that presence significantly affects consumers perceived usefulness, perceived ease of

participants had to try out an online clothing store's online fitting room and then mark their responses about the AR online fitting room. The questions were measured on a five-point Likert scale (strongly disagree 1 to strongly agree 5)	Service excellence, Perceived playfulness, Presence, Sustainable relationship behaviour	use, perceived aesthetics, perceived service excellence, and perceived playfulness of the ARIT. Presence was found to have the strongest influence on consumer service excellence in highly cognitive innovative consumers. In contrast, presence strongly influences consumers' perceived aesthetics in low cognitive innovative consumers. The study reported that perceived usefulness, service excellence, and aesthetics enhance highly cognitive innovative consumers to create sustainable relationships with retailers implementing the AR interactive technology. In contrast, usefulness, ease of use and playfulness facilitate low cognitive innovative consumers to build sustainable relationships with retailers considering AR technology.
6. Shopping in the digital world: Examining customer engagement through augmented reality mobile applications - (McLean and Wilson 2019) **Journal: Computers in Human Behavior (Citation:250)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study was conducted on 474 consumers in the UK who had downloaded and retained the app for at least one month and used the AR feature more than once. The questions were measured using a seven-point Likert scale (strongly disagree 1 to strongly agree 7)	Model: TAM Constructs: Perceived ease of use, Perceived usefulness, Perceived enjoyment, Subjective norms, Customer brand engagement (Cognition, Affection, Activation) AR interactivity, AR vividness, AR novelty, Satisfaction, Brand usage intention	The research examined the various factors influencing customer brand engagement through AR technology attributes. The study also inspected the role of customer brand engagement on customer satisfaction and brand usage intent, the consumer's purpose of using AR and the moderating role of utilitarian and hedonic use. Brand engagement is reported to have a strong influence on brand usage intention. The measured research constructs were found to have a significant role in the technology attributes, brand engagement, customer satisfaction and brand usage intent. However, results indicated the insignificant role of AR novelty on subjective norms. The multigroup analysis showed that vividness and interactivity significantly influence the perceived ease of use and

		usefulness of the AR feature for a helpful purpose. Perceived ease of use and perceived usefulness of the AR feature have more influence on brand engagement in utilitarian purpose than hedonic nature. The AR attributes are essential in influencing customers' enjoyment of AR features for hedonic purposes. Novelty affects AR technology's perceived ease of use and usefulness in a utilitarian context. Likewise, brand engagement was found to have more influence on satisfaction with AR experience in a hedonic context, whereas brand engagement highly influences future brand usage intent for a utilitarian purpose.
7. How augmented reality apps are accepted by consumers: A comparative analysis using scales and opinions - (Rese et al. 2017) **Journal: Technological Forecasting and Social Change (Citation:236)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study among German students was conducted. Four laboratory experiments were performed with more than 200 participants for each experiment. At the end of the experiment, participants had to fill in a survey questionnaire measuring users' personal experience towards the AR app. The study used markerless and marker-based AR. Four apps were used in the study.	Model used: TAM Constructs: Perceived usefulness, Perceived ease of use, Attitude towards using, Perceived enjoyment, Perceived informativeness, Behavioral intention to use	The research has examined the perception and acceptance of AR apps. Perceived ease of use, perceived usefulness, and attitude significantly influenced behavioral intention. Perceived informativeness and perceived enjoyment have a positive impact on perceived usefulness. However, results indicated the insignificant influence of perceived ease of use on perceived usefulness. The results showed that the positive effect of perceived enjoyment and perceived informativeness on the usefulness of the technology was not supported in the case of the four apps.

8. Augmented reality smart glasses: an investigation of technology acceptance drivers - (Rauschnabel and Ro 2016) **Journal: International Journal of Technology Marketing (Citation:199)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study used a cross-sectional survey of 201 participants with laptop computers in German shopping centres. The items were measured on a seven-point Likert scale (Totally disagree=1 and Totally agree=7), whereas brand attitude was measured on a seven-point semantic differential scale	Constructs: Social norms, Self-presentation, Functional benefits, Ease of use, Attitude towards the manufacturer brand, Data privacy image of the manufacturer brand, Technology innovativeness	The research study investigated the drivers and barriers to using AR smart glasses and how they influence the attitude and intention to adopt them. Functional benefits, attitude towards the manufacturer's brand and users' technology innovativeness were predictors of consumer attitudes (model 1) and adoption intention (model 2 without attitude) to use smart glasses. Likewise, attitudes towards manufacturer brands, social norms and consumer technology innovativeness significantly influence the attitude towards using smart glasses. It was also found that functional benefits and attitude towards the manufacturer brand affect the adoption intention towards smart glasses through the mediating role of attitude.
9. 'It's an illusion, but it looks real!' Consumer affective, cognitive and behavioural responses to augmented reality applications - (Javornik 2016b) **Journal: Journal of Marketing Management (Citation:196)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The research used two experimental studies among 60 participants: students and Swiss university alumni. Study 1 consists of the experimental group (with AR app) and the control group (with non-AR app) for selecting the chair. In Study 2, the participants have to choose sunglasses. It	Model: Model of theory of interactive media effects Constructs: Perceived augmentation, Flow, Affective responses (application attitude, brand attitude),	This research analysed the differences in consumer responses towards AR and non-AR app media characteristics. The study examined how perceived augmentation leads to flow (consumer immersion) and how flow mediates between perceived augmentation and consumer's affective, cognitive and behavioral intentions. The results of the experimental studies reported that perceived augmentation captures consumer perception of the relevant AR media features. Furthermore, in Study 1, the flow mediates the effects of perceived

comprises the same group, but participants were swapped between chairs and sunglasses. A seven-point Likert scale was used.	Behavioral intention (Purchase intention, revisit intention and recommendation intention), Cognitive responses (Number of thoughts, site-related thoughts)	augmentation on affective responses and behavioral intentions. In contrast, flow did not mediate the relationship between perceived augmentation and cognitive responses. In study 2, flow partially mediated the relationship between perceived augmentation and affective responses, behavioral intention and cognitive responses.
10. The Role of Augmented Reality for Experience-Influenced Environments: The Case of Cultural Heritage Tourism in Korea - (Chung et al. 2018) Journal: Journal of Travel Research (Citation:195)		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study on 162 visitors at three palace buildings in Korea using the mobile application with the AR feature "Deoksugung, in My Hands" was used. Visitors are presented with videos and materials explaining AR and how to use it so that visitors become aware of the AR app. The items were measured on a seven-point Likert scale ranging from strongly disagree 1 to strongly agree 7	Model: Post-acceptance model IS continuance, Motivational theory and experience economy, Balance theory Constructs: Prior expectation, Expectation confirmation, Perceived advantage, Aesthetic experience, Perceived enjoyment, AR satisfaction, Attitude towards destination through AR, Behavioral intention to a destination	The study examined how AR influences attitudes and behavioural intentions towards a cultural heritage destination. The results indicated that perceived advantage and aesthetic experience offered by AR impact AR satisfaction. Further, AR satisfaction influences the behavioral intention towards the destination through the attitude towards the destination experience over AR. The study has reported the insignificant influence of perceived enjoyment on AR satisfaction and AR satisfaction on behavioral intention towards a destination. AR satisfaction emerged as the most substantial factor influencing behavioral intention towards visiting a destination and recommending others.

11. Enhancing the online decision-making process by using augmented reality: A two country comparison of youth markets - (Pantano et al. 2017) Journal: Journal of Retailing and Consumer Services (Citation:187)		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional design with samples drawn from student populations of Germany (168 students) and Italy (150 students) to examine the behavioral intention towards virtual try-ons. Two separate laboratory experiments were conducted where students had to try out the AR smart mirror and then fill out the questionnaire, which will measure their experience.	Model: TAM Constructs used: Attitude, Behavioral intention, Ease of use, Interactivity, Usefulness, Enjoyment, Quality of information, Response Time, Aesthetic quality	The present study measures the influence of AR technologies (smart mirrors for virtual glasses) on consumer intention by comparing two cultural settings: Italy and Germany. The results indicated similarities and dissimilarities in consumers' interest towards using AR to aid online purchase decisions. The ease of use offered by the technology significantly influenced the attitude towards AR in the German sample, whereas it was found to be contrary in the Italian sample. Likewise, the ease of use of the technology significantly influenced the Italian sample, whereas it was found to be insignificant in the German sample. Both the samples revealed interactivity as a negligible predictor of perceived enjoyment. Consumers' attitude was the most vital factor in the study.
12. Tourist's responses to mobile augmented reality travel guides: The role of emotions on adoption behavior - (Kourouthanassis et al. 2015) Journal: Pervasive and Mobile Computing (Citation:187)		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study consisting of 105 respondents was selected. The visitors of Corfu city in Greece had to use the mobile AR app and fill out the questionnaire. Items are measured on a seven-point scale ranging from completely disagree (1) to completely agree (7).	Model used: UTAUT Constructs used: Performance expectancy, Effort expectancy, Price value, Behavioral intention, Personal innovativeness, Pleasure, Arousal, Dominance	This research study has investigated the adoption of the mobile AR app travel guide ‘CorfuAR’ through the impact of emotional elements, namely pleasure, arousal and dominance. The functional attributes of the MAR app (CorfuAR) induce the emotional aspects of pleasure and arousal, impacting the user’s behavioural intention towards the MAR app. Performance expectancy emerged as the most substantial factor influencing the user's pleasure. However, effort

		expectancy was an insignificant predictor of users' arousal. Likewise, price value and dominance were trivial factors of behavioral intention.
13. Relationship between student profile, tool use, participation, and academic performance with the use of Augmented Reality technology for visualized architecture models - (Fonseca et al. 2014) **Journal: Computers in Human Behavior (Citation:184)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study of 57 students was divided into groups based on their campuses (Tarragon campus and Barcelona campus). A pretest (technological profile test) and post-test (usage/ satisfaction test) were conducted. The items were measured on a five-point Likert scale (1 = never or strongly disagree, 5 = always or strongly agree).	Constructs used: Effectiveness, Efficiency Satisfaction, AR variables (Usefulness, level of improvement of project presentations, and difficulty of use)	This research investigated the feasibility of using AR on mobile phones in an educational context and also evaluated the relationship between the use of AR, student participation and the improvement in academics with the use of AR. The study has collected data from students by conducting pretest and post-tests. The results indicate that using AR is highly related to the student's motivation and influences academic performance. Though AR is helpful, it is found to be problematic in the case of complex content models.
14. Effects of perceived interactivity of augmented reality on consumer responses: A mental imagery perspective - (Park and Yoo 2020) **Journal: Journal of Retailing and Consumer Services (Citation:147)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study on 302 female online consumers in South Korea was conducted. The participants must shop for cosmetics using the AR feature of the mobile app (YouCam Makeup) and then fill out the survey questionnaire. Participants who have	Constructs used: Controllability of interactivity, Responsiveness of interactivity, Playfulness of interactivity, Elaboration Quality, Attitudes, Behavioral Intention	This study examined the perceived interactivity dimensions of controllability, responsiveness and playfulness on mental imagery (comprised of elaboration and quality), influencing the attitude towards the product and behavioral intention. The responsiveness dimensions of perceived interactivity resulted as an insignificant predictor of elaboration and quality of mental imagery. The results indicated that consumers with a positive attitude towards a product are

used the app were excluded from the study. Items were measured on a seven-point Likert scale (Strongly Disagree=1 to Strongly Agree=7)		highly inclined to purchase the product, recommend it, and reuse the app in the future.
15. Cross-cultural differences in adopting mobile augmented reality at cultural heritage tourism sites - (Jung et al. 2018) **Journal: International Journal of Contemporary Hospitality Management (Citation:142)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study was conducted at two locations (Deoksugung Palace in South Korea and the An Post Museum in Ireland). Visitors at the location were given AR materials to raise awareness about AR. Visitors who have used the app only can participate in the survey. 264 participants were taken from both the sites. The questionnaire items are measured on a seven-point Likert scale ranging from Strongly Disagree 1 to Strongly Agree 7.	Model: Experience economy, Motivational theory, TAM, Constructs used Aesthetics of AR, Perceived usefulness, Perceived ease of use, Perceived enjoyment, Social influence, Behavioral intention, Cultural differences	This study has explored the impact of aesthetics and perceived attributes on the intention to use AR in cultural heritage tourism. Further, the study investigated the influence of cultural differences (masculinity/femininity, power distance, individualism/collectivism, uncertainty avoidance) between Ireland and South Korea. The results indicate that the aesthetics of AR have a high influence on perceived enjoyment. Further, the study found that the impact of masculine and feminine culture on the relationship between beliefs (perceived usefulness and ease of use) and behavioral intention was insignificant.
16. A Human Factors Study of Technology Acceptance of a Prototype Mobile Augmented Reality System for Science Education - (Arvanitis et al. 2011) **Journal: Advanced Science Letters (Citation:135)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
This cross-sectional study consists of potential users of CONNECT mobile AR	Model used: TAM Constructs used:	The study has examined the user perceptions, attitudes and beliefs towards mobile augmented reality systems in the education context. The perceived

from Sweden, the UK, Greece and Finland. All the items were measured on a seven-point Likert scale, from Strongly Disagree 1 to Strongly Agree 7. However, attitude was measured on a seven-point semantic differential scale, and satisfaction was measured on a nine-point semantic differential scale	Satisfaction, Perceived usefulness, Perceived ease of use, Attitude towards use, Behavioral intention	usefulness of the technology was found to be a strong predictor of behavioral intention. In contrast, perceived ease of use of the technology emerged as an insignificant predictor of attitude towards using the mobile AR in science education.
17. Augmented reality tools for industrial applications: What are potential key performance indicators and who benefits? – (Jetter et al. 2018) Journal: Computers in Human Behavior (Citation:131)		
Data / Methodology	*Model used/Constructs*	*Remarks*
Items were measured on a seven-point Likert scale (Strongly disagree 1 to strongly agree 7). In contrast, attitude is measured using semantic differential pairs (simple-complex, fast-slow, precise-inaccurate, work relevant-unrealistic, worthwhile-negligible, reliable-unreliable). The study comprises 93 participants with technicians and managers in the UK and Italy.	Model used: TAM Constructs used: Perceived usefulness, Perceived ease of use, Attitude towards using, Behavioral intention, KPI (Cognitive workload, Spatial representation, Reduction of time and errors)	This research study evaluated how key performance indicators (KPI) for AR are related to the perceived usefulness and intention to use Bosch common AR platform (Bosch CAP) before and after training situations. The study's results have proved the significant role of KPI on user's perception of industrial AR applications. The KPI reduction of time and errors was found to be a significant predictor of the perceived usefulness of the technology. Perceived ease of use was found to be an insignificant predictor of attitude.

18. Technology acceptance modelling of augmented reality at the point of sale: Can surveys be replaced by an analysis of online reviews? - (Rese et al. 2014) Journal: Journal of Retailing and Consumer Services (Citation:123)		
Data / Methodology	*Model used/Constructs*	*Remarks*
This study followed a cross-sectional design involving online ratings (480 students) and an experimental setting (275 students) at a German university. The participants were explained the app; hence, prior experience was not required. They are given a tablet with the installed app. In the next stage, the participants had to complete a questionnaire rating the app and open-ended questions. In the other section, the constructs of the study were measured on a seven-point Likert scale (strongly disagree=1 to strongly disagree=2).	Model used: TAM Perceived informativeness, Perceived enjoyment, Perceived usefulness, Perceived ease of use, Attitude towards using, Behavioral intention to use	This study examined whether online reviews of customers can replace the traditional methods of assessing the technology acceptance of the IKEA mobile catalogue app with AR features using a questionnaire. The study consists of four samples comprising online ratings and offline student ratings. The results indicate that online reviews offer valuable inputs to the improvement of the app. Hence, it is essential that the experimental setting be realistic to a great extent to provide valuable input.
19. Consumer adoption of smart in-store technology: assessing the predictive value of attitude versus beliefs in the technology acceptance model - (Kim et al. 2017) **Journal: International Journal of Fashion Design, Technology and Education (Citation:111)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study of 657 participants in three contexts was used (virtual mirror, socially interactive dressing room and radio frequency identification music tag). The	Model used: TAM Perceived ease of use, Perceived usefulness, Perceived enjoyment Attitude, Intention,	This research study investigated the consumer adoption of smart in-store technology. Participants found virtual mirrors easy to use and useful and gave a more enjoyable experience than RFID and socially interactive dressing rooms. The study also revealed that the inclusion of attitude into the model has changed

constructs were measured on a seven-point likert scale (strongly disagree 1 to strongly agree 5), whereas attitude was measured on a seven-point semantic differential scale (Bad-good, Inferior-Superior, Unpleasant-Pleasant, Boring-Interesting, Poor-excellent, Not worthwhile- worthwhile, Not useful-useful)		the strength of the relationship. With the inclusion of attitude, perceived usefulness was found to be a significant factor in influencing the attitude in the case of virtual mirrors and RFID music tags, whereas perceived enjoyment emerged as an important factor in all the settings. This indicates that perceived enjoyment is equally essential to the perceived usefulness of the technology for all forms.
20. The Role of Perceived Enjoyment in the Student's Acceptance of an Augmented Reality Teaching Platform: A Structural Equation Modelling Approach - (Balog and Pribeanu 2010) **Journal: Studies in Informatics and Control (Citation:106)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study of 278 students who were not familiar with AR was conducted to test the platform with AR modules. The students were tested with two modules combined, as there was no significant difference between the two data sets. The items were measured on a five-point Likert scale (strongly disagree 1 to strongly agree 5)	Model used: TAM Ergonomics of AR platform, Perceived ease of use, Perceived usefulness, Perceived enjoyment, Intention to use	This research investigated students' behavioral intention to use the AR teaching platform. The ergonomics of AR (hardware and accessories) strongly influence the perceived ease of use of the AR platform. In contrast, perceived ease of use is an insignificant predictor of students' behavioral intention towards the AR platform. It was also found that perceived enjoyment contributes more towards enhancing the usefulness of the AR platform than the perceived ease of the system. This revealed perceived enjoyment as a critical variable in accepting AR teaching platforms among students.

21. Augmented reality in smart retailing: A (n) (A) Symmetric Approach to continuous intention to use retail brand's mobile AR apps - (Nikhashemi et al. 2021) **Journal: Journal of Retailing and Consumer Services (Citations:101)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study was conducted among customers in Malaysia who have experience with at least two AR apps (Gap, IKEA, or Amazon). The customers who had downloaded any two of these apps kept the app for at least one month and used the app more than once were taken for the survey. All the items were measured on a 7-point Likert scale (strongly disagree 1, strongly agree 7). The final sample consisted of 304 respondents who were selected based on the criteria fixed in the data collection.	Model used: Technology continuance theory (TCT) and Uses gratification theory (UGT) Constructs used: AR quality, AR novelty, AR interactivity, AR customisation, AR vividness, Utilitarian benefits, hedonic benefits, Retail brand app engagement, psychological inspiration, Continuance Intention to Use the App, Willingness to pay a price premium	This research study examined the influence of AR attributes with psychological inspiration and engagement on the intention to use an AR shopping app. The study found that all direct relationships were significant except for the influence of AR interactivity on the hedonic benefits. Utilitarian benefits were found to be the most substantial factor influencing psychological inspiration. The moderating role of AR customisation was found to be an influential factor in enhancing the relationships.
22. A virtual market in your pocket: How does mobile augmented reality (MAR) influence consumer decision making? - (Qin et al. 2021) **Journal: Journal of Retailing and Consumer Services (Citation:90)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study among college students in the US was selected. Data was collected in the laboratory via an online	Constructs used: Stimulus organism response model (SOR) Interactivity,	The research study investigated how a mobile augmented reality app influences the shopping experience and how mobile AR can influence user attitudes towards adopting and behavioral intention to use the technology. Results indicated that

survey. Students must watch the recommended AR video, install and use the app (IKEA & Ray-ban try-on), and fill in the survey questionnaire to share their experiences. Items were measured on a seven-point Likert scale from strongly disagree 1 to strongly agree 7.	Virtuality, Hedonic Gratification, Utilitarian Gratification, Informativeness, Ease of use, Attitude, Behavioral Intention	consumer attitudes strongly affect the behavioral intention to use MAR. Interactivity also emerged as a decisive factor among the stimuli influencing the perceived ease of use offered by the MAR. However, virtuality was an insignificant predictor of perceived ease of use, which had a negligible influence on the consumer's attitude towards MAR. Further, it was also confirmed that when consumers believe that the app can offer enjoyment, be helpful, and aid in acquiring information, they create a positive attitude towards the app.
23. Predicting the use of smartphone-based Augmented Reality (AR): Does telepresence really help? - (Kim and Hyun 2016) **Journal: Computers in Human Behavior (Citation:84)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study of 134 undergraduate students in South Korea was selected. Participants must use the OJVET app for one hour and then complete the questionnaire. Items were measured using a five-point Likert scale ranging from strongly disagree=1 to strongly agree=5.	Constructs used: TAM & TMH System quality, Service quality, Information quality Usefulness, Telepresence AR reuse intention	The study investigated what factors determine the reuse intention of smartphone-based AR apps through two models: model 1 indicates a revised TAM model consisting of usefulness, and model 2 indicates a telepresence mediation model consisting of telepresence. The results showed that in the case of model 1, all quality factors were found to be significant determinants of the usefulness of the technology, in turn positively influencing the reuse intention of AR. However, service quality was found to be an insignificant factor influencing telepresence. System quality was found to be a significant factor among the quality constructs influencing the usefulness of the technology. The mediation results pointed out that system quality and information quality impact the reuse intention of AR apps through usefulness and telepresence. Service quality had both direct and indirect influence on AR reuse intention. The model with usefulness was found to be superior to the model with telepresence.

24. Understanding users' continuance intention toward smartphone augmented reality applications - (Kim et al. 2016) **Journal: Information Development (Citation:84)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study of 178 users who had used AR apps before was selected. Items were measured on a Likert scale (strongly disagree 1 to strongly agree 7).	Model used: Motivation theory, Expectation confirmation model -ECM Constructs used: Information quality, Interactivity, Visual quality Perceived usefulness, Perceived enjoyment, Satisfaction, Continuous intention	This research examined the various factors influencing the user's continuance intention towards smartphone AR apps. The study found information quality as a decisive factor among the AR factors, whereas interactivity proved to be an insignificant predictor of the perceived usefulness of the technology. Likewise, perceived enjoyment is confirmed as an insignificant antecedent of continuous intention towards smartphone AR apps. The results of this study revealed that information quality and visual quality are more relevant than interactivity.
25. The role of perceived enjoyment and perceived informativeness in assessing the acceptance of AR wearables - (Holdack et al. 2022) **Journal: Journal of Retailing and Consumer Services (Citation:83)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
A cross-sectional study of 143 visitors to a department store in Germany was conducted. The study did not include participants with prior experience with these devices. The HoloLens device was adjusted for each participant. They had to use the device before filling out the questionnaire. The items were	Model used: TAM Perceived informativeness, Perceived ease of use, Perceived usefulness, Perceived enjoyment, Attitude, Behavioral intention	This study examined the factors influencing the consumer adoption of augmented reality smart glasses (Microsoft HoloLens) and the role of perceived enjoyment and perceived informativeness in accepting the same. Perceived informativeness was a strong and significant predictor of perceived usefulness. However, results indicated an insignificant relationship between perceived ease of use and perceived usefulness, which was also found to be an insignificant predictor of behavioral intention. Further, perceived ease of use was found to

measured on a five-point Likert scale with strongly disagree 1 and strongly agree 5.		have an insignificant role in consumer attitudes. The study has also found the presence of attitude as a mediator.
26. Augmented Reality and Virtual Reality for Learning: An Examination Using an Extended Technology Acceptance Model - (Jang et al. 2021) **Journal- IEEE ACCESS (Citation-82)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study used a cross-sectional design. Data was collected from 292 elementary school teachers in South Korea. Teachers were taught how wireless systems work and trained on using the required technologies. The questions were measured on a five-point scale (Strongly disagree 1 to strongly agree 5).	Model used: Ertmer and Ottenberit-Leftwich's TAM Constructs used: Technological Pedagogical And Content Knowledge, Social norms, Motivational support, Perceived ease of use, Perceived usefulness, Attitude towards technology use, behavioral intention	The study examined teachers' intention to use AR and VR technologies in their teaching practices. Perceived ease of use emerged as the most substantial factor influencing the user's attitude towards using the technologies. Furthermore, all the factors significantly influenced the intention to use the technologies.
27. Integrating TTF and UTAUT2 theories to investigate the adoption of augmented reality technology in education: Perspective from a developing country - (Faqih and Jaradat 2021) **Journal: Technology in Society (Citation-69)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study used a cross-sectional research design. The items are measured on a seven-point Likert scale ranging from strongly	Model used: UTAUT2 and TTF Constructs used:	The study examined the adoption of AR technologies in Jordan's education sector. The factors were found to be significant except for price value. Task characteristics were found to be the most vital factor influencing the task-

disagree to strongly agree. The data was collected from undergraduate students (281) at the University Al-al-Bayt in Jordan. The respondents were shown AR videos with educational content, which will make them aware of the benefits of using it in the learning context.	Performance expectancy, Effort expectancy, Social Influence, Facilitating conditions, Hedonic motivation, Price value, Behavioral intention, Task characteristics, Technology characteristics, Task-Technology Fit	technology fit, whereas performance expectancy was found to be the most vital factor in the UTAUT theory influencing the student's behavioral intention towards using AR technologies in their academic activities.
28. Applying the technology acceptance model to understand maths teachers' perceptions towards an augmented reality tutoring system - (Ibili et al. 2019) Journal: Education and Information Technologies (Citation-67)		
Data / Methodology	*Model used/Constructs*	*Remarks*
The research used a cross-sectional design. Data was collected from mathematics teachers who were given training videos demonstrating how to use the teaching materials and were given adequate support facilities. The final data consists of 148 respondents. The respondents completed the survey after analysing the AR study content over 3-7 days. The items of the survey instrument were measured on a seven-point	Model used: TAM Constructs used: Perceived ease of use Perceived usefulness Attitude Satisfaction Social norms Anxiety	This research investigated the acceptance and intention of primary school mathematics teachers to use the mobile AR app "Augmented Reality Geometry Tutorial System (ARGTS)", which enhances the 3D geometric skills of students. Attitude was found to be the most vital factor influencing teachers' behavioral intention to use the technology. In contrast, satisfaction was found to be the most critical factor affecting the attitude of teachers towards using the system. On the contrary, a few factors were found to be insignificant predictors. For instance, perceived ease of use was a negligible predictor of the attitude towards the technology. Anxiety was found to have a negative influence on the perceived usefulness as well as on the satisfaction towards the technology, which in turn

Likert scale (Strongly disagree-1 to strongly agree-7)		has a negative impact on the user behavioral intention. Similarly, social norms negatively influence the intention to use the technology.
29. Exploring player behavior and motivations to continue playing Pokémon GO - (Ghazali et al. 2019) **Journal: Information Technology & People (Citation-65)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study used a cross-sectional survey. Data was collected only from the existing Pokemon Go game players in Malaysia, as the study's objective was to examine the intention to continue. The final data consists of 362 respondents. The survey instrument items were measured on a seven-point Likert scale (Strongly disagree 1- Strongly agree-7).	Model used: Uses and Gratification Theory Constructs used: Achievement, Challenge Escapism, Social interaction, Need-to-collect, Nostalgia, Network externality, Enjoyment, Flow, Community involvement, Continuance intention, Purchase intention	This research examined the factors influencing the current players of the Pokemon Go game to continue playing the game and create the desire to make in-app purchases. The results indicated enjoyment as the strongest predictor influencing the player's intention to continue playing the game. However, results indicated escapism on enjoyment and social interaction on flow were found to have insignificant relationships. Likewise, flow and nostalgia were identified as insignificant predictors of continuance intention.
30. Technology Acceptance Model For Augmented Reality And Building Information Modeling Integration In The Construction Industry - (Elshafey et al. 2020) **Journal: Journal of information technology in construction (Citation-64)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study follows a cross-sectional design. Data was collected from construction professionals in Malaysia, Egypt, Saudi Arabia and Turkey. The items are measured	Model used: TAM 3 Constructs used: Perceived ease of use, Perceived enjoyment, Image, Behavioral intention,	This study investigated the acceptance of BIM and AR technologies in construction industries among construction professionals. The results found that the perception of external control was the strongest predictor of perceived

on a seven-point Likert scale (Strongly disagree 1 to strongly agree 7). The final data consist of 58 respondents	Perceived usefulness, Computer anxiety, Job relevance, voluntariness, Result demonstrability, Perception of external control	usefulness. However, computer anxiety on perceived ease of use and image on perceived usefulness were found to have an insignificant relationship.
31. Intention to reuse AR-based apps: The combined role of the sense of immersion, product presence and perceived realism - (Daassi and Debbabi 2021) Journal: Information & Management (Citation-61)		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study has followed a cross-sectional design comprising 224 female students. The mobile application 'Youcam Makeup" was used to try out lipstick and eyelashes. Participants interested in cosmetics and wearing makeup without prior experience using the app were considered for the study. The participants have to fill out the questionnaire after trying out the app. The items were measured on a seven-point Likert scale ranging from strongly agree 1 to strongly disagree 7. Attitude was measured on a seven-point semantic differential scale	Model used: Stimulus organism response framework Constructs used: Perceived augmentation, sense of immersion, sense of product presence, perceived realism, attitude towards AR, intention to reuse.	This study examines the factors influencing the intention to use and adopt AR-integrated apps in mobile shopping. The results found that the sense of immersion as a vital factor in the study affecting the sense of product presence. All factors were found to be significant. Furthermore, the study found the full mediation of product presence between the sense of immersion and perceived realism. Likewise, the study has pointed out attitude towards AR as a partial mediator between perceived realism and reuse intention of AR apps.

32. Mobile augmented reality (MAR) game as a travel guide: insights from Pokémon GO - (Aluri 2017) **Journal - Journal of Hospitality and Tourism Technology (Citation-60)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study has followed a mixed-method design. Data was collected from smartphone users who have played Pokemon Go games. The final data comprises 488 respondents who responded to the survey questionnaire with 11 questions assessing the usage, preferences and intention to use mobile AR game apps as guides for travel purposes.	Constructs used: Usage of the Pokemon Go app, Source of information of the app, Intention to use the app and further in future as a travel guide,	The study examined the behavioral intention of smartphone users who have played the Pokemon Go app and used the mobile augmented reality app as a tour guide. The results pointed out that 71 percent of the respondents had the app installed on their smartphone, 77 percent of the respondents showed high interest towards using the app as a travel guide, and 73 percent of the respondents had a keen interest in trying the Pokemon Go app as a travel guide in future.
33. Me or just like me? The Role of Virtual Try-on and physical appearance in apparel M-retailing - (Plotkina and Saurel 2019) **Journal - Journal of Retailing and Consumer Services (Citation-51)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional design with mixed methods (quantitative and qualitative methods). Data was analysed for the experimental study with 415 respondents and 49 respondents for qualitative research. The experimental study only compared AR-based virtual try-on apps and m-commerce interfaces with images. The data was collected only from female respondents with	Model used: TAM Constructs used: Purchase intention, Attitude towards the shopping technology, convenience to examine the product, perceived enjoyment from the shopping experience, perceived ease of use of the shopping technology, perceived	The study examined users' attitudes towards virtual try-on technology and their purchase intention. The results highlighted that virtual try-on technology was less enjoyable than m-commerce. On the contrary, VTO was found to be less convenient and highly useful when compared to the images of the m-commerce apps. It was found that the small screen of mobile devices creates difficulty in assessing the size and style of the garments on the users. Further, consumers above 33 have raised high concerns about privacy issues while using the technologies, suggesting the need to control personal information access, enhancing the application's overall performance. Respondents pointed out that

experience with shopping technology and involvement in shopping apps. The items are measured on a seven-point Likert scale (Strongly disagree 1 to strongly agree 7). Purchase intention was measured on a three-point scale	ease of the shopping technology, Evaluation of the dress, Involvement in online retailing shopping, experience with shopping technologies, Attention check	the realistic presentation of online products with real models creates a favourable attitude towards VTO technologies and higher purchase intention than VTO technologies.
34. Determinants of the Intention to Adopt Mobile Augmented Reality Apps in Shopping Malls among University Students - (Saprikis et al. 2021) Journal: Journal of Theoretical and Applied Electronic Commerce Research (Citation-48)		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional design targeting college student of various institutions in Greece who visited shopping malls at least once a month. The final data used for the empirical analysis consisted of 381 students. The students were well informed about the study, with a detailed description of the questionnaire and a demo video of AR. The items are measured on a five-point Likert scale consisting of Strongly Disagree 1 to Strongly Agree 5.	Model used: UTAUT Constructs used: Performance expectancy, Effort expectancy, Social Influence, Facilitating conditions, Innovativeness, Enjoyment, Reward, Trust, Behavioral intention	This study investigated the factors influencing the student's behavioral intention towards using mobile AR in shopping malls. The construct facilitating conditions emerged as the most vital factor affecting the effort expectancy of users. However, the study also revealed insignificant relationships among the UTAUT constructs. For instance, the influence of effort expectancy on behavioral intention, social influence on behavioral intention, and facilitating conditions on behavioral intention. Likewise, the construct innovativeness was found to be an insignificant predictor of behavioral intention.

35. A systematic review of augmented reality tourism research: What is now and what is next? - (Jingen Liang and Elliot 2021) **Journal: Tourism and Hospitality Research (Citation-48)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
Literature review using databases such as Scopus, EBSCO Host, Web of Science and Google Scholar were used with keywords 'augmented realit*' and 'tourism'. The study has used only 32 articles for the review after removing research areas which do not match the context of the study.	Systematic literature review. Bibliometric analysis and Meta-analysis	This study examined the present scenario of AR research in the tourism area through a systematic review. The results highlighted the need to expand studies using theories other than TAM. The review results also emphasised the need to explore studies outside European countries with different methods focusing on the negative side. The review also suggested to have mixed methodologies combining quantitative and qualitative studies.
36. Understanding mobile augmented reality adoption in a consumer context - (Paulo et al. 2018) **Journal: Journal of Hospitality and Tourism Technology (Citation-48)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional design with an empirical analysis of 335 respondents. The research used TTF adoption behaviour towards internet services and UTAUT2 to examine mobile AR technologies' user behavioral intention and usage behavior. The items of the survey instrument were measured on a seven-point Likert scale consisting of Strongly disagree 1 and strongly agree 7. The respondents were	Model used: UTAUT2 and TTF Constructs used: Performance expectancy, Effort expectancy, Social Influence, Facilitating Conditions, Hedonic motivation, price value, Habit, Behavioral intention, Usage behavior, Task characteristics, Technology characteristics, and Task technology fit.	The study investigated the factors influencing users' intention to adopt mobile AR during travel and destination visits. Technology characteristics emerged as the strongest factor in the model affecting effort expectancy. A few factors in UTAUT2 were found insignificant (such as effort expectancy, social influence and price value) in explaining behavioral intention to use mobile AR. Likewise, facilitating conditions proved insignificant in predicting the future usage of Mobile AR.

well-informed about the research objective with a video demonstration of mobile AR.		
37. Augmented reality in online retailing: a systematic review and research agenda - (Kumar 2022) **Journal: International Journal of Retail & Distribution Management (Citation-47)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study has used domain-based and framework-based reviews to conduct the systematic literature review. It also used the ADO framework (antecedents, decisions and outcomes) and TCM framework (Theory, context and method). The PRISMA method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) was utilized to select the research papers, which resulted in 53 articles. Scopus database was used to extract the articles. Reviewing 53 articles	Systematic literature review ADO framework PRISMA method	This research study conducted a systematic literature review of AR in online retailing by assessing the antecedents, outcomes, typology and methodology adopted. The study utilized the keywords to search the research papers. The results indicated the need to examine how AR in social media platforms can enhance self-brand connections and users' continuance intention. The paper also reflected the need to analyse the dark side of AR, focusing on the privacy concerns posed by the technology on the users. They also emphasised the need to examine the "Augmented reality marketing" concept. There is a need to conduct more qualitative studies on how AR can be used to create customer engagement and experiential value.
38. Can augmented reality satisfy consumers' need for touch? - (Gatter et al. 2022) **Journal: Psychology & Marketing (Citation-45)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional design consisting of four studies. Study 1 used Sephora's make-up product AR app, where data was collected at two time	Constructs used: Need for touch, Utilitarian benefits, Hedonic benefits, Attitude towards the	This study investigated how AR can help compensate for the need for touch by virtually presenting the product in the user environment. Study 1 used Sephora's AR make-up product app; Study 2 used the AR and non-AR features of the

periods, i.e., a few days before and after using the AR feature, by 173 female students at a German university. The participants were contacted after 18 days to fill out the questionnaire. The items were measured on a seven-point scale (Totally disagree-1 to Totally agree-7). Study 2 used the AR and non-AR features of the Amazon app by 212 participants (aged 18-35) recruited by an agency. Study 3 was conducted among 92 female participants recruited from an agency with imaginary carpet-selling outlets. Study 4 used 113 female participants recruited from agencies and were randomly assigned with AR or Non-AR conditions.	brand, Attitude towards the product, Autotelic NFT,	Amazon app; Study 3 used imaginary carpet-selling outlets, and Study 4 was randomly assigned with AR or non-AR conditions. The research study consists of four studies to examine the role of AR. Results indicated that AR can replace the physical in-store experience. Consumers with a high need to touch the products experience higher hedonic benefits than those with a low need to feel the products. The study also noted the differences between expected and experienced hedonic and utilitarian benefits.
39. A new reality: Fan perceptions of augmented reality readiness in sports marketing - (Goebert and Greenhalgh 2020) **Journal: Computers in Human Behavior (Citation-44)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study has followed a cross-sectional design. The final data set consists of 142 participants. The study has formed three AR models for customer service: hedonic	Model used: TAM Constructs used: Perceived ease of use, Perceived usefulness	The study investigated the fans' viewpoint on the application of AR in sports marketing. Attitude is identified as the most vital factor influencing AR usage intention. On the contrary, the research study has reported insignificant relationships, such as the absence of a significant relation between perceived

(videos of players), hedonic and utilitarian (tracking of in-game player tracking). Participants were shown three different videos. The items were measured on a seven-point scale.	AR attitude, AR usage intention, Word of mouth Technology readiness, Visual appeal, Facilitating conditions	ease of use on perceived usefulness and perceived ease of use on attitude towards AR. The study pointed out that AR through smartphones will be easier to use as users are more familiar.
40. Exploring the factors influencing the adoption and usage of Augmented Reality and Virtual Reality applications in tourism education within the context of the COVID-19 pandemic - (Shen et al. 2022) **Journal: Journal of Hospitality, Leisure, Sport & Tourism Education (Citation-44)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional research design. Data was collected from 604 tourism students at Chinese universities. The participants were explained about the research and a demonstration video. The items were measured on a five-point Likert scale (Strongly disagree 1 to strongly agree 5).	Model used: TAM Perceived usefulness Perceived ease of use Hedonic motivation Perceived price value Attitude to use Behavioral intention	This study has investigated the acceptance and usage of AR and VR applications in the tourism education sector, focusing on the pandemic situation. The results have confirmed the attitude towards using AR and VR as the strongest factor influencing the attitude towards using AR and VR apps in the research investigation. All the factors were found to have significant relationships among the constructs except for the perceived ease of use on student's attitudes towards using AR.
41. Extending the technology acceptance model to explain how perceived augmented reality affects consumers' perceptions - (Oyman et al. 2022) **Journal: Computers in Human Behavior (Citation-42)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study used an AR-powered mobile application to virtually try cosmetic products by female consumers. The study followed a	Model used: TAM Constructs used: Consumer novelty seeking	This research examined the effect of AR in mobile apps on consumers' intention to use them. The study used an independent app (YouCam Makeup app), which the participants used, and responses were collected after using the app. Perceived

cross-sectional design with 278 female respondents. The participants had to try the YouCam Makeup application and complete the questionnaire. The items are measured on a five-point Likert scale (Strongly disagree1 to strongly agree 5).	Technology anxiety, Perceived augmented reality Perceived enjoyment Perceived usefulness Perceived informativeness Perceived ease of use Behavioral intention to use	augmented reality was the most vital factor in the study influencing the perceived usefulness of augmented reality. However, results have indicated the absence of a significant relationship between technology anxiety on perceived augmented reality and perceived ease of use on behavioral intention to use AR.
42. Privacy concerns when using augmented reality face filters? Explaining why and when use avoidance occurs - (Cowan et al. 2021) **Journal: Psychology & Marketing (Citation-42)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study follows a cross-sectional design with a survey and an experimental study. Study 1 used only those respondents (251 respondents) who were experienced with AR face filters. The participants have to select one app which was previously used and give responses accordingly. The items were measured on a five-point Likert scale. Study 2 used Snapchat users, and those ready to respond through computers were selected. The respondents have to use the smartphone as per instructions and respond through computer systems.	Model used: Construal theory Constructs used: Privacy risk, Perceived usefulness, Flow Behavioral intention, Word of mouth	This study examined how privacy concerns affect users' responses to AR face filter apps. The study comprises two studies: a survey study and an experimental one. The findings indicated that the privacy concerns associated with the AR face filters indirectly impact behavioral intentions. It was found that privacy concerns related to AR in social media decrease the user behavioral intention and word of mouth, mediated through the perceived usefulness and flow. Further, the study also pointed out that privacy concerns make users rethink the app's potential risks and benefits, which change the experience and use of the AR filters.

43. Assessing the impact of full-fledged location-based augmented reality games on tourism destination visits- (Lacka 2020) **Journal - Current Issues in Tourism (Citation-40)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional design using a survey method. Data was collected from active users of location-based AR games, resulting in 461 respondents. The items were measured on a seven-point scale.	Constructs used: Intention to visit Intention to use AR games Focused knowledge gain Incidental knowledge gain Extrinsic motivation Intrinsic motivation	This research investigated the influence of location-based AR game apps on visitors' intention to visit tourist destinations. Further, it also evaluated the role of knowledge on the point of interest and the various factors impacting the use of AR games. Intrinsic motivation was the most vital factor influencing the intention to use AR games. The research also pointed out the insignificant influence of focused knowledge gain on intention to use and incidental knowledge gain on intention to use.
44. Meet the Virtual Jeju Dol Harubang—The Mixed VR/AR Application for Cultural Immersion in Korea's Main Heritage (Jung et al. 2020) **Journal – ISPRS International Journal of Geo-Information (Citation-40)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional design consisting of 251 participants who were visitors to Korea. The items are measured on a five-point scale ranging from strongly disagree 1 to strongly agree 5.	Model used: TAM Task Technology fit model Constructs used: Perceived visual design, Perceived task technology fit, Perceived usefulness, Perceived ease of use, Intention to use and Intention to visit.	This study examined the JejuView application to explore the destination spots on Jeju Island. Results indicated that users focus more on the hedonic benefits than the information's utilitarian benefits. Perceived visual design was reported as the most vital factor influencing the perceived fit of task technology. In contrast, perceived usefulness was an insignificant predictor of the intention to use the AR and VR application and the intention to visit the destination.

45. A collaborative apparel new product development process model using virtual reality and augmented reality technologies as enablers - (De Silva et al. 2019) **Journal - International Journal of Fashion Design, Technology and Education (Citation-40)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
This study has adopted a mixed-method approach with quantitative and qualitative methods and a cross-sectional survey design. The qualitative research was conducted through 10 semi-structured interviews with academicians and practitioners with at least ten years of experience. The data for the quantitative study was collected from 94 students (undergraduate and graduate students) who are aware of VR and AR. The survey instrument consists of 10 closed-ended questions and one open-ended question. Consumer awareness and perceived usefulness were measured using closed-ended questions, whereas intention to use technology was measured using open-ended questionnaires.	Model used: TAM Constructs used: Consumer awareness Perceived usefulness Intention to use	This study examined the application of AR and VR technologies in the new product development process. This research consists of qualitative and quantitative studies. The qualitative approach assessed the perspective of the designated team in the application of AR and VR in the new product development. In contrast, the quantitative study evaluated consumers' awareness of AR and VR technologies and their intention to use them. The results pointed out that customers prefer customisation of their products, and it is crucial for the new product development team to integrate with the customers for the development process. VR is suitable for the product development stage. In contrast, AR tools are ideal at the customer integration level, such as assessing and evaluating the size and fit of the products.

46. User acceptance of augmented reality welding simulator in engineering training- (Papakostas et al. 2022) **Journal- Education and Information Technologies (Citation-38)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional design, and quantitative research was utilized through the survey method. Data was collected from 200 male trainees at the Institute of Vocational Training. Data was taken at the end of the training program and before they entered the real welding lab. The questionnaire items were measured on a seven-point Likert scale (Strongly disagree 1 to strongly agree 7).	Model used: TAM Constructs used: Perceived ease of use, Perceived usefulness, Perceived enjoyment Attitude towards using, Behavioral intention to use	This study examined the factors affecting the trainee's acceptance of the Soldamatic AR welding simulator. The results of this study will aid AR developers in improving the quality of the AR simulation training systems, which will enhance the user experience and the intention to use them. Attitude towards using the AR system was the strongest predictor of behavioral intention, followed by perceived ease of use on attitude. However, the influence of perceived enjoyment and usefulness on attitude towards using the system was insignificant.
47. Measuring User Experience, Usability and Interactivity of a Personalized Mobile Augmented Reality Training System - (Papakostas et al. 2021) **Journal - Sensors (Citation-38)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The research study followed a cross-sectional design with 200 volunteer firefighters. Participants were given the chance to interact with the system. The items are measured on a seven-point scale, from strongly disagree 1 to strongly agree 7.	Model used: TAM Constructs used: Perceived interactivity Perceived personalization Perceived usefulness Perceived ease of use Behavioral intention to use	This research study examined the acceptance of the NAFTES AR application by firefighters who have experience in using this AR application for firefighting training purposes. The results indicated that all the proposed hypotheses were significant in the study. Perceived usefulness was the most vital factor influencing users' behavioural intention towards accepting the AR application.

48. User Experience of Augmented Reality System for Astronaut's Manual Work Support - (Helin et al. 2018) **Journal- Frontiers in Robotics and AI (Citation-38)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The first evaluation consisted of 14 participants, with 39 participants for the second evaluation. In the initial assessment, the development team observed the users using the system and freely commented on their experiences. In the second evaluation, the development team conducted interviews to assess users' opinions on smart glasses.	Constructs used: Smart glasses user satisfaction. The scale consists of 11 statements. User interaction satisfaction with 15 items	This research study examined how the AR system can reduce errors and improve efficiency in training. The evaluation has been done in two phases. The first phase of the assessment looked at the user experience for future system development. In contrast, the second evaluation consisted of an in-depth assessment wherein 39 participants were assessed to get their feedback on the system. The results showed a satisfactory response to the overall experience of the AR system and further indicated the high potential of the system for offering enhanced user experience.
49. Enhancing cultural heritage outdoor experience with augmented-reality smart glasses - (Litvak and Kuflik 2020) **Journal-Personal and Ubiquitous Computing (Citation-37)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study has adopted field and lab studies to explore using augmented reality smart glasses. The field study consisted of 30 participants, comparing the AR smart glasses and smartphone AR guide. The lab study instructed the participants to assess the AR smart glasses display in certain conditions. The field study participants need to be	System usability scale Satisfaction	This research study examined how augmented reality smart glasses can elevate visitors' experience at outdoor cultural heritage locations with value-added information and help in navigation among buildings and heritage monuments. The evaluation was done through field study and lab study. The results indicated that visitors are highly optimistic about accepting ARSG to explore their cultural heritage. Findings also pointed out the presence of challenges in the implementation of ARSG in cultural heritage locations. The visitor's positive attitude towards ARSG technology indicates the potential acceptance of the technology in cultural heritage tourism.

familiar with the mobile AR guide. The items are measured as good, poor, and excellent.		
50. Factors Affecting Augmented Reality Adoption in the Retail Industry - (Alam et al. 2021) **Journal - Journal of Open Innovation: Technology, Market, and Complexity (Citation-35)**		
Data / Methodology	*Model used/Constructs*	*Remarks*
The study followed a cross-sectional research design. Data was collected from 233 owners and managers of retail stores in Malaysia. The items of the survey instrument are measured on a five-point Likert scale with strongly disagree 1 to strongly agree 5.	Model used: TAM Constructs used: Perceived ease of use Perceived usefulness Attitude, Intention to use AR Self-efficacy, Personal innovativeness, Technological knowledge, Perceived cost Competitive pressure, Trading partner pressure, Customer pressure, External support	This study investigated the adoption of augmented reality in the retail industry. The data was collected through the survey method. Perceived usefulness was reported to be the most vital factor influencing the attitude towards using the technology, followed by the influence of self-efficacy on the perceived ease of use. However, the results also reported the presence of insignificant influence such as perceived ease of use on attitude towards using the technology, trading partner pressure on behavioral intention towards using AR technology and external support on user behavioral intention towards using AR technologies in the retail industry.

Source: Secondary data

2.5 CHAPTER SUMMARY

The chapter has presented the systematic approach undertaken in the literature review adopted in the study. It has also offered an overview of AR technology and its role in online product presentation through AR. A brief review of the scopus metrics and bibliometric analysis was discussed, exploring the various research studies investigating the behavioral intention towards accepting AR technologies. The use of scopus metric analysis and bibliometric analysis has highlighted the growth of the research studies and the contribution of authors and countries, which has shown the significance of the research area. Based on the inputs of the literature review, the study has framed its research hypothesis, which is presented in the next chapter.

CHAPTER 3

THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

3.1 INTRODUCTION

The literature review is highly crucial in the development of the theoretical framework. Researchers need to focus on developing the theoretical framework and research hypothesis as the foundation of the research study lies in it. This chapter explains the theoretical framework and research hypothesis of the study. Along with the theoretical framework, this chapter also emphasises the identified research gaps leading to creating the study's research model. Each variable selected is clearly explained with the concerned literature work for the proposed hypothesis of the study. Further, based on the literature review, the conceptual framework of the research study is examined with a detailed elucidation of the proposed hypothesis. This chapter concludes with a summary of the various areas discussed in the theoretical framework and hypothesis development.

3.2 THEORETICAL BACKGROUND OF THE STUDY

Technology development has sparked interest among researchers towards exploring technology acceptance in various fields. Several theories examine technology acceptance; however, a single theory cannot explain individual behavior. Technology acceptance theories have been developed from psychology, sociology and information technology systems. Fishbein and Ajzen (1975) proposed the theory of reasoned action (TRA) posits that the individual’s attitude and subjective norms highly influence the behavioral intention and actual behavior. TRA theory is the most applied theory in technology acceptance in attitude and behavioral research. TRA theory states that behavioral beliefs affect an individual’s favourable and opposing views of behaviour. Likewise, normative beliefs influence the social pressure regarding performing a specific behaviour. Therefore, the theory of reasoned action indicates that attitude and subjective norms influence the individual’s behaviour. TRA considers that behaviours within their control influence and is regarded as a limitation in examining user behavioral intention. This calls out the need to explore situations where individuals have low control. Ajzen (1991) developed the theory of planned behaviour (TPB) to overcome the limitations of the TRA. The theory of planned behavior extended the TRA, including perceived behavioural control (Ajzen 1991).

The TPB theory postulates that the behavioral intention and the actual behavior of individuals are influenced by perceived behavioral control, attitude, and subjective norms. Perceived behavioral control indicates the factors which assist or hinder performing the behavior (Ajzen 1991). As per TPB, the individual's technology adoption behaviour is influenced by the information from social media platforms and influences from family and social groups (Ma et al. 2020). Perceived behavioral control significantly predicts behavioral intention (Mathieson 1991). Though TPB is a prominent theory, it nevertheless has certain limitations identified by researchers and academicians. Ajzen (1991) has reflected the need for further expansion of the TPB theory for exploring the various other factors influencing the user behavioral intention, indicating that the theory lacks adequacy in explaining the behavioral intention. TRA and TPB predict behavioral intention, but there is a need for a particular situation for accurate prediction. The study included only one variable (perceived behavioral control) influencing the user behavioral intention, whereas researchers have argued that incorporating more factors can improve the model's predictive power with the existing measures of the theories (Davies et al. 2002).

The Technology Acceptance Model (TAM) proposed by Davis (1989) measures user behavioural intention towards technology use. This model was parsimonious with high predictive power (Yousafzai et al. 2010). As per the TAM model, user behavioural intention must be explored through the other external variables. The TAM model is based on the TRA framework (Fishbein and Ajzen 1975). This model substituted the attitude beliefs of TRA with measures such as perceived ease of use and perceived usefulness. The subjective norms of the TRA model were also excluded from the TAM model. The TAM model is an information system theory which discusses how users accept a new technology. Perceived ease of use is the expectation that the technology can be used with minimum effort, and perceived usefulness indicates the user's expectation that the technology will help improve their activities (Davis 1989).

The TAM model highlights that the user's attitudes are influenced by perceived usefulness and perceived ease of use, leading to the user's behavioral intention. The proposed TAM model consists of external variables, perceived ease of use, perceived usefulness, attitude and behavioral intention. However, prior research indicated the

insignificant role of attitude; hence, attitude was dropped from the model (Davis and Venkatesh 1996). Despite the model being simple and widely used, researchers stated that it is inadequate, and the method to identify the various factors influencing perceived usefulness and ease of use has not been ascertained (Bagozzi 2007). Furthermore, researchers cited that TAM is inadequate as it fails to explain users' benefits from using the technology (Turner et al. 2010). These shortcomings led to TAM2 (Venkatesh and Davis 2000) and TAM3 (Venkatesh and Bala 2008). The Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003) examined the users' behavioral intention towards technology and the successive usage behaviour. The UTAUT model is developed with the combination of several technology acceptance theories, namely, the theory of reasoned action (Fishbein and Ajzen 1975), the social cognitive theory (Bandura 1986), the model of PC utilisation (Thompson et al. 1991), the technology acceptance model (Davis 1989), the theory of planned behaviour (Ajzen 1991), the innovation diffusion theory (Moore and Benbasat 1991), the motivational model (Davis et al. 1992) and the combined TAM-TPB model (Taylor and Todd 1995).

The UTAUT theory (Venkatesh et al. 2003) consists of four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions which measure the user's behavioral intention to use technology and actual usage behaviour. The UTAUT model is considered superior as the combination of factors has increased the model's predictive power to 70 percent (Oye et al. 2014). Though the theory had high predictive power, it focused on examining users' (employees) behavioral intention towards technology acceptance in an organisation context. Based on prior research investigations and identified shortcomings, Venkatesh et al. (2012) extended the UTAUT theory with constructs such as habit, hedonic motivation, and price value to examine the acceptance of technology in a consumer context led to improved variance in behavioral intention to seventy-four percent and an increase in technology use to fifty-two percent (Loo et al. 2023). Earlier studies conducted in the area of food ordering apps (Alalwan 2020), mobile commerce adoption (Tarhini et al. 2019) and smart banking services (Hassaan et al. 2023) have successfully implemented the UTAUT2 theory for examining the technology acceptance. Though UTAUT2 theory is

considered significant, it has several shortcomings due to low parsimony and absence of focus on rationale (Tamilmani et al. 2021).

Venkatesh et al. (2012) cited the need to explore user behavioral intention by extending the theoretical framework of UTAUT. Later on, this framework was revised as UTAUT3 theory by Farooq et al. (2017), encompassing personal innovativeness in information technology. The UTAUT3 consist of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit and personal innovativeness. Farooq et al. (2017) examined the UTAUT3 theory with personal innovativeness in the acceptance of the lecture capture system by business students in Malaysia. The study revealed that all the factors significantly predict the user's behavioral intention. Farooq et al. (2017) reported that all factors significantly predicted user behavioral intention at 58.1 percent, and constructs such as facilitating conditions, habit, and personal innovativeness predicted 68.2 percent of the variance in usage behaviour. The predictive power attained by the model is higher than that of previous UTAUT models, indicating the high reliability of the model in examining user behavioral intention (Farooq et al. 2017). Though the theory has high predictive power, the model has not been tested and validated in other contexts, indicating a scarcity of studies based on the application of UTAUT3 theory (Farooq et al. 2017; Gunasinghe et al. 2020b).

Various researchers have adopted the UTAUT3 theory in the context of virtual communication technology (Gupta et al. 2023), e-learning systems (Gunasinghe et al. 2020a; Tiwari et al. 2022), neobanking (Bhatnagr and Rajesh 2023), AR in tourism (Pinto et al. 2022), but the model has not been investigated in developing countries such as India (Gupta et al. 2023) in the area of AR in online shopping apps. Henceforth, this research study aims to address the research gap by using UTAUT3, including trust, privacy risk, information quality, and system quality, to predict the user behavioral intention towards AR technology in online shopping apps in the Indian context. The research gaps identified through the literature review are discussed in the following section.

3.3 RESEARCH GAPS

Research gaps indicate the unresolved problem in an area of study which needs to be explored by researchers to collect meaningful solutions for the same. It is a topic or area that researchers need further investigation due to a lack of adequate information (Robinson et al. 2013). The current study has identified research gaps through prior literature. Identifying the research gap is pivotal in the research investigation process as it helps to have a better focus and narrow down the research activities to have an in-depth investigation of the research study.

Research Gap 1: Limited empirical studies on AR adoption by consumers in developing countries

The growth of developing countries has opened the doors to international markets and acceptance of new technologies. AR has sparked interest among stakeholders towards attaining efficiency and effectiveness in activities. There is rapid growth in immersive technologies such as AR in developing countries. Prior research in countries such as the USA (Barta et al. 2023), Germany (Kowalczuk et al. 2021), and China (Chiu et al. 2021) gave valuable insights towards using AR technologies. However, studies have highlighted the need to explore the adoption of AR technologies in developing economies such as India (Abed 2021; Saleem et al. 2022). Further, prior research in AR has focused on a specific population group, such as students or a particular gender group. For instance, the study by Barta et al. (2023) examined the influence of website shopping experience using AR in an online cosmetics store among the female population. Dogra et al. (2023) investigated customer user behaviour towards AR-based shopping websites using the student population. They noted an abundant opportunity to explore the behavioral intention towards AR with a heterogeneous population. Similarly, the study by Saleem et al. (2022) examined AR adoption among students and stated the need to explore the adoption of AR apps in the retail sector of developing countries. Hence, this research is conducted in India, focusing on Tier 1 cities in South India with diverse populations.

Research Gap 2: Need to investigate the adoption of AR technologies on online shopping apps

The implementation of AR offers numerous benefits to users and e-commerce portals. Before implementing the technology, it is essential to understand the consumer perspective towards the technology. Understanding the user perspective towards AR technology helps in its successful implementation. For instance, Harborth (2017) indicated a lack of research on user acceptance of AR technologies. Prior research (Chandra and Kumar 2018) investigated the adoption of AR in e-commerce in an organisation context using a technology organisation environment model. However, the study indicated the need to explore in a consumer context, highlighting the consumer perspective towards accepting AR technology. Further, Jung et al. (2020) examined the influence of cultural diversity among users and suggested the need to explore adopting novel technologies such as AR. These prior studies have indicated the relevance of investigating the adoption of AR technologies. Hence, this study examines the acceptance of AR technologies in online shopping apps.

Research Gap 3: Examining the role of privacy concerns on the intention to use AR technologies in online shopping apps.

AR technology functions by capturing information from the user's surroundings. Further, it requires camera access and user information to function in the desired manner. Prior research by Dacko (2017) found that users have high concerns over sharing personal information in AR apps. Further, users may be reluctant to give camera access due to a lack of awareness of its potential benefits in online shopping (Smink et al. 2019). Research showed that privacy concerns must be investigated as privacy risks can influence the user's decision to use or not to use AR-based apps (Smink et al. 2019). Furthermore, prior studies have pointed out a dearth of studies focusing on the privacy risk of using new technology such as AR (Hilken et al. 2018; Poushneh 2018). Earlier scholarly inquiries (Harborth 2017; Harborth and Pape 2021) pointed out the lack of research emphasising the need to investigate the role of privacy factors influencing the behavioral intention to use AR in mobile apps. Considering these future directions highlighted by prior researchers, this study examines the role of privacy risk on users' behavioural intention towards using AR in online shopping apps.

Research Gap 4: Examining the role of Trust on the intention to use AR technologies

Trust is an essential factor influencing the customer's choices and decision-making in online shopping (Pavlou 2003). The rapid use of technology in daily life has demanded the need to build trust in the technology. It is essential to build trust in technology, which has a significant role in consumer decision-making, particularly towards using innovative technologies such as AR (Kalinic et al. 2019). The acceptance of a new technology is highly influenced by the extent of trust towards the technology. Prior studies (Akbari et al. 2020; Tams et al. 2018) have emphasised the role of trust and the need to examine trust in the consumer adoption of novel technology. Prior scholarly work (Saprikis et al. 2021) emphasised the need for further research in AR, including factors such as security, innovativeness and trust. Likewise, research has highlighted the dearth of studies examining the role of trust in AR apps (Arghashi and Yuksel 2022).

Research Gap 5: Investigating the role of quality dimensions on the intention to use AR technologies

Quality dimensions play a significant role in the acceptance of a technology. These dimensions are a benchmark for attaining good performance in the app activities. The qualitative research by tom Dieck and Jung (2018) identified information quality and system quality as essential themes to focus on in future research on AR acceptance. Further, prior research investigating the role of visual and service quality on user satisfaction pointed out the need for future research on information quality and system quality (David et al. 2021). The success of an information system can be adequately measured using system quality and information quality (Yoo 2020). These studies indicated the need to explore the role of information quality and system quality on consumer behaviour towards adopting AR technology in mobile apps. Henceforth, this research examines the role of information quality and system quality on users' behavioural intention towards AR technologies in online shopping apps.

3.4 RESEARCH MODEL & HYPOTHESES DEVELOPMENT

The research study adopted the UTAUT3 theory as the theoretical framework. The constructs of the theory are crucial determinants towards the user adoption of technology. However, the research study has not considered a few constructs, such as price value and habit towards the investigation. AR technology in online shopping is a new feature drawing attention from users. As it’s a new technology included in online

shopping apps, it is offered for free, and further users of online shopping will take time to use the technology as a tool in their online shopping activities (Enaizan et al. 2020; Vimalkumar et al. 2021). Hence, this research study has excluded the construct price value and habit but has extended it by including external variables, namely information quality, system quality, privacy risk, and trust, to examine the user behavioral intention towards using AR technology in online shopping apps. The following sections give an in-depth embellishment of the exogenous and endogenous constructs adopted in the study's conceptual framework with the proposed hypothesis in the research investigation.

3.4.1 Performance Expectancy

When introducing new technology, users quickly accept technologies that can improve productivity. They are keen towards technologies which can help them attain their goals, enhancing efficiency and effectiveness in performing their task. Performance expectancy is the degree to which an individual believes that using the system will help them attain desired results in job performance (Venkatesh et al. 2003). The construct performance expectancy is a combination of constructs such as perceived usefulness from the Technology Acceptance Model (TAM) and combined TAM and Theory of Planned Behaviour (TPB), extrinsic motivation from the Motivational Model, relative advantage from Innovation diffusion theory and outcome expectation from Social Cognitive Theory (Venkatesh et al. 2003). Hence, performance expectancy refers to factors that enhance job performance by adopting technology, motivating users with valuable outcomes, offering better benefits than previous technology, and meeting user expectations. When a customer decides to adopt a technology, they examine the extent to which the technology will add value to the task performed, enhancing the productivity and efficiency of the user in task performance.

Performance expectancy is a significant determinant of user behavioral intention. Several studies have demonstrated an essential relationship between performance expectancy and behavioural intention (Sia et al. 2023; Venkatesh et al. 2003). Sharma et al. (2023) found the most substantial influence of performance expectancy on behavioral intention towards news apps among Indian users. Vimalkumar et al. (2021) investigated the acceptance of voice-based digital assistants such as Siri, Alexa, Google

assistant, and Bixby among Indian users and found performance expectancy to be the strongest predictor of behavioral intention. Tewari et al. (2023) reported that performance expectancy is a significant factor influencing the use of online learning by students at public and private universities in India. Nandru et al. (2023) explored the acceptance of mobile payment services among Indian users during the pandemic and found that technology's usefulness influences user behavioral intention. Extant AR literature also reported a significant relationship between performance expectancy and behavioral intention. For instance, the study (Ates and Garzón 2023) concluded that performance expectancy is an essential predictor of the use of AR among science teachers of public middle schools in Turkey. A study by Paulo et al. (2018) in Portugal placed performance expectancy as a significant predictor of visitors' use of mobile AR in destination spots.

While there is no uncertainty that performance expectancy is a significant predictor, few studies have demonstrated that it has no discernible impact on user intention. For instance, Altalhi (2021) reported a non-significant relationship between performance expectancy and user behavioural intention regarding the acceptance of MOOCs among students in Saudi Arabia. The study by Parayil Iqbal et al. (2023) focussed on delineating the various factors among Islamic mobile banking customers in Maldives and found the insignificant role of performance expectancy on user behavioral intention. Similarly, the study by Holdack et al. (2022) has also reported the insignificant role of the perceived usefulness of the technology in the research investigation towards the acceptance of AR smart glasses in retail stores among customers in Germany. When users perceive the high productivity offered by AR features, they feel more comfortable and more inclined to accept the technology. Though prior studies have investigated the role of performance expectancy on user behavioral intention, its impact on adopting AR technology in e-commerce applications remains unmapped. Considering the above-described disparities in viewpoint, this study puts forth the following hypothesis.

H_1: Performance expectancy (PE) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.2 Effort Expectancy

When users experience a smooth and effortless experience in using technology, it will gradually increase their intent to use it. Effort expectancy indicates the level of ease which an individual experiences while using a technology. Venkatesh et al. (2003) defined effort expectancy as “the degree of ease associated with using the system”. The construct effort expectancy includes perceived ease of use from the Technology Acceptance Model (TAM), ease of use from Innovation diffusion theory and complexity from the Model of PC Utilization. When a new technology is introduced, individuals pay attention to how much effort is required to use the technology. The simplicity of a new technology highly influences the user’s intention to accept the technology. However, when a technology is highly complex and challenging to operate, it will negatively impact the intention to adopt. Though effort expectancy is a crucial behavioural intention factor, it becomes insignificant with repeated usage (Venkatesh et al. 2003). This is because, in the initial stage of using technology, users must put more effort into learning and using the technology. With continuous usage, the effort required to use the technology gradually reduces, and users become experts, leading to the insignificant role of effort expectancy. Hence, effort expectancy is a significant construct in adopting new technology but becomes insignificant with the usage of technology.

Previous research has examined the role of effort expectancy in the context of technology acceptance. Tewari et al. (2023) found effort expectancy to influence student adoption of online learning technology. The study by Bajunaied et al. (2023) investigated customers' adoption of FinTech services in day-to-day financial activities and found the significant influence of effort expectancy on users' behavioural intention in Saudi Arabia. Chan et al. (2023) examined the adoption of VR in telerehabilitation services among the public in Hong Kong and recognized effort expectancy as a significant predictor of behavioral intention. Prior literature has investigated the significance of effort expectancy in AR. For instance, Faqih (2022) reported perceived ease of use as a prominent predictor of user behavioral intention towards mobile AR games among students in Jordan who were aware of mobile AR games. The significant

role of perceived ease of use was observed in the study among customers using AR in online shopping in Malaysia (Shah Alam et al. 2023).

Effort expectancy strongly predicts user intention, although few research studies have shown that it has no significant effect. For instance, Rizun et al. (2024) noted the insignificant role of effort expectancy on the behavioral intention of users to use open government data in India. Likewise, Mishra et al. (2023) found the negligible role of effort expectancy in adopting cryptocurrency among Indians. Moreover, several research studies have shown a negligible impact of effort expectancy on the adoption intention of AR. For example, Paulo et al. (2018) found the insignificant role of effort expectancy on the tourists' intention to use AR during destination visits. Saprikis et al. (2021) examined the adoption behavior of students towards using mobile AR in shopping malls in Greece and emphasised the insignificant role of effort expectancy. Prior research has investigated the intention of management professionals in the South African construction industry to use immersive technologies and reported the insignificant role of perceived ease of use in using the technology (Okoro et al. 2023). Concerning the adoption of AR, users should perceive that AR technology can be used without difficulty while using e-commerce apps. Hence, based on the evidence above, it is hypothesized that

H_2: Effort expectancy (EE) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.3 Trust

Trust is a significant factor that influences the use of technology. Users consider the reliability of a technology before adopting it. Trust indicates the degree to which users perceive that the AR app is trustworthy and functions as per prescribed terms and conditions (Saprikis et al. 2021). It also shows users' reliability and interest in using AR technology in e-commerce apps (Kang et al. 2023). When users are concerned about the uncertainty and the risk involved in using the technology, trust helps to build assurance among users (Gefen et al. 2003; Pavlou and Gefen 2004). Furthermore, trust makes customers more confident about the technology's potential risks and security concerns. Trust is a multidimensional and unitary construct influencing behavioral

intention (McKnight et al. 2002). As a multidimensional construct, it consists of competence, benevolence and integrity (Chen and Dhillon 2003). Competence indicates the company's capability to accomplish its promises to customers. Benevolence represents the degree to which a company prioritises the customer's interest and welfare ahead of self-interest. Integrity measures how well the company follows ethical practices and high reliability while fulfilling customer promises.

In e-commerce, prior research has measured competence as the e-tailer's ability to provide goods or services per the customers' expectations regarding price, quantity, and conditions at the preferred time (Mayer et al. 1995). Benevolence shows the selfless service the e-tailers offer by focusing on customer satisfaction and welfare. Integrity represents the ethical practices, fairness and justice established while fulfilling customer agreements. Several studies have measured trust as a multidimensional construct. For instance, prior research in recommendation systems measured trust in terms of competence, benevolence, and integrity and reported a significant effect on increasing product promotion effectiveness (Low et al. 2023). Likewise, prior research has investigated the adoption of mobile government in China and measured trust, taking the two dimensions, namely integrity and benevolence (Liu et al. 2014). They found trust to be a significant predictor of near-term usefulness.

The qualitative investigation through semi-structured interviews on artificial intelligence found several subcategories within the dimensions of trust (Bedue and Fritzsche 2021). Similarly, prior studies have measured the role of integrity, benevolence and competence of blockchain-based donation systems in increasing the trust of non-profit organisations in Korea (Sung et al. 2023). Though studies have considered the multifaceted nature of trust, prior studies have investigated trust as a one-dimensional construct. For instance, previous research (Chandra et al. 2010) examined the role of trust as a unitary construct in consumer adoption of mobile systems in Singapore. Prior research explored the role of trust in the adoption of mobile payments among consumers in the United Kingdom (Slade et al. 2015). The study by Calisto et al. (2022) investigated the role of trust in the acceptance of artificial intelligence in medical imaging among clinicians globally. Likewise, a recent study

(Soren and Chakraborty 2024) measured trust as a unitary construct in adopting over-the-top (OTT) video streaming platforms among Indian users in popular cities.

Therefore, these investigations suggest trust, viewed as a single-dimensional concept, has received significant validation(Calisto et al. 2022). Researchers have emphasized the role of trust in behavioral intention on technology adoption (Calisto et al. 2022). Prior studies have reported trust as the strongest predictor of user behavioral intention in India in mobile banking (Kumar et al. 2023) and open government data (Rizun et al. 2024). The study by Sarkar et al. (2020) examined the drivers and outcomes of trust in mobile commerce and noted trust as a significant driver of the behavioral intention of social commerce. Similarly, Nandru et al. (2023) investigated the adoption of mobile payment services and found trust as a significant factor influencing the intention to use mobile payment among Indians.

Though trust is a substantial factor in technology adoption studies, limited studies in AR focus on trust. For instance, Kang et al. (2023) examined the role of trust among AR technology users in the USA. They reported trust as a significant factor influencing users' behavioural intention towards AR apps. Li et al. (2022) studied the driver's intention to use augmented reality head-up displays (AR-HUD) and found trust as an essential factor influencing technology adoption. Prior research has indicated a dearth of studies in the AR context examining the role of trust (Arghashi and Yuksel 2022). Furthermore, trust is a significant construct in examining consumer adoption of AR technology, emphasising the need to explore the role of trust. Though these studies have highlighted the role of trust on behavioral intention on adopting technology, few studies have reported the insignificant role of trust on user behavioral intention. For instance, Jajic et al. (2022) proved trust to be an insignificant predictor of users' intention to use AR technology in supermarkets. Slade et al. (2015) have reported trust's negligible role in adopting remote mobile payments. Like Chandra et al. (2010) and Slade et al. (2015), the current study considers trust a one-dimensional construct due to novelty and parsimony. Hence, based on the prior literature studies, this research investigation has proposed the following hypothesis.

H_3: Trust (TR) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.4 Social Influence

Social influence is "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al. 2003). It indicates how an individual gives priority to the perception and opinion of people who are important to them in their decision-making. The construct of social influence consists of variables such as subjective norms from the theory of reasoned action, technology acceptance model (TAM), theory of planned behaviour (TPB), Combined TAM-TPB, social factors from the Model of PC utilisation and Image from Innovation Diffusion Theory (Venkatesh et al. 2003). Subjective norms reflect how people who are important to an individual want them to perform a specific behaviour. Social factors refer to the internalization of the subjective culture possessed by the community and the interpersonal agreements made by individuals with others in certain circumstances.

The image denotes the extent to which the use of innovation will improve the image of an individual in the societal groups. Social influence predicts an individual's behavioral intention to use technology (Venkatesh et al. 2012). It strongly predicts user behavioral intention. Prior studies have examined the role of social influence on the user adoption of technology in the Indian context. For instance, as per the study by Mishra et al. (2023), social influence was reported as the most decisive factor influencing cryptocurrency adoption among Indians. Singh et al. (2023) investigated the adoption of online classes by students from various schools and colleges in India and found the substantial role of social influence on the adoption intention of technology. Individuals prefer to adopt technology such as AR when family, friends, and social groups highly accept it. Studies in the area of AR have examined the role of social influence in adopting technology. For instance, Abed (2021) explored the adoption of AR technology among consumers in Saudi Arabia and reported social influence as a significant predictor of user behavioral intention. A recent investigation by Faqih (2022) on the adoption of mobile AR games among IT students in Jordan confirmed social influence as a predictor of user adoption. Okoro et al. (2023) inquired about the various factors influencing the acceptance of immersive technologies (AR and VR) in the

construction industry and found social norms to be a critical factor in behavioral intention among construction management-level experts in South Africa. Though social influence is a significant predictor of user behavioral intention, prior studies have reported the trivial role of social influence in technology adoption. For instance, prior studies (Dmello et al. 2023) found no significant impact of social influence on learner's intention to use online learning platforms in Indian universities. The study by Sharma et al. (2023) examined the usage intention of news apps in India and reported the insignificant role of social influence on mobile news app users.

Prior research has examined the role of social influence in adopting AR technology. For instance, as per the study by Jajic et al. (2022), social influence is an insignificant predictor of AR technology adoption in supermarkets by university students. The study by Saprikis et al. (2021) reported a non-significant relationship between social influence and students' intention to use mobile AR apps in shopping malls in Greece. Similarly, Paulo et al. (2018) testified to the insignificant role of social influence on the adoption of mobile AR in the tourism context. This research examines the role of social influence on the behavioral intention to adopt AR technology in e-commerce apps. Therefore, the following hypothesis is formulated:

H_4: Social influence (SI) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.4.1 Mediation of Performance Expectancy between Social Influence and Behavioral Intention

Social influence comprises the belief of potential users regarding how friends, family, and other users perceive using and accepting a new technology. Social groups' beliefs influence the creation of a positive attitude towards using technology (Nandru et al. 2023). Prior studies have investigated the role of social influence on the user adoption of the technology. The present study investigates the impact of social influence on behavioral intention towards using technology. When social groups positively impact the technology's usefulness, it significantly influences the behavioral intention towards technology adoption. Prior studies have examined the mediating role of performance expectancy on social influence on the user adoption of technology. For instance, Fagan

(2019) examined the adoption of iPad mobile devices for mobile learning by students at a public university in Texas and reported that performance expectancy has fully mediated the relationship of social influence on behavioral intention.

However, prior studies have reported findings contrary to those of Fagan (2019). For example, Chen and Aklikokou (2020) investigated the factors influencing the citizen's adoption of e-government in Togo and found perceived usefulness as an insignificant mediator between social influence and intention to use technology. Similarly, the study by Oentoro (2021) explored Thai consumers' decision to adopt mobile payment and reported perceived usefulness as an insignificant mediator in strengthening the relationship between social influence and user behavioral intention to adopt a technology. Though this study has proposed to examine the direct impact of social influence on behavioral intention to adopt AR technology in online shopping, measuring the mediating role of performance expectancy on the relationship between social influence and user behavioral intention is essential. Therefore, the following hypothesis is formulated:

H_{4a}: Performance expectancy (PE) mediates the positive relationship between Social Influence (SI) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.4.2 Mediation of Effort Expectancy between Social Influence and Behavioral Intention

Social influence predicts users' behavioral intention towards technology adoption (Venkatesh et al. 2003). Prior studies have established the significant role of social influence on user intention (Mishra et al. 2023; Sharma et al. 2023). The opinions of social groups create a positive perception of ease in learning and operating the technology, which directly enhances the behavioral intention to use the technology. By examining the direct effect of social influence on behavioral intention, this study attempts to investigate the indirect impact of social influence on behavioral intention through effort expectancy. Prior studies have investigated the mediating role of effort expectancy between social influence and behavioral intention. For example, the research on mobile payment adoption among Thai consumers noted the significant indirect effect of social influence on behavioral intention through effort expectancy

(Oentoro 2021). However, the study on e-government adoption (Chen and Aklikokou 2020) reported the insignificant role of effort expectancy as a mediator on the indirect effect of social influence on users' technology adoption. Based on prior literature studies, this study investigates the mediating role of effort expectancy. This research examines the indirect effect of social influence on user behavioral intention through effort expectancy. Hence, it is hypothesized that

H_{4b}: Effort Expectancy (EE) mediates the positive relationship between Social Influence (SI) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.4.3 Mediation of Trust between Social Influence and Behavioral Intention

The role of social groups highly influences consumers and hence is considered a significant predictor in adopting technology (Venkatesh et al. 2003). Prior studies have confirmed the positive role of social influence on influencing the user behavioral intention towards technology adoption (Mishra et al. 2023; Singh et al. 2023). The current study investigates the role of social influence in adopting AR technologies in online shopping apps. Trust plays a significant factor and is essential to examine the role of trust in adopting AR technologies (Akbari et al. 2020; Arghashi and Yuksel 2022). Hence, it is necessary to investigate the role of trust in the indirect effect of social influence on user behavioral intention. Prior studies have investigated the mediating role of trust in various technology adoption studies. For instance, prior studies (Namahoot and Jantasri 2023) investigated user adoption intention to use cashless payment systems among Thai consumers who have experienced cashless transactions and reported a significant indirect effect of social influence on behavioral intention in the presence of trust as a mediator. Similarly, Mostafa and Kasamani (2021) explored the antecedents and outcomes of Chatbot initial trust among individuals in Lebanon who are experienced in using Chatbots and have confirmed trust as a significant mediator in strengthening the relationship between social influence and behavioral intention. Furthermore, the study by Rahman et al. (2021) investigated the acceptance of social media learning by students and faculties of reputed universities in Bangladesh and noted trust as a significant mediator. These indicate the relevance of trust as an

effective mediator in strengthening the impact of social influence on user behavioral intention. Henceforth, based on the evidence of prior studies, this research proposes the following hypothesis.

H_{4c}: Trust (TR) mediates the positive relationship between Social Influence (SI) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.5 Facilitating Conditions

When a user decides to adopt novel technologies, the availability of technical support, knowledge, and workforce support is an essential requirement. The construct facilitating conditions indicate the availability of adequate resources, which will extend support in technology adoption. Facilitating conditions refer to the extent to which a user presumes the accessibility of resources in the form of knowledge, technical assistance, and organisational framework supporting the use of technology in the best possible way. It is the combination of constructs from three theories: perceived behavioral control from the theory of planned behavior, combined technology acceptance model- theory of planned behavior, facilitating conditions from the Model of PC utilisation and compatibility from Innovation Diffusion Theory (Venkatesh et al. 2003). Perceived behavioral control indicates the various internal and external constraints on the individual's behavior and comprises all resources that aid in technology usage.

Facilitating conditions refer to the presence of all the objective factors that will help act most efficiently. Compatibility denotes the extent to which an innovation is consistent with the value systems and beliefs of prospective adopters of technology. Despite facilitating conditions being a highly significant factor, Venkatesh et al. (2003) observed that while performance expectancy and effort expectancy are present, facilitating conditions have an insignificant impact on user behavioural intention. UTAUT theory is more focused on employee context. Later, it was revised as UTAUT2 theory, which deals with the relationship between facilitating conditions, user behavioral intention, and the technology's actual usage (Venkatesh et al. 2012). The UTAUT 2 theory is more consumer-focused, and facilitating conditions are not free of cost, indicating that it may impact user intention. It is considered the most robust

predictor influencing users' behavioral intention in technology adoption (Hooda et al. 2022). Prior studies have found the significant influence of facilitating conditions on user behavioral intention. For instance, prior research (Bajunaied et al. 2023) found a direct relationship between facilitating conditions and user behavioral intention in adopting FinTech services by experienced users in Saudi Arabia. A recent study by Parayil Iqbal et al. (2023) examined mobile banking adoption by Islamic banking customers in Maldives. It noted the significant role of facilitating conditions as a predictor of behavioral intention. Preceding studies in the adoption of telemedicine by pharmacists in Italy have reported facilitating conditions as a significant predictor of technology use and adoption (Cobelli et al. 2023).

Few scholarly enquiries in India have observed the significant role of facilitating conditions. For instance, prior studies (Srivastava et al. 2023) have evaluated the adoption behavior of Indian users comprised of Gen Y and Gen Z towards FinTech services and noted that the availability of resources influences the acceptance of technologies. Likewise, past research has emphasised the significant role of facilitating conditions for the acceptance of online learning among students of Indian universities (Tewari et al. 2023). Previous scholarly inquiries in AR technology in various contexts have examined the role of facilitating conditions on the behavioral intention to use AR. As an illustration, Abed (2021) studied the consumer acceptance of AR technology in Saudi Arabia and found the significant role of facilitating conditions on user behavioral intention. Paulo et al. (2018) examined the mobile AR adoption by visitors in tourist destination spots in Portugal and reported the significant role of facilitating conditions. Similarly, former studies (Marto et al. 2023) investigated the visitors' intention to use AR in Portuguese archaeological sites and demonstrated the positive influence of facilitating conditions in the acceptance of AR technology. Nevertheless, few studies exhibited opposing findings. For the case in point, the study by Rizun et al. (2024) assessed the adoption behaviour of the open government data (OGD) in the Indian context and reported the insignificant role of facilitating conditions. Likewise, studies in the adoption of mobile payment systems in Jordan (Al-Okaily et al. 2023) and the adoption of massive open online courses in Saudi Arabia (Altalhi 2021) are in line with the prior studies reflecting the inconsequential contribution of facilitating conditions in

the technology adoption. Similar to the observation of the studies mentioned above, Saprikis et al. (2021) and Mutterlein et al. (2019) also reported the ineffectual impact of facilitating conditions on student adoption behavior towards AR technologies. Based on the review of prior studies, it is assumed that the role of facilitating conditions differs with the context, which necessitates examining the role of facilitating conditions on the user's intention to adopt AR technologies in online shopping apps. Hence, the research aims to investigate the following hypothesis.

H_5: Facilitating conditions (FC) will positively influence the user behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.5.1 Mediation of Performance Expectancy between Facilitating conditions and Behavioral intention

The user acceptance of technology is highly influenced by the technical and infrastructural support, which will help in the smooth use of the technology. Facilitating conditions significantly predict user behavioral intention towards accepting a technology (Farooq et al. 2017). Furthermore, the usefulness of technology plays a pivotal role in enhancing the influence of facilitating conditions on user behavioral intention (Chen and Aklikokou 2020). Preceding investigations have noted the mediating role of performance expectancy between facilitating conditions and user behavioral intention. As evidence, the study by Chen and Aklikokou (2020) assessed the adoption of e-government among Togolese and found that the availability of technical support and technology to offer varied services to users, leading to the completion of tasks has a significant role in the user behavioral intention. Similarly, prior research (Prasanna and Huggins 2016) investigated the factors influencing the user intention to use emergency operations centre information and noted the significant role of performance expectancy as a mediator between facilitating conditions and user behavioral intention. On the contrary, some studies have identified opposing results. To illustrate, the study by Sulaiman et al. (2023) tested the acceptance and usage of the learning management system by university lecturers in Iraq and noted the insignificant role of facilitating conditions and the absence of indirect influence of facilitating conditions on behavioral intention through performance expectancy. The availability of

resources and the usefulness of the technology play a significant role in technology adoption. Therefore, examining the mediating role of performance expectancy in adopting AR technology in online shopping apps will offer valuable insights into technology usage. Henceforth, based on the earlier scholarly work, it is hypothesized that

H_{5a}: Performance expectancy (PE) mediates the positive relationship between Facilitating conditions (FC) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.

3.4.5.2 Mediation of Effort Expectancy between Facilitating conditions and Behavioral intention

Facilitating conditions highlight the user's accessibility to various resources that help to use the technology. The technical and infrastructure support make the users perceive that the technology can be quickly learned with minimum effort. This calls out the need to examine the mediating role of effort expectancy between facilitating conditions and behavioral intention. Former studies have examined the mediating role of effort expectancy. For instance, the study by Chen and Aklikokou (2020), in the context of e-government adoption, confirmed the significant indirect influence of facilitating conditions on user adoption through perceived ease of use. However, Sulaiman et al. (2023) reported contrasting results, wherein perceived ease of use was an insignificant mediator in the indirect influence of facilitating conditions on user behavioral intention. Users prioritize the availability of resources in the adoption of new technologies such as AR. Hence, based on the former investigations, the study attempts to investigate the mediating role of effort expectancy by examining the following hypothesis.

H_{5b}: Effort expectancy (EE) mediates the positive relationship between Facilitating conditions (FC) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.

3.4.5.3 Mediation of Trust between Facilitating conditions and Behavioral intention

The availability of adequate technical and infrastructure support positively influences the user's behavioral intention. Users who perceive technology as trustworthy feel the

support systems will ease technology adoption. The presence of trust as a mediator in the indirect influence of facilitating conditions on behavioral intention has been investigated in various contexts. For instance, the research (Octaviani et al. 2023) into the facilitating conditions examined customers' purchase behaviour through online travel agent platforms in Indonesia and reported trust as a significant mediator between facilitating conditions and user behavioral intention. Hooda et al. (2022) conducted an empirical investigation using meta-analytic structural equation modelling (MASEM) on ninety studies of e-government, which testified that trust partially mediates the indirect influence of facilitating conditions on user behavioral intention. Similarly, Enaizan et al. (2020) also reported trust as a mediator on the influence of facilitating conditions on user acceptance of electronic medical record systems in Malaysia. Likewise, trust is assumed to play a significant role in strengthening the influence of facilitating conditions on the adoption of AR technology in online shopping apps. Considering the preceding scholarly works, the present study investigates the indirect influence of facilitating conditions on user behavioral intention through trust in AR technology. Hence, it is hypothesized that

H_{5c}: Trust (TR) mediates the positive relationship between Facilitating conditions (FC) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.

3.4.6 Hedonic Motivation

The UTAUT theory developed by Venkatesh et al. (2003) consists of factors, namely performance expectancy, effort expectancy, social influence and facilitating conditions, focusing on the intention to use technology in an organisational context. However, various studies pointed out the limitation of the theory for overlooking the consumer perspective towards the acceptance and usage of technology. As a result, the UTAUT theory was revised as UTAUT 2 by adding constructs such as hedonic motivation, price value and habit with moderators age, gender and experience to explore the adoption of technology in a consumer context (Venkatesh et al. 2012). Hedonic motivation is a significant factor in consumer behavior and information systems in a consumer context. This construct complements performance expectancy and motivation theory (Venkatesh

et al. 2012). Hedonic motivation influences an individual's intrinsic motivation to do something, creating satisfaction. Prior studies indicate that individuals prioritise intrinsic needs and hence prefer to adopt and use technologies that can satisfy their intrinsic motivation (Faqih and Jaradat 2021; Lowry et al. 2012). Hedonic motivation measures the fun or enjoyment experienced by a user using technology. In the context of AR in online shopping, hedonic motivation consists of factors such as entertainment, pleasure and fun, which a customer experiences while using the AR feature (Arghashi 2022). Hedonic motivation significantly predicts technology adoption (Farooq et al. 2017; Venkatesh et al. 2012). Prior studies found hedonic motivation to strongly predict technology adoption (Aydin 2023; Parayil Iqbal et al. 2023). When a technology creates excitement among users, it directly influences their intention to adopt it. As an illustration, the study by Parayil Iqbal et al. (2023) investigated mobile banking adoption by Islamic banking customers in Maldives and reported hedonic motivation as a significant factor. Mishra et al. (2023) researched the acceptance of cryptocurrencies in India, proving the positive influence of hedonic motivation on technology use and acceptance.

Hedonic motivation, also conceptualized as perceived enjoyment, was also examined in the context of AR. For instance, Abed (2021) found hedonic motivation to significantly influence the consumer adoption of AR technology in Saudi Arabia. Similarly, the study by Oyman et al. (2022) examined the use of AR-supported make-up apps by female consumers, citing that AR feature apps give enjoyable real shopping experiences, leading to the intention to use the app further. Though hedonic motivation significantly predicts technology adoption, few studies have opposing results. For instance, research into the adoption of mobile payment services by Nandru et al. (2023) found the hedonic motivation to be an insignificant factor influencing the behavioral intention of m-payment users. Okoro et al. (2023) investigated the acceptance of immersive technology among construction professionals. They found that when users are less experienced with such technologies, they may not get pleasurable experiences, resulting in hedonic motivation as an insignificant predictor. These studies indicate the need to examine the role of hedonic motivation in Indian users on the acceptance of AR

technology. Hence, regarding the insights from the abovementioned studies, the current research study attempts to investigate the following hypothesis.

H_6: Hedonic motivation (HM) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.6.1 Mediation of Performance Expectancy between Hedonic Motivation and Behavioral Intention

Users tend to accept technologies when they experience positive, fun and pleasurable experiences from the technologies. Furthermore, users look forward to taking technologies that offer both hedonic and utilitarian benefits. This research investigation attempts to examine the mediation analysis to investigate the relationship between hedonic motivation (independent variable) and performance expectancy (mediator) to analyse their effect on the user behavioral intention (dependent variable). Previous scholarly inquiries have examined the indirect influence of hedonic motivation on user behavioral intention through performance expectancy. For evidence, Humida et al. (2022) investigated university students' acceptance of e-learning systems in Bangladesh and found that hedonic motivation can highly influence technology adoption only in the presence of performance expectancy, indicating performance expectancy as a significant mediator. Similarly, the study by Fagan (2019) examined the adoption of mobile learning using iPad mobile devices among students at Texas University have reported the significant role of performance expectancy as a mediator in the absence of a positive relationship between hedonic motivation and user behavioral intention. AR offers a virtual shopping experience that enables a pleasurable and entertaining user experience that adds value. The influence of performance expectancy leads to positive user behavioral intention. Hence, based on the prior research investigations mentioned above, this research aims to examine the following hypothesis.

H_{6a}: Performance Expectancy (PE) mediates the positive relationship between Hedonic motivation (HM) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.

3.4.6.2 Mediation of Effort Expectancy between Hedonic Motivation and Behavioral Intention

Hedonic motivation, also operationalized as perceived enjoyment, is pivotal in adopting technology. Though hedonic benefits offered by the technology create curiosity among users to explore the technology, the extent of simplicity and ease of operating the technology can create a favourable attitude towards the acceptance of the technology. This indicates that hedonic motivation can influence the user acceptance of technology when there is a high influence on effort expectancy. As hedonic motivation is a crucial predictor of user acceptance of technology (Venkatesh et al. 2012), this study examines the presence of effort expectancy as a mediator in the indirect influence of hedonic motivation and user behavioral intention. Former studies in technology adoption have examined the indirect effect of hedonic motivation on user behavioral intention in the presence of effort expectancy. For instance, effort expectancy was a significant mediator in the prior studies (Humida et al. 2022) in adopting e-learning systems among students in Bangladesh. However, previous research investigation by Fagan (2019) has reported the insignificant indirect influence of hedonic motivation on user behavioral intention, as effort expectancy emerged as a negligible predictor in the research. Based on the insights of the prior research investigations, this research study has proposed the following hypothesis.

H_{6b}: *Effort Expectancy (EE) mediates the positive relationship between Hedonic motivation (HM) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.*

3.4.6.3 Mediation of Trust between Hedonic Motivation and Behavioral Intention

Trust is a critical factor in the adoption of a new technology. When users get hedonic benefits from technology, it is essential to know the influence of trust on the indirect effect of hedonic motivation on user behavioral intention. Trust is insignificant when individuals use technology solely for hedonic and utilitarian benefits (Pitardi and Marriott 2021). Though hedonic motivation is an important construct in technology adoption, it may hinder acceptance due to the lack of trust (Hegner et al. 2019). Prior studies in technology adoption, namely the study by Enaizan et al. (2020), found the significant indirect influence of hedonic motivation on the behavioral intention of

medical professionals to adopt electronic medical records. Preceding studies (Alalwan et al. 2015) found a significant influence of hedonic motivation on user behavioral intention and trust towards adopting Internet banking; however, examining the role of trust as a mediator is essential. This results in an indirect path of hedonic motivation to behavioral intention to use Internet banking, wherein trust acts as a mediator. Thus, the current study has proposed the following hypothesis based on the above-mentioned theoretical support.

H_{6c}: Trust (TR) mediates the positive relationship between Hedonic motivation (HM) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.

3.4.7 Personal Innovativeness

The UTAUT2 theory focuses more on consumer acceptance of technologies and can examine information technology by including other constructs. Though the constructs of UTAUT2 are highly significant in investigating user technology adoption, the innovativeness trait of an individual plays a pivotal role in the technology adoption process. This resulted in the expansion of UTAUT2 theory as UTAUT3 by Farooq et al. (2017) through including the construct of personal innovativeness. Personal innovativeness is dominant in adopting technology (Agarwal and Prasad 1998). Personal innovativeness refers to the user's inclination to adopt a new technology or risk-taking tendency to try the latest technology or gadgets (Agarwal and Prasad 1998). It is considered a stable personality attribute that can create the desire to try new technologies (Farooq et al. 2017).

The construct of personal innovativeness varies with the one in the innovation diffusion theory (Rogers 1995). The innovativeness construct of innovation diffusion theory relates to the earlier adoption of technology than others (Rogers 1995). In contrast, the personal innovativeness construct in UTAUT3 measures the individual's traits, creating an interest in trying new technologies in the information technology domain (Farooq et al. 2017). Prior studies have examined the role of personal innovativeness in technology adoption. For instance, the study by Bhatnagr and Rajesh (2023) investigated the neobanking adoption in India, noted personal innovativeness as a significant factor

influencing the behavioral intention of digital banking customers. Gupta et al. (2023) cited personal innovativeness as a prominent factor in educational leaders' adoption of virtual communication technology in Malaysia. Further, similar results were reported in the study by Abed (2021), which examined the adoption of AR among consumers in Saudi Arabia. On the contrary, a handful of studies have reported contrasting results. For instance, research (Gunasinghe et al. 2020a) into the acceptance of e-learning among academicians (Gunasinghe et al. 2020a)found the insignificant role of personal innovativeness in adopting technology in higher educational institutions in Sri Lanka. Personal innovativeness was a trivial factor in the intention to use mobile AR in tourism in Porto (Pinto et al. 2022). Similar findings were reported in the study by Maisha and Shetu (2023), which investigated the adoption of e-learning by Bangladeshi students in the post-pandemic period. As AR technology is novel, personal innovativeness can influence individuals' intention to use the technology. Hence, it is essential to examine the role of personal innovativeness in using AR technology in online shopping apps. Therefore, based on the abovementioned theoretical underpinnings, this research investigation has proposed the following hypothesis.

H_7: Personal innovativeness (PI) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.7.1 Mediation of Trust between Personal innovativeness and Behavioral intention

Personal innovativeness is a fundamental element in the user acceptance of technology. Former studies have claimed that individuals with high personal innovativeness are open towards novelties and take risks using them (Yusra and Agus 2020). This argument was further validated by prior research on electronic banking services, which stated that highly innovative individuals are prone to risks and uncertainties in adopting new technologies (Chauhan et al. 2022). The personal innovativeness of an individual with high trust towards the technology can influence the user's behavioral intention. However, the study by Chan and Lee (2021) reported contrary findings wherein the insignificant indirect effect of personal innovativeness on behavioral intention through trust was reported. Trust is a prominent factor in technology adoption. Based on the preceding research studies, this study examines the role of personal innovativeness on

user behavioral intention to adopt AR technology in online shopping apps. Hence, it is hypothesized that

***H_{7a}**: Trust (TR) mediates the positive relationship between Personal innovativeness (PI) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.*

3.4.8 Information Quality

Information quality is an essential criterion which users consider in technology acceptance studies. A system providing accurate, relevant information enhances the user's behavioral intention to accept the technology. Information quality discusses how the user perceives the output quality (Algharabat and Zamil 2013). Researchers have used content quality as an alternative to information quality (Alzahrani et al. 2022). The research by Poushneh (2018) stated information quality is the extent to which AR delivers useful, reliable, customized virtual content on the user's device's screen, meeting the user's expectations. The acceptance of AR technology is highly influenced by the quality of the information offered to the users (Chiu et al. 2021). AR technology provides more relevant product information and is considered more effective than the information displayed in conventional online shopping websites or apps (Javornik 2016a). Though information quality is a pivotal factor, Poushneh (2018) pointed out the need to ensure that only essential content is displayed on the user screen, as information overload may make customers doubtful of choices, making them more frustrated.

Preceding studies have examined the role of information quality in the information technology domain. Previous research (Alismail 2023) examined school teachers in Saudi Arabia to determine their behavioural intention to use the Zoom application. The study found that information quality plays a crucial influence on technology adoption. Oyman et al. (2022) examined the behavioral intention of female consumers towards AR-powered make-up applications and found that information received through the app enhanced the usage intention of the app. Li et al. (2022) investigated the driver's acceptance of augmented reality head-up displays during driving. They found that accurate and reliable information enhances trust and the intention to use the system. The study by Tarhini et al. (2019) on adopting online shopping in Lebanon shows that

customers rely on website information for decision-making. Even though information quality is a pivotal determinant, few studies have reported contrary findings. For instance, prior research (Al-Fraihat et al. 2020) evaluated the e-learning systems used by students in UK universities and found that offering high-quality output to students does not initiate their intention to use e-learning systems. Considering the theoretical underpinnings, this research study aims to investigate the influence of information quality offered by AR apps. Hence, it is hypothesized that

H8: *Information quality (IQ) will positively influence the behavioural intention (BI) to adopt AR technologies in online shopping apps.*

3.4.8.1 Mediation of Performance Expectancy between Information quality and Behavioral intention

Information quality offered by technology plays a significant role in behavioral intention. The system's content enhances the technology's usefulness, impacting the user's behavioral intention towards accepting the technology. Hence, it is essential to examine the role of technology's usefulness in the relationship between information quality and user behavioral intention. The study by Yang et al. (2017) investigated the quality factors influencing students' acceptance and continuance intention towards massive open online courses and proved the mediating effect of performance expectancy. Research by Handarkho (2020) in the area of social commerce noted the presence of a significant indirect influence of information quality on user behavioral intention through the influence of performance expectancy. Similarly, Lee et al. (2019) examined the role of information quality on behavioral intention through performance expectancy on the acceptance of food delivery applications among Korean users, testifying the role of performance expectancy as a mediator. Based on the above-mentioned theoretical support, the following hypothesis is proposed.

H8a*: Performance Expectancy (PE) mediates the positive relationship between Information quality (IQ) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.*

3.4.8.2 Mediation of Effort Expectancy between Information quality and Behavioral intention

Information quality is a significant factor influencing the acceptance of technology. When users get quality output, it enhances their perception of the ease of use of the technology, creating a favourable attitude towards the intention to use the technology. Prior studies have examined the mediating role of effort expectancy between information quality and behavioral intention. For instance, prior research (Chen et al. 2021) examined the factors affecting the intention to use online platforms among students who selected online courses in universities in China and confirmed the presence of indirect effects through effort expectancy. However, few studies have reported contrary findings. For instance, the study by Lee et al. (2019) investigated the acceptance of food delivery apps among Korean users and reported the insignificant role of effort expectancy as a mediator, indicating that information quality does not enhance the user's behavioral intention to use food delivery apps. Based on the prior studies, this research aims to investigate the mediating role of effort expectancy between information quality offered by AR apps and the intention to use AR technologies in online shopping apps. The hypothesis thus framed to investigate the mediating role of effort expectancy is as follows.

H_{8b}: Effort Expectancy (EE) mediates the positive relationship between Information quality (IQ) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.

3.4.8.3 Mediation of Trust between Information quality and Behavioral intention

Information quality is a critical element influencing the technology adoption decision. When an information system offers accurate and reliable content, it directly impacts the user's trust towards the technology (Sarkar et al. 2020). The quality of the AR technology's content highly influences the user behavioral intention with the influence of trust. Hence, investigating the mediating role of trust is essential to examine the indirect influence of information quality on user behavioral intention. Prior research studies have examined the influence of information quality on trust; however, limited studies have investigated the mediating role of trust. For instance, the study by

Handarkho (2020) investigated the indirect influence of information quality on behavioral intention through trust and reported the insignificant indirect effect. As output quality and trust in the technology influence the acceptance of AR technology, it calls out the need to investigate the mediating role of trust in the context of AR technology. Hence, it is hypothesized that

H_{8c}: *Trust (TR) mediates the positive relationship between Information quality (IQ) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.*

3.4.9 System Quality

The technical qualities of the information system highly influence the acceptance of a technology. System quality significantly affects users' satisfaction and behavioral intention towards accepting a technology (Anand et al. 2023; Tseng et al. 2021). It is measured in terms of the reliability in performance, responsiveness, and flexibility offered by the information system (Nookhao and Kiattisin 2023). The system quality of AR technology positively influences satisfaction, which forms a favourable attitude towards AR technology, making users give positive word of mouth about the AR app. The study by Jung et al. (2015) emphasised the relevance of system quality to user satisfaction. System quality influences customer satisfaction and loyalty when using AR technologies (tom Dieck and Jung 2018). It also shows the extent to which information systems offer visually appealing and interactive content that gives users an enhanced virtual experience (Chiu et al. 2021).

Understanding the technical specifications of the information system is essential to impact user satisfaction with a system. Prior studies have examined the role of system quality on user behavioral intention. For instance, the study by Chiu et al. (2021) investigated the acceptance of AR applications in the food chain reported a positive influence on user satisfaction and continuance usage intention. Nookhao and Kiattisin (2023) examined the factors influencing the user behavioral intention of citizens of Thailand towards e-government and reported the significant role of system quality on user behavioral intention. Research into system quality by Sharma et al. (2023) in adopting news apps among Indian users found system quality to be a significant

predictor of user behavioral intention. The positive role of system quality was reported in the study by Baabdullah et al. (2019) in the customers' acceptance of mobile banking.

Though system quality is pivotal in information technology, prior studies have reported divergent results. For instance, the study on mobile commerce adoption (Tarhini et al. 2019) by Omani mobile commerce users found the insignificant role of system quality on user behavioral intention. Likewise, prior research (Chan et al. 2022) analysed the intention to use and adopt mobile shopping among consumers in Malaysia and reported the trivial role of the system quality of the online platform on the user intention. Similar results were reported in mobile health applications in Indonesia (Mangkunegara et al. 2018) and the E-appointment system in Taiwan (Lee et al. 2020). Based on the above discussions on prior theoretical underpinnings, this study considers system quality to influence the behavioral intention to use AR technology in online shopping apps. The hypothesis thus proposed is as follows.

H9: *System quality (SQ) will positively influence the behavioural intention (BI) to adopt AR technologies in online shopping apps.*

3.4.9.1 Mediation of Performance Expectancy between System quality and Behavioral intention

System quality is a critical element in determining the user adoption of technology. The technical specifications of an information system positively influence the users' performance expectancy (Bashir and Madhavaiah 2015; Rahi et al. 2019). System quality can affect the user's behavioral intention towards technology based on the performance expectancy of users. This reflects that a technology's usefulness plays a significant role in strengthening the influence of system quality on user intention. Prior studies have examined the impact of system quality on user behavioral intention (Baabdullah et al. 2019; Sharma et al. 2023). However, prior research (Alshammari 2020) cited that system quality can directly or indirectly influence the user's behavioral intention towards using technology. However, the study by Sulaiman et al. (2023) investigated university lecturers' behavioral intention to use a learning management system in Iraq and reported the insignificant indirect effect of system quality on user intention through performance expectancy. Users' behavioural intention towards AR

technology in online shopping apps can be enhanced in the presence of high system quality and performance expectancy of users. The current study aims to investigate the following hypothesis based on the research studies discussed above.

***H_{9a}**: Performance Expectancy (PE) mediates the positive relationship between System quality (SQ) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.*

3.4.9.2 Mediation of Effort Expectancy between System quality and Behavioral intention

System quality is a significant factor determining the successful performance of the technology. The technical characteristics of the information system were found to have a positive influence on the effort expectancy of users (Papakostas et al. 2022; Rahi 2022) as well as performance expectancy and user behavioral intention (Abed 2021; Ates and Garzón 2023). Research by Rahi et al. (2019) found that system quality and perceived ease of use are connected, as are perceived ease of use and user behavioral intention suggesting that system quality may influence user behavioral intention. Hence, when users find difficulty in using the system, they are less likely to use it further. Prior studies have examined the indirect influence of effort expectancy on the influence of system quality on user behavioral intention. For instance, Rahi et al. (2019) examined the Internet banking adoption among banking customers in Pakistan reported effort expectancy as a mediator on the influence of system quality on user behavioral intention. Sulaiman et al. (2023) reported effort expectancy as a significant mediator between system quality and behavioral intention on the learning management system among academicians of Iraq. However prior studies (Yang et al. 2017) have reported contradictory findings indicating the absence of mediation effect of effort expectancy. Considering the results of the prior investigations, this research aims in examining the mediating effect of effort expectancy on the relationship between system quality and user behavioral intention. Thus, the study hypothesizes that

***H_{9b}:** Effort Expectancy (EE) mediates the positive relationship between System quality (SQ) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.*

3.4.9.3 Mediation of Trust between System quality and Behavioral intention

The system quality specifications are expected to improve the performance of the AR technology of online shopping apps. When the technology has adequate technical qualities for the successful performance of the information system, it directly influences the intention to use the technology. For instance, the study by Sarkar et al. (2020) examined the drivers and outcomes of trust in mobile commerce and found that the system quality enhanced the trust towards mobile commerce, increasing the behavioral intention to use the technology. Likewise, similar results were observed in the area of mobile payment (Gao and Waechter 2017) and location-based apps (Wang and Lin 2017). Though it is hypothesized that system quality directly influences the user's behavioral intention to use, it is essential to investigate the role of trust between system quality and user behavioral intention. Prior studies have examined the mediating role of trust. For instance, Chiu et al. (2017) found that trust enhances the impact of system quality on users' behavioural intention to use mobile banking services among non-adopters in the Philippines. As system quality can improve the user's trust, it can create a more favourable intention to use AR technology in online shopping apps. Thus, the study aims to test the following hypothesis.

H_{9c}: Trust (TR) mediates the positive relationship between System quality (SQ) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.

3.4.10 Privacy Risk

As there are two sides to the coin, technology is considered a blessing and a curse. Technologies help enhance the productivity of individuals; on the other hand, they can negatively impact users or groups. Privacy risk is one factor from the technology's dark side, which can negatively influence the user’s perception towards accepting a technology. Privacy risks indicate possible risks and losses that may occur with the disclosure of personal information (Vimalkumar et al. 2021). When mobile apps function on camera access and sensors, it creates concerns about privacy risks among users. Mobile apps with AR technology differ from traditional apps as AR-powered apps request camera access, voice capture and use of other sensors to provide helpful information. Hence, unlike conventional apps, AR apps are highly vulnerable to user

information (Taub et al. 2023). Further, AR mobile app users have high privacy concerns about being recorded by the AR app, sharing personal data with third parties without the user's prior consent and feeling of being constantly observed by the AR app (Dacko 2017; Harborth 2019; Harborth and Pape 2018). Hence, the risks encountered due to privacy and cyber threats are highly alarming in the user adoption of technology. Privacy risk can negatively influence the adoption decision for technology. For instance, Faqih (2022) investigated the adoption of mobile AR games by IT students at the University of Al al-Bayt, Jordan found the negative effect of privacy risk on the acceptance and adoption of technology. Prior study (Harborth and Pape 2021) found that privacy risk negatively influences the behavioral intention to use mobile AR apps among smartphone users in Germany. The study by Wang and Lin (2017) examined the perceived privacy risk involved in location-based services among LBS users in Taiwan, testified that the negative influence of privacy risk hinders the adoption of technology. Henceforth, these studies reflected that privacy risk could negatively influence user behavioral intention. Nevertheless, few studies have presented opposing findings wherein the negative effect of privacy risk did not influence technology acceptance. For instance, Vimalkumar et al. (2021) investigated the consumer acceptance of voice-based digital assistants in India. The study has reported that consumers prefer to use the technology despite its privacy risks, which indicates that the negative effect of privacy risk does not influence the user acceptance of technology.

Prior research (Rauschnabel et al. 2017) into the adoption of mobile AR games by German users noted that the negative effect of privacy risk does not influence the users' attitude towards playing AR games. Likewise, former studies that examined mobile payment adoption among mobile payment users in Indonesia have reported similar findings, as users were willing to use mobile payment services despite privacy risks (Widyanto et al. 2022). These studies reflected that the nature of technology, benefits offered, knowledge, and experience of the users significantly influence how privacy risk affects the user's behavioral intention towards accepting a technology. This research has proposed the following hypothesis based on the studies stated above that focus on the impact of privacy risk on user behavioural intention.

H_{10}: Privacy risk (PR) will negatively influence the behavioural intention (BI) to adopt AR technologies in online shopping apps.

3.4.10.1 Mediation of Trust between Privacy risk and Behavioral intention

Users are concerned about the privacy risk involved in the technology. However, users may be inclined to use the technology despite the adverse effects of privacy risk. It is also observed that users are more concerned about others' privacy rather than their privacy (Rauschnabel et al. 2018). Privacy risk may not negatively affect the user's behavioral intention. Still, it may negatively influence trust towards the technology, demonstrating that users with high privacy risk do not trust it (Gu et al. 2016). Prior studies have examined the mediating role of trust. Liu and Tao (2022) investigated the role of trust in the acceptance of smart healthcare services among users, and non-users reported trust as a mediator on the indirect influence of loss of privacy on user behavioral intention. The study by Enaizan et al. (2020) also confirmed the significant indirect influence of privacy risk on user behavioral intention towards electronic medical records through the presence of trust. Comprehending the role of trust on the indirect influence of privacy risk and behavioral intention, this research investigates the mediating role of trust between the privacy risk and user behavioral intention to use AR technology in online shopping apps. Hence, it is hypothesized that

H_{10a}: Trust (TR) mediates the negative relationship between Privacy risk (PR) and the user's Behavioural Intention (BI) to adopt AR technologies in online shopping apps.

3.5 CONCEPTUAL FRAMEWORK

The research study has explored the factors influencing the user's behavioral intention towards accepting AR technology in online shopping apps. Based on the literature review, the research study formulated the research hypotheses illustrated in the conceptual model. The conceptual framework demonstrates the expected relationship between the constructs. It explains how researchers recognize the various factors included in the study and the presumed relationships between the constructs (Luft et al. 2022). The proposed conceptual model is presented in Figure 3.1. The conceptual model consists of eleven constructs. The seven constructs on the left side of the

conceptual model are the independent variables (exogenous variables). There are three mediators in the middle of the figure. The independent and mediating variables are connected to the dependent variable (outcome variable) behavioral intention. The proposed hypothesis of the research study is presented in Table 3.1

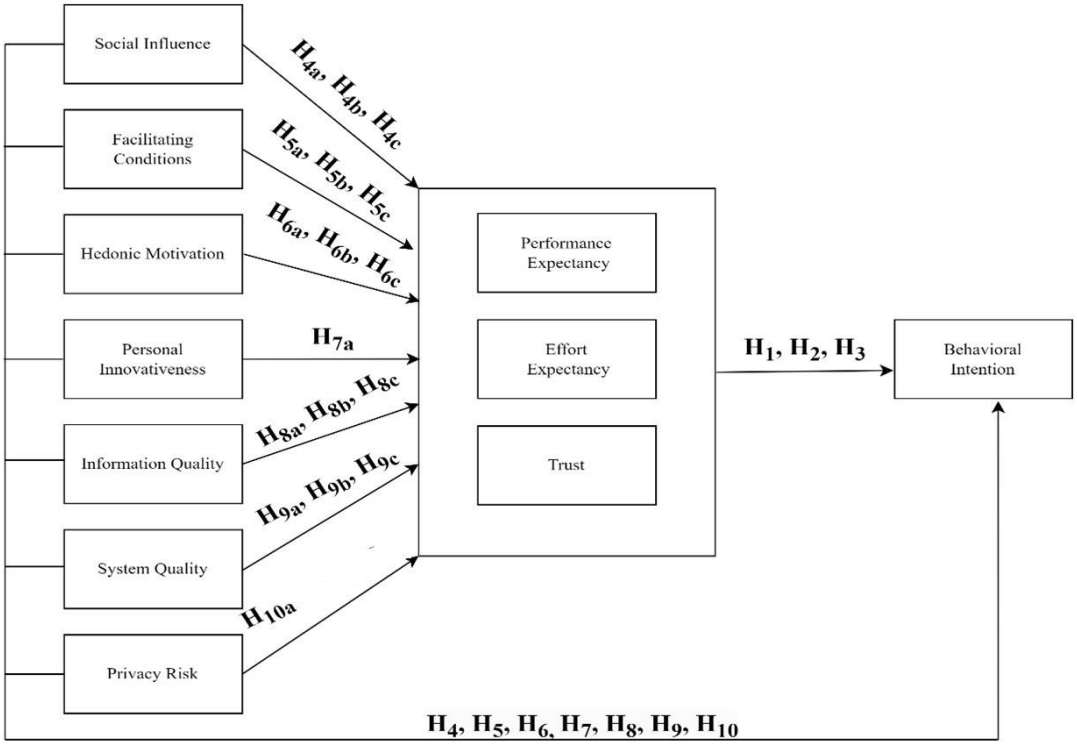

Figure 3.1: Conceptual model
Source: Author

Table 3.1: Proposed hypothesis of the study

H_1	Performance expectancy (PE) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.
H_2	Effort expectancy (EE) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.
H_3	Trust (TR) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.
H_4	Social Influence (SI) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.

	H_{4a}	*Performance expectancy (PE) mediates the positive relationship between Social Influence (SI) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
	H_{4b}	*Effort Expectancy (EE) mediates the positive relationship between Social Influence (SI) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
	H_{4c}	*Trust (TR) mediates the positive relationship between Social Influence (SI) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
H_5	Facilitating Conditions (FC) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.	
	H_{5a}	*Performance expectancy (PE) mediates the positive relationship between Facilitating Conditions (FC) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
	H_{5b}	*Effort Expectancy (EE) mediates the positive relationship between Facilitating Conditions (FC) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
	H_{5c}	*Trust (TR) mediates the positive relationship between Facilitating Conditions (FC) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
H_6	Hedonic Motivation (HM) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.	
	H_{6a}	*Performance expectancy (PE) mediates the positive relationship between Hedonic Motivation (HM) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
	H_{6b}	*Effort Expectancy (EE) mediates the positive relationship between Hedonic Motivation (HM) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
	H_{6c}	*Trust (TR) mediates the positive relationship between Hedonic Motivation (HM) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*

H_7	Personal Innovativeness (PI) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.	
	H_{7c}	*Trust (TR) mediates the positive relationship between Personal Innovativeness (PI) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
H_8	Information Quality (IQ) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.	
	H_{8a}	*Performance expectancy (PE) mediates the positive relationship between Information Quality (IQ) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
	H_{8b}	*Effort Expectancy (EE) mediates the positive relationship between Information Quality (IQ) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
	H_{8c}	*Trust (TR) mediates the positive relationship between Information Quality (IQ) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
H_9	System Quality (SQ) will positively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.	
	H_{9a}	*Performance expectancy (PE) mediates the positive relationship between System Quality (SQ) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
	H_{9b}	*Effort Expectancy (EE) mediates the positive relationship between System Quality (SQ) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
	H_{9c}	*Trust (TR) mediates the positive relationship between System Quality (SQ) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*
H_{10}	Privacy Risk (PR) will negatively influence the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.	

H_{10a}	*Trust (TR) mediates the positive relationship between Privacy Risk (PR) and the user's behavioural intention (BI) to adopt AR technologies in online shopping apps.*

3.6 CHAPTER SUMMARY

This chapter discussed the study's theoretical framework with the research gaps identified from prior literature studies. It also deliberated on the developed research model with the relevant constructs of the study and the formulation of the research hypothesis with the connected literature on the research area. In short, this research has undertaken an in-depth investigation of the prior studies, which has made a strong foundation for the theoretical as well as conceptual framework of the study. After forming a solid foundation with preliminary literature, the next step is to carry out the proposed research by following a suitable research methodology, which will be discussed in the next chapter.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 INTRODUCTION

Research is an investigation which requires a systematic way of undertaking the research process to attain the best results. This chapter outlines the various procedures involved in the research methodology, such as research philosophy, approaches, methods, and techniques followed in this research study. The chapter on research methodology indicates the steps the researcher takes to scientifically investigate the research problem, leading to accomplishing the research objectives. The study has followed a systematic approach in the research work by following the research onion framework proposed by Saunders et al. (2009), which explains the sequence to be followed in the research process comprising of research philosophies, research approaches, research strategies, research choices, time horizons and techniques and procedures adopted in the study. This chapter concludes with a summary of the entire methodology.

4.2 RESEARCH PROCESS

The success of any research process strongly depends on the research methodology adopted in the research investigation. Research methodology indicates a researcher's various steps to solve the formulated research problem (Kothari 2004). Furthermore, research methodology also suggests the logic of selecting a specific method in the research context, which clarifies the research investigation process more. The research process is critical as it consists of the essential steps or actions and the logical sequencing of the activities to be carried out. The case-based research process comprises five steps, namely research question (stage 1), instrument development (stage 2), data gathering (stage 3), data analysis (stage 4) and dissemination (stage 5) (Stuart et al. 2002). This case-based research process can be applied to any social science research as it consists of the guidelines in the research process. However, this study has followed a more in-depth procedure in the research methodology process. As a result, the study followed the ‘research onion’ proposed by Saunders et al. (2009) as a foundation for the research methodology. As Saunders et al. (2009) suggested, the research onion consists of six layers that must be uncovered while deciding the study's research methodology. The six layers of research onion consist of the following: research philosophy (onion layer 1), research approach (onion layer 2), research

strategy (onion layer 3), choices (onion layer 4), time horizon (onion layer 5), techniques and procedures (onion layer 6). Figure 4.1 indicates the Saunders et al. (2009) research onion model. The following section discusses each layer adopted in the research study.

4.2.1 Research Philosophy - Onion Layer 1

Researchers need to know the basic assumptions for a research study. These basic assumptions indicate the research philosophy and research paradigm. Research philosophy suggests principles that help evolve knowledge (Saunders et al. 2009). A research philosophy reveals a researcher's critical assumptions about how they view the world. It also indicates how the research study will be investigated, resulting in new knowledge contributing to the literature studies. Hence, identifying the research problem and selecting appropriate data collection methods and techniques for the data analysis are entirely grounded on the research philosophy adopted in the research study (Zukauskas et al. 2018).

Before deciding on the research philosophy, it is essential to understand the assumptions of the research philosophy. Assumptions are crucial as they support the research strategy and the methods adopted in the data collection process (Saunders et al. 2009). The basic assumptions, namely ontology, epistemology and axiology, are the essential elements of research philosophy. Ontology indicates the assumptions about reality. It refers to the researcher's view of reality and to what extent it can be investigated through the research study. Second is epistemology, which relates to the assumptions of acceptable knowledge and the different methods of acquiring the knowledge. It further indicates the relationship between reality and what the researcher aims to examine. The third assumption is axiology, which refers to the nature of value in ethics or values in general. The value held by the researcher is reflected in the research approach, techniques or data collection procedures adopted. Hence, precisely examining these assumptions will help the researcher properly select the research philosophy. Four major research approaches are positivism, realism, interpretivism and pragmatism.

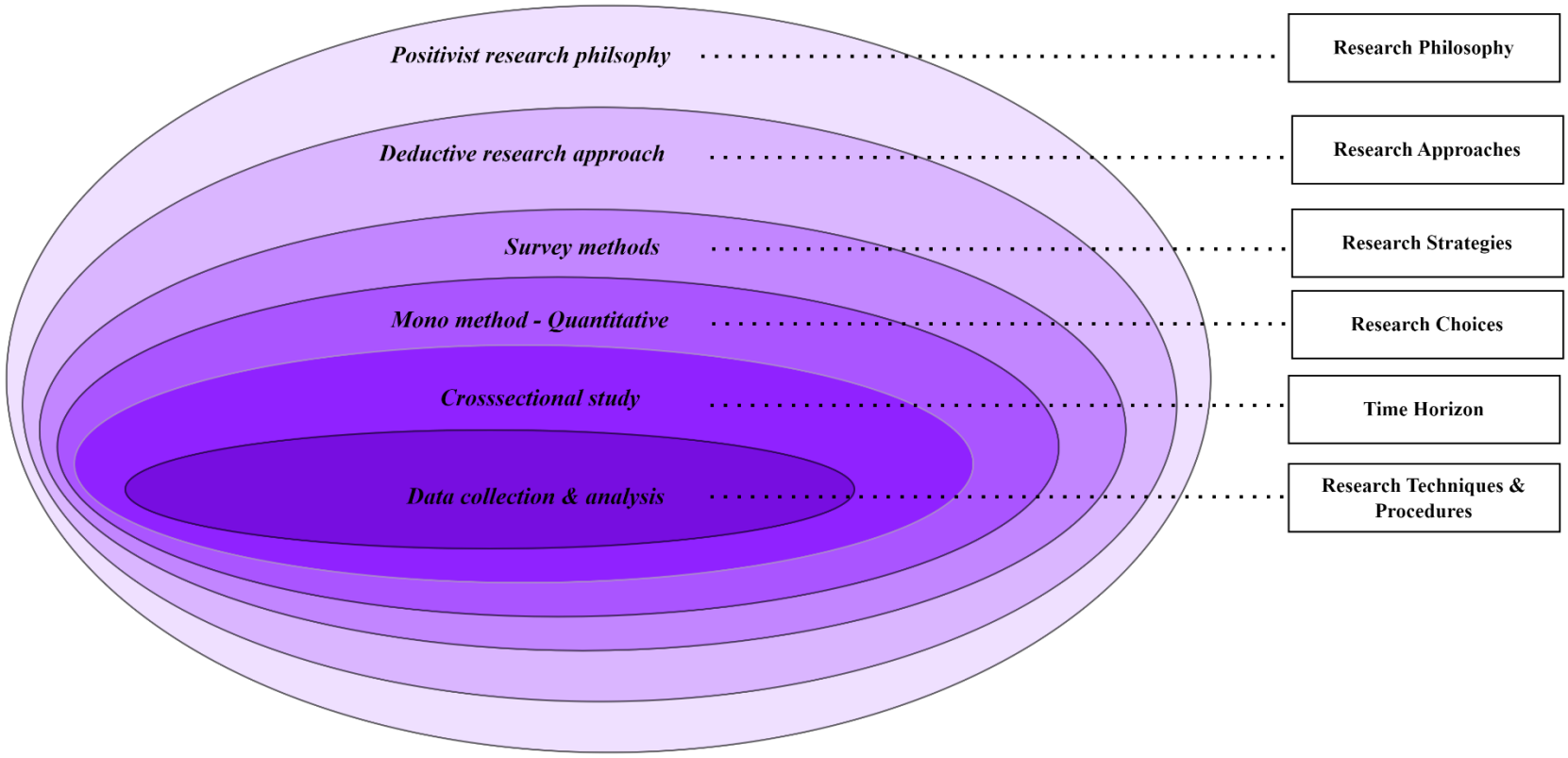

Figure 4.1: Research onion framework

Source: Adapted from Saunders et al. (2009)

4.2.1.1. Positivism research philosophy

The positivism research philosophy follows an objective way of understanding reality. Here, research is undertaken objectively without considering any personal values. The researcher is independent and works purely on the data and works to attain results (Saunders et al. 2009). The positivism research philosophy considers the scientific method wherein the theories related to the research investigation are used to formulate the research hypothesis of the study. These theories are further validated using a data analysis process. This research philosophy has assumptions such as deductive research, highly and systematically arranged with large sample size measurement and a more quantitative method in the research study (Saunders et al. 2009).

4.2.1.2. Interpretivist Research Philosophy

Interpretivist research philosophy assumes a subjective evaluation of the phenomena. It believes that each individual is distinct from physical phenomena; hence, there is a need to evaluate with subjective perception (Saunders et al. 2009). Therefore, an individual's experience with reality will have a different perspective than another individual's perception. This is because individuals have distinctive personalities with different cultural backgrounds, experiences, etc. Hence, this philosophy seeks to elicit information by following a more in-depth inquiry of a qualitative nature. The interpretivism research philosophy follows a more value-centric approach as there is a subjective evaluation by the researcher. As this research is more subjective, it follows an inductive approach with a small sample size for an in-depth qualitative investigation.

4.2.1.3. Pragmatist Research Philosophy

Pragmatist research philosophy assumes that different ways of conducting research exist to understand reality, wherein combining other methods and approaches can also generate a comprehensive perspective of the topic under investigation (Saunders et al. 2009). As a result, researchers consider mixed techniques, which can give answers to the research investigation, enabling them to conduct research most innovatively. This philosophy is more oriented towards realistic output. Furthermore, as the researchers are focused on understanding reality, values play a significant role in influencing the subjective and objective evaluation. This research philosophy focuses more on the

results of the research investigation rather than on the methods adopted in the research study. As a result, pragmatist research philosophy employs mixed designs with quantitative and qualitative approaches to have a more profound investigation system.

4.2.1.4. Realistic Research Philosophy

The realistic research philosophy is based on the ideas of two research philosophies: positivist and interpretivist. This research philosophy indicates scientific enquiry and shows that what researchers see as reality is considered truth (Saunders et al. 2009). Like the positivist research philosophy, the realistic research philosophy presumes following a scientific method to develop knowledge. This research philosophy also considers both quantitative and qualitative data analysis. Saunders et al. (2009) have two forms of realistic research philosophy: direct realism and critical realism. Direct realism presumes that researchers obtain what is experienced through the senses, giving a more accurate representation of the world. Critical realism has a contradictory view to direct realism. Critical realism points out that researchers experience sensations that may also be deceived in some situations. The significant assumptions of realistic research philosophy are following an in-depth analysis of the established systems with quantitative and qualitative methods (Saunders et al. 2009).

These are the research philosophies with assumptions considered before undertaking the research investigation. This study is based on technology adoption and follows a positivist research philosophy. The primary objective of this study is to explore and identify the various factors influencing the adoption of AR technology in e-commerce apps in Tier 1 cities. This investigation is carried out using a quantitative method with a highly structured research methodology wherein people's perception is examined through the data collected by the survey method. A structured questionnaire was developed based on the previous literature studies considering the various factors adopted in the study with a large sample. This collected data was further analysed using SEM for hypothesis testing, and inferences were made based on the data analysis results with supporting literature. Hence, this research has followed the assumptions of positivist research philosophy.

4.2.2 Research Approaches - Onion Layer 2

With the determination of the research philosophy, the next stage is to decide the research approach to be followed in the study. Research approaches indicate the theory development. There are three main research approaches: inductive, deductive, and abductive (Saunders et al. 2009)**.** In inductive research, the researchers observe a specific phenomenon of the study and make conclusions. There is no concept of hypothesis testing due to a lack of contrary evidence. Hence, inductive research is more focused on theory building. In contrast, the deductive approach is focused on theory testing. Researchers following the deductive approach have a supporting theory for the research investigation, which is further extended and validated using hypothesis testing with both quantitative and qualitative methods. Abductive research is a type of research approach that has both inductive and deductive research approaches.

Here, the researcher aims to have a more logical and creative output from the investigation. Hence, the researcher observes the reality and develops the theory, which is empirically tested using various methods and techniques (Saunders et al. 2009). This research study has adopted an existing view, examined and tested in a different context. The proposed research model of the study is designed based on the UTAUT3 framework with other context-specific variables. As the theory has been widely used in different contexts, such as online banking, MOOCs, and blockchain technology, this study aims to test AR technology adoption in the e-commerce sector. Further, the study has proposed a hypothesis based on the research objectives and the supporting literature in technology adoption studies. The study has used an inductive research approach as it helps explore individuals' perspectives towards accepting AR technology. Hence, the study has adopted a deductive research approach to examine the influence of factors affecting the user's adoption of AR technology through hypothesis testing based on the UTAUT3 theory.

4.2.3 Research Strategies - Onion Layer 3

With the peeling of layer 1 (research approach) and layer 2 (research philosophy), the next decision is related to how the research should be conducted to attain the research objectives. The remaining three layers indicate the study's research design, wherein the research question of the investigation is transformed into the research project (Saunders

et al. 2009). The type of research strategy selected depends on the research question, objectives, resource availability, and supporting research philosophies. Research strategies comprise experiment surveys, case studies, action research, grounded theory, ethnography and archival research. The experiment is a research strategy to examine the causal relationship between variables. This research strategy is more used in exploratory and explanatory research to uncover the how and why the perspective of the research investigation (Saunders et al. 2009). Another type of research strategy is a case study, which involves the empirical investigation of a phenomenon in a particular situation with supporting evidence. This research strategy answers the researcher's questions about why, what, and how (Saunders et al. 2009). The data for the case study may be collected through interviews, observations and analysis of related documentaries. The third type of research strategy is action research. Action research indicates the scientific investigation of the fundamental problems of a situation wherein the researcher actively participates in the situation to come up with practical solutions (Saunders et al. 2009; Sekaran and Bougie 2009).

Grounded theory is the next type of research strategy, which is a combination of inductive and deductive aimed towards theory building. The data collection in this research strategy is undertaken without any theoretical framework. In contrast, the theory is developed based on collected data (Saunders et al. 2009). Ethnography is another type of research strategy. This research strategy aims to explore and examine the social world and further analyse the research objects of the study through complete participation in the social world. It is time-consuming and demands active participation in the investigation process (Saunders et al. 2009). Another type of research strategy is archival research. Archival research is a scientific investigation wherein the researcher uses the documents in the archives as a source of information (Saunders et al. 2009). However, all the documents in the archive may not contain the information on the research question, which is a downside of this research strategy. The final research strategy is the survey method. The researcher uses the survey method to collect data through questionnaires from a large population. It is a popular deductive approach and aids researchers in answering questions such as who, what, where, how much and how many in a study.

This research investigation has adopted the survey method. The survey method collects information from respondents through various questions about the research topic. The data obtained through survey questionnaires with fixed alternative questions are reliable as the respondent's choice of answers was limited (Malhotra 2010). Survey methods are simple, easy to administer, and hence preferred in business and management literature (Saunders et al. 2009). When the research investigation consists of many constructs, the survey method is appropriate for measuring the respondents' perspectives (Engel and Schutt 2012). Furthermore, if the data is collected from the sample representing the population study, then the results from the sample survey can be generalized. The study has adopted a survey method using a self-administered questionnaire. The research instrument used in this study was designed using prior literature in the technology adoption area.

4.2.4 Research Choices- Onion layer 4

Research choices indicate the combination of quantitative and qualitative techniques (Saunders et al. 2009). It also shows the mixture of adopted data collection methods and analysis procedures. Research choices, also termed research design (Tashakkori and Teddlie 2003), consist of mono and multiple methods. The Mono method consists of only a single data collection (quantitative or qualitative data) with the corresponding data analysis techniques used. In contrast, various methods are adopted when the study considers more than one data collection procedure and data analysis technique to attain the research objective. Quantitative data is collected through highly structured surveys and observations, whereas qualitative data is collected through focus groups, in-depth interviews, and projective techniques (Malhotra 2010). When a researcher adopts the mono method, it will consist of only quantitative data collection through questionnaires with quantitative data analysis procedures. It may also consist of qualitative data collected through interviews analysed through qualitative data analysis (Saunders et al. 2009). Multiple methods indicate the combination of more than one data collection technique but are restricted to quantitative or qualitative data. The current study has adopted the mono method as the research choice or research design, with quantitative data collected through a structured self-administered questionnaire. Based on the research objectives, this research formulated the theoretical framework. The constructs

of the study were based on the identified research gaps in the literature. Further, the research aims to test the hypothesis, resulting in the acceptance or rejection of the proposed hypothesis. The study collected quantitative data using the survey method (Malhotra 2010), which was analysed using a statistical data analysis with SEM through the SPSS and AMOS software. A structured self-administered questionnaire was prepared considering the prior literature studies in technology adoption, which was pretested with a smaller sample size before carrying out the major data collection process. The pilot study results indicate the successful attainment of recommended validity and reliability measures. Based on the inputs of the pilot study results, few changes were made to the questionnaire. The major data collection was undertaken using the revised questionnaire, resulting in the final sample of 1029 respondents.

The research model consists of seven independent variables, three mediators and one dependent variable. The final data was analysed to evaluate the direct effect and indirect influence on the user's behavioural intention to use AR technology. The results of the data analysis were further examined with supporting literature, which was additionally presented as having implications for academicians and practitioners. The use of quantitative data through survey-based data collection has contributed towards the attainment of research objectives. Hence, the in-depth evaluation of the research study was accomplished through the mono method.

4.2.5 Time horizons- Onion layer 5

The fifth layer of the research onion shows the time horizon. It indicates the time frame within which the research data is collected and depends on the depth of the research question (Saunders et al. 2009). The time horizon comprises cross-sectional design and longitudinal design. A research study follows a cross-sectional design, collecting data at a particular point in time. Cross-sectional studies are mainly based on survey-based data collection (Saunders et al. 2009) and are considered suitable when the research investigation has resource constraints. In a longitudinal study, the researcher collects data for an extended duration. Here, the sample population is approached at regular intervals, which will give more in-depth knowledge about the research (Creswell 2014). Longitudinal studies help the researcher evaluate the data collected at two different times, providing meaningful information about the research study. This study has

followed a cross-sectional design. The research data was collected from April 2020 to June 2021.

4.2.6 Research techniques and procedure - Onion layer 6

The first five layers of the research onion indicate the basic steps and procedures to be followed in the research investigation. The next stage (sixth layer) of the research onion indicates the research techniques and procedures adopted by the researcher to accomplish the research objectives (Saunders et al. 2009). In this stage, the researcher has to decide the type of data (primary or secondary data) and the data collection method (survey, observation, reports). Once the data collection method is decided, the researcher has to prepare the data collection instrument. The researcher must also determine the sampling method for selecting the respondents from the sample population. The selection of the sampling method depends on the nature of the study, research objectives, and availability of resources (time, budget, etc). The data analysis technique should be decided based on the research objective of the study. A properly structured and systematic research procedure is essential for accurate and reliable results. The following are the procedures adopted in this study.

4.2.6.1 Population and Sample

Population consists of a set of objects which share a common set of characteristics. It can be a collection of people, items, events, or anything the researcher would take up for research investigation (Sekaran and Bougie 2009). Population can be classified into finite and infinite (Kothari 2004). The total number of items can be ascertained in a finite population, whereas the number of items in an infinite population is uncertain. The study has used a finite population as there is certainty in the number of items in the population set. However, it is difficult to cover the entire population owing to time and budget constraints. Therefore, selecting a sample that can represent the study population is essential. A sample is a subgroup of the population (Sekaran and Bougie 2009). The study has taken the population data of tier 1 cities in South India. Hence, the three cities, namely Bangalore, Chennai and Hyderabad, are taken as the total population of the study. The population of these cities were retrieved from census survey data (Census of India 2011). The method of selecting the respondents and the number of respondents

from each city was decided using the sampling method and sample size estimation formulae.

4.2.6.2 Sampling method

Investigating the entire population is time-consuming; hence, a sample is taken to undertake the research. The selected sample should represent the study population. Therefore, the study has adopted a proportionate stratified sampling approach. In this sampling method, the sample size taken from each stratum is proportional to the total population size (Malhotra 2010). Each stratum represents a tier 1 city, and the entire population indicates the three cities' total population. The researchers estimate the number of samples taken from each stratum through the proportionate sampling method, ensuring a more proportionate allocation of the samples drawn. The next decision of the researcher is regarding the method of selecting the respondents. The sampling method guides the researcher in selecting respondents for the data collection (Malhotra 2010). Following a sampling method ensures that respondents are chosen according to the proper methodology. The sampling method can be classified into probability sampling and non-probability sampling. In probability sampling, every element has an equal chance of being selected, whereas in the case of non-probability sampling, the researcher decides the selection of the item.

The study adopted non-probability sampling techniques as they were suitable when a large amount of data was required and could better represent the study population (Malhotra 2010). Like the sampling method adopted by prior research (Saxena and Janssen 2017), convenience and snowball sampling were utilised to select the respondents in India. These techniques are considered better when the study population is large, it is challenging to identify respondents, and resources are limited. Furthermore, several studies adopted the combination of convenience sampling and snowball sampling (Khatoon et al. 2023; Saab et al. 2022).

4.2.6.3 Sample size estimation

Sample size indicates the number of items selected from the study population. The sample size should be optimum, giving more flexibility and reliability in the data analysis. Furthermore, the decided sample size should be within the budgetary

constraints (Kothari 2004). The Solvin formulae were used to calculate the sample size of the study.

$$n = \frac{N}{1 + Ne^2}$$

Here *n* is the sample size

N is the total population size

e is the margin of error with a 95% confidence interval and a five percent margin of error (MOE)

This study has adopted SEM for data analysis. The minimum sample required for executing the SEM technique should be at least ten times the number of items used to measure the constructs in the questionnaire (Hair 2010). The research study consists of eleven constructs with forty-five items. As per the thumb rule, the minimum sample required for the study is 450. The number of respondents to be taken from each city is computed by (Population of the city ÷ Total population) × Total sample size. Table 4.1 shows the sample size estimation. The results of sample size estimation indicate that the minimum sample size required for the study, as per the solvins formula, is 400, and the thumb rule method is 450.

Table 4.1: Sample size estimation

	Population	**Solvin's Formulae**	**Hair et al. (2010) (10 × no. of items)**
Tier 1 Cities	***20083669***	***400***	***450***
Chennai	4,646,732	93	104
Bangalore	8,443,675	168	189
Hyderabad	6,993,262	139	157

Source:(Census of India 2011; Lata et al. 2021)

4.2.6.4 Data collection

With the formulation of the research problem and research objectives, the next decision pertains to the data collection (Kothari 2004). The decision of the data collection

process depends on the type of data to be used in the research investigation. There are two types of data viz primary and secondary data. Primary data is original and collected for the first time by the researcher, whereas secondary data is the data already collected by the researcher and further processed using statistical analysis (Malhotra 2010). The research study has focused on primary data; hence, the study is quantitative research. Primary data was collected through structured questionnaires. A structured questionnaire is more suitable as it is easy to manage and affordable (Kothari 2004). The survey instrument was administered through both online and offline modes. The survey forms and links were distributed through peer groups and relatives through social media platforms and emails. The data collection process elicited 362 printed forms and 916 online forms. The data collection was conducted from April 2020 to June 2021. The data collection was delayed due to the nationwide lockdown. However, convenience and snowball sampling have helped collect data more efficiently (Khatoon et al. 2023; Saab et al. 2022). The study has attained a sample size more than the recommended levels as per the sample size estimations.

4.2.6.5 Research Instrument Development

The research study mainly focuses on primary data collection through offline and online survey questionnaires. Structured questionnaires are considered the most preferred mode of data collection in investigations with large sample sizes (Kothari 2004). Once the data is collected, the researcher executes the editing, coding, translating and data cleaning with statistical tools (Malhotra 2010). Prior studies in the area of social networking tools (Alvi 2021), voice-based digital assistants (Vimalkumar et al. 2021), and news apps (Sharma et al. 2023) have used survey questionnaires for primary data collection in the Indian context. The research study has used close-ended questions with a 5-point Likert scale anchored from '1= Strongly Disagree' to '5= Strongly Agree'. A five-point scale is recommended in the survey instrument as it can increase the response rate and quality and decrease respondents' frustration levels while answering the questionnaire (Babakus and Mangold 1992; Dawes 2008).

The survey instrument was divided into three parts. The first part contained a small introduction to know more about the topic of investigation and the purpose of undertaking the study. It also had a confidentiality statement of the respondents'

information and instructions for answering the questions. The second part consists of questions measuring the constructs of the study. The research study consists of eleven constructs. Each item measuring the constructs was drawn from prior literature in technology adoption studies. The study used validated scales, which were further modified to the research study without losing the essence of the items measured. The number of items taken for a construct influences the model fit indices and validity measures. The validity of the results is highly compromised when few indicators are used to measure a construct (Rigdon et al. 2017). It is recommended that each construct should have at least three indicators to attain the recommended results (Marsh et al. 1998). Further, a construct with one or two indicators affects the model identification and validation problems in CB-SEM analysis (Hair et al. 2018). Following this recommendation, the research study has taken at least three items for each construct. The items taken from the validated scales were improved to attain the model fit indices. The following indicates the sources of literature used to adopt the various items to measure the constructs.

- Performance expectancy - The items to measure performance expectancy were adopted from Abed (2021), Farooq et al. (2017) and Venkatesh et al. (2012). The scale adopted for performance expectancy consists of four items measuring users' performance expectancy towards adopting AR technology.
- Effort expectancy - Effort expectancy consists of four items to measure the effort expectancy of individuals towards accepting AR technology in e-commerce apps. The items for measuring effort expectancy were adopted from Abed (2021), Farooq et al. (2017) and Venkatesh et al. (2012).
- Social influence - Social influence was measured with four items adopted from Abed (2021) and Venkatesh et al. (2012). The item SI4 was deleted due to its poor loadings. Hence, the final analysis considered only three items to measure social influence.
- Facilitating conditions - Facilitating conditions consist of items measuring the availability of resources, support systems, etc., influencing the user’s adoption of technology. Four items to measure facilitating conditions were adopted from Abed (2021) and Venkatesh et al. (2012).

- Hedonic motivation - The construct of hedonic motivation measures the pleasure an individual derives while using technology. The construct was measured using three items adopted from the studies of Abed (2021) and Venkatesh et al. (2012).
- Personal innovativeness - The scale to measure personal innovativeness was adopted from Farooq et al. (2017), Abed (2021) and Saprikis et al. (2021). The construct of personal innovativeness was measured using five items. However, two items were removed owing to their poor loadings. Therefore, the final data analysis was carried out using only three items.
- Information quality - The construct information quality was measured based on the scales adopted from Kim and Hyun (2016). The construct consists of four items that evaluate the user's perception of the information quality of the output from AR technology.
- System quality - The items to measure system quality were adopted from the prior research studies (Kowalczuk et al. 2021; Park et al. 2015). The construct system quality consists of six items. However, three items were removed due to poor loadings during the EFA iteration process. Hence, only three items were considered for the SEM analysis.
- Trust - The scale adopted to measure trust was from prior research investigations (Chai and Kim 2010; Harborth and Pape 2021). A four-item scale was used to measure this construct.
- Privacy risk - Privacy risk was measured using a four-item scale adopted from the study of Rauschnabel et al. (2018).
- Behavioral intention - Behavioral intention is the study's significant variable, which measures users' behavioural intention towards AR technology. It is measured using the three-item scale adopted from the studies by Venkatesh et al. (2012) and Abed (2021).

This study has modified all the items from the prior literature studies to match the study's context. Hence, modifications were made considering the background of the study, respondents' knowledge, etc., without losing the essence of the statement measuring the constructs. The third part includes demographic information questions, including location, age, gender, education, income and occupation. Following these

items, two questions asked the respondents whether they were aware of AR technology and were willing to use AR in online shopping apps. These measures are filler questions. The research has excluded those respondents who are unaware of AR technology and unwilling to use AR. The survey questionnaires were adequately designed considering the expert opinions and were distributed among respondents. The survey questionnaire used in the research study is documented in the appendix.

4.2.6.6 Data Analysis Technique

The present study has used statistical tools and techniques for the data analysis. The data analysis comprises primary investigation and secondary investigation. The primary investigation is undertaken to compute the descriptive statistics of the data distribution. The descriptive statistics of research data examine the mean and standard deviation. Descriptive statistics of the research data aid the researcher in drawing meaningful information, which will help interpret the study. The primary investigation of the data was performed through IBM SPSS Statistics version 24 software. Further, this investigation phase also verifies the factors measured in the study through the exploratory factor analysis process considering the principal component analysis with varimax rotation. The results of exploratory factor analysis offer a broad overview of the validity and reliability of the measured data. After completing these steps in the preliminary investigation, the next step is to undertake the hypothesis testing of the research.

The secondary investigation stage is concerned with validating the proposed research model and testing the study's research hypothesis through structured equation modelling (SEM).SEM combines factor analysis techniques and multiple regression analyses (Hair 2010). It is a widely used and popular technique in various disciplines of quantitative research (Nusair and Hua 2010). The multiple regression technique is suitable for evaluating the constructs and the proposed relationships between the constructs. However, these techniques can only test a single relationship between the independent and dependent variables. In contrast, the SEM technique can evaluate complex models wherein one dependent variable in a model may be the independent variable in other relationships. Prior studies have proved SEM more effective than multiple regression in management research (Cheng 2001). Further, SEM considers

both indicator and latent variables in the analysis, allowing the analysis of direct and indirect effects among the latent variables.

The SEM analysis comprises a two-stage approach (Anderson and Gerbing 1988). The first stage is the assessment of the measurement model. The assessment of the measurement model is performed through confirmatory factor analysis (CFA). The CFA process was executed based on the EFA iteration results. The clean matrix obtained in the EFA process was extracted using the pattern matrix builder plugin of the AMOS software to produce the measurement model of the research study. The measurement model consists of the observed indicators, which measure the latent variable. Hence, CFA is directed to verify the measurement model (Cheng 2001). The measurement model assessment confirms various tests such as construct reliability, item reliability, and construct validity (convergent and discriminant validity). The measurement model should be further assessed to check the model fit in terms of recommended model fit indices, namely Normed chi-square (CMIN/df), Goodness of fit index (GFI), Adjusted goodness of fit index (AGFI), Comparative fit index (CFI), Tucker Lewis index (TLI), Standardized root mean square error of approximation (SRMR), Root mean square error of approximation (RMSEA). The measurement model should attain the recommended model fit indices for a good fit (Hair 2010).

The second stage of SEM analysis is comprised of structural model assessment. The structural model connects the constructs and indicates the constructs' relationships (Hair Jr et al. 2021). The relationship between the constructs is based on theoretical support, the researcher's experience, or a combination of both (Hair Jr et al. 2021). The structural model assessment involves verifying the proposed relationships between the latent variables. The structural model analysis consists of two stages. Stage one comprises testing the proposed research model, and stage two consists of verifying the proposed hypothesis with the path coefficients. The structural model assessment assesses the direction of the proposed hypothesis, the significance of the path relationships, the strength of the path coefficient values, and the verification of the coefficient of determination (R^2). Similar to the measurement model, it is essential to check the model fit indices of the structural model. If the measurement and structural models do not achieve the recommended model fit indices, then the model can be modified based on

the results of modification indexes (Cheng 2001). The current research investigation has adopted a well-structured data analysis technique for the empirical results.

4.2.6.7 An Overview of CB-SEM

The SEM analysis can be used by applying covariance-based structural equation modelling (CB-SEM) and partial least squares structural equation modelling (PLS-SEM). Even though these approaches are part of SEM analysis, it is essential to understand the difference between them before executing the research investigation. Researchers use CB-SEM when the research investigation aims to test and confirm the adopted theory. In contrast, PLS-SEM predicts new phenomena and develops theories (Dash and Paul 2021). CB-SEM and PLS-SEM also differ based on the type of analysis. CB-SEM functions on a common factor model, and PLS-SEM is based on a composite model. The common factor model is grounded on the assumption analysis, which should be performed based on the common variance in the data. Hence, the predictor variables' specific variance and error variance are removed before the validation of the research model (Hair et al. 2017). In contrast, PLS-SEM considers all variances (common variance, specific variance and error variance) from the predictor variables to predict the variance in the outcome variable. CB-SEM evaluates the structural and measurement models for goodness of fit (GOF) through Chi-square statistic, GFI, AGFI, TLI, CFI, SRMR and RMSEA. PLS-SEM, however, assesses the predictive power of the model using the coefficient of determination (R^2) and does not have recognized goodness of fit measures like CB-SEM. CB-SEM works on research data with normal distribution with a large sample size (<100). On the other hand, PLS-SEM can use both normal and non-normal distribution data and works with small (>100) and large sample sizes (Usakli and Rasoolimanesh 2023). CB-SEM minimize the difference between the empirical model and estimated covariance matrices through the use of the maximum likelihood estimation method (ML) (Rigdon et al. 2017), whereas in the case of PLS-SEM, regression-based ordinary least squares (OLS) estimation method is used to increase the variance explained by the outcome variable (Hair et al. 2011).

The current research investigation has developed a model based on theory and literature support. The research objective of the study is to test the model and validate the theory with a large sample size; henceforth, the research has used CB-SEM. The study used

IBM AMOS version 23, designed by the IBM Corporation. AMOS (Analysis of Moment Structures) is a widely used software for executing the CB-SEM. Researchers in various areas have widely used AMOS. Many empirical studies in technology adoption have used the CB-SEM using the AMOS and are well accepted with papers published in reputed journals such as Information Systems Management, Technological Forecasting and Social Change, Journal of Retailing and Consumer Services, and Computers in Human Behavior. In addition, many doctoral dissertations have performed CB-SEM using the AMOS software. Hence, the study used AMOS software for the research data analysis.

4.2.6.8 Pilot Study

It is essential to undergo a thorough examination of the prepared questionnaire. The survey instrument was designed by adapting scales from prior literature studies, which were further modified to suit the context of the study. Hence, there is a need to undertake a pilot study to check the validity and reliability of the survey instrument. A pilot study investigates potential errors and difficulties that may affect the major data analysis. It also helps determine an appropriate research investigation plan (Kothari 2004). A pilot study is only concerned with the critical evaluation of the questionnaire and does not test the study's proposed hypothesis (Leon et al. 2011). The face validity of the questionnaire was performed by consulting experts from academics and industries. The questionnaire was modified based on the expert opinions. The pilot test for the study was conducted in Bangalore, one of the cities in the investigation. A minimum of 30 participants are recommended for the pilot study (Johanson and Brooks 2010).

The pilot test was performed with 132 responses, well above the recommended sample size. Before collecting the data, the respondents explained the purpose of the study and the future of AR in the e-commerce industry. The participants were requested to identify errors such as repeated questions, confusing words, lengthy questions, etc. The questionnaire was circulated among respondents as an online form. The pilot study examined the KMO values, Bartlett's test of sphericity, validity, and reliability. The test results have attained the recommended values, indicating a positive sign for conducting the major study. Although the results of the pilot study are relevant, these results need not be supported by prior pilot studies (Leon et al. 2011). Similar to the pilot testing,

the validity and reliability were checked after the major data collection. The questionnaire was slightly modified based on the opinions of the respondents. The pilot study data results were not combined with the primary study data to ensure accuracy in the major data analyses (Leon et al. 2011). With satisfactory test results, the major data collection focusing on three cities was undertaken.

4.3 ETHICAL CONSIDERATIONS

Research ethics consist of moral values and principles which guide the researcher in the investigation process. Researchers should apply rules and norms and how to make ethical decisions in various situations. As a part of following ethical practices, a report on the research topic was submitted and presented to the research committee and was duly approved. Consequently, before data collection, the researcher furnished all the information about the research study and assurance was given to the respondents regarding the confidentiality of the responses. The research ensured that respondents participated voluntarily and were free to withdraw from the research investigation process. The respondents were given the researcher's contact details to contact in case of any query regarding the investigation process. The questionnaire has no questions that may collect personal information such as name, contact number, address, or identity card details. Respondents were also informed that information would not be given to any third party and would only be used for academic purposes. The study has followed the integrity of the work by reporting accurate data. The literature utilised in the study was given due credit and cited. Proper data management is a critical element in research ethics. The study has followed good data management by retaining the data for some time and disposing of the same later by shredding off the paper documents to prevent information retrieval and overwriting or permanently deleting the electronic data.

4.4 CHAPTER SUMMARY

This chapter is the compilation of the research methodology followed in the study. The research study has followed the Saunders research onion framework. The chapter has discussed the research philosophy, approaches, strategies, choices, data collection period, data analysis and procedures. Furthermore, the chapter has elucidated the use of CB-SEM through Amos software. The pilot study adopted in the research

investigation has been discussed, indicating the attainment of the recommended measures. Lastly, the chapter briefly explains the relevance of research ethics in the study by examining the ethical considerations adopted. Hence, this research study followed a systematic methodology throughout the investigation. The forthcoming chapter discusses the results of the data analysis of the research study.

CHAPTER 5

DATA ANALYSES AND INTERPRETATIONS

5.1 INTRODUCTION

This chapter summarises the data analyses undertaken in the study. Data analysis helps understand the nature of the data and offers fruitful information to the research. Furthermore, it gives insights into the process involved after collecting data to the testing of the hypothetical relationships. The data analysis is carried out in four phases. In this first phase, the collected data passes through data screening, which aims to eliminate irrelevant data by identifying the potential outliers, unengaged responses and missing data. The second phase comprises computing the descriptive statistics of the demographic data and variables of the study by calculating the mean, standard deviation, skewness and kurtosis. The computation of descriptive analysis helps to understand the data distribution. The third phase encompasses the assessment of the measurement model. The measurement model is evaluated through confirmatory factor analysis (CFA). In this phase, the validity and reliability of the constructs is checked. Furthermore, the model fit of the measurement model is also evaluated.

With the assessment of the measurement model, the next phase (phase four) consists of the evaluation of the structural model. In this phase, the proposed hypothetical relationships are investigated through path analysis, and the model fit is assessed. The coefficient of determination (R^2) is also verified to check the strength of the variable in explaining the factors. The study has used model fit indices, namely CMIN/df, Goodness of fit index (GFI), Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Residual (SRMR), Tucker Lewis Index (TLI), Comparative Fit Index (CFI), and Adjusted Goodness of Fit Index (AGFI). Phase four encases the mediation analysis. Likewise, investigating the direct effect, this research has investigated the indirect effect, i.e., mediation analysis, to explore the strength of mediators among the variables. The results obtained in the data analysis are summarised at the end of this chapter.

5.2 DATA SCREENING

The quality of the data influences the results obtained. Therefore, it is necessary to perform data screening to identify the outliers. Data screening is an inevitable step in the research study. Any data (primary or secondary data) should be screened to discover

the observations that may turn into potential outliers in the research study. The statistical analysis results depend on the quality of the responses obtained. Hence, a proper data screening is required before performing any statistical analysis. Data screening analysis the data for errors and further helps the researcher to fix or remove the data, which may affect the final results. The research study obtained 1,278 responses from the three-tier one cities in south India. These responses were checked to identify the potential outliers. The initial stage has removed responses based on filter questions such as awareness of AR and willingness to use AR. The study has excluded responses where respondents are unaware of AR and unwilling to use AR. Hence, 143 responses were removed based on filter questions.

The remaining 1135 responses were checked for outliers. In the second phase, the researchers scanned for incomplete responses. Nineteen observations with more than 20 percent missing data were removed from the data set. Further, the observations with missing data were replaced with values taking the mode function. Repetitive or unengaged responses were also checked. Unengaged responses were identified by applying the standard deviation. The observations with standard deviation values below 0.30 were removed from the sample (Makkar and Singh 2021). Hence, 28 responses were removed from the dataset due to repetitive responses. After eliminating incomplete responses and unengaged responses, the next step is to identify the potential outliers in the dataset. Outliers are those observations with extreme data points that do not match the rest of the dataset. The outliers were identified using Mahalanobis distance with Cook's distance. Fifty-nine responses were identified as multivariate outliers. Hence, after removing the missing data, unengaged responses and outliers, 1029 responses were taken for the final data analysis.

5.3 DESCRIPTIVE ANALYSIS OF DEMOGRAPHIC DATA

Demographic data of the respondents helps in understanding the nature of the sample population. The demographic data include age, gender, income, education, occupation and location. The background of the users highly influences the adoption of any technology. This socio-demographic profile helps understand the respondents' profile, which impacts the data analyses. Further, this information can help researchers

investigate the study area. This section summarises the demographic profile of the respondents of the study.

5.3.1 Age of the respondents

Table 5.1 shows the age category of the respondents. Five categories were formed in age group.

Table 5.1: Age of the respondents

Demographic Profile	Category	Frequency	Percentage
Age	18 years- 24 years	364	35.4%
	25 years- 31 years	359	34.9%
	32 years- 38 years	190	18.5%
	39 years-45 years	91	8.8%
	Above 45 years	25	2.4%

Source: Primary data

The maximum number of respondents falls in the age category of 18-24 years (35.4%), followed by 25-31 years (34.9%). There is 18.5 percent of respondents in the age group of 32-38 years. In contrast, a very small percentage of respondents belong to the 39-45 years category (8.8%) and above 45 years (2.4%). The study has focused mainly on those individuals who are aware of AR technology and are willing to use AR. As a result, the demographic data indicate that most respondents fall in the middle age category and very few people in higher categories.

5.3.2 Gender of the respondents

The following table (Table 5.2) indicates the gender information of the respondents.

Table 5.2: Gender of the respondents

Demographic Profile	Category	Frequency	Percentage
Gender	Male	501	48.7%
	Female	514	50.0%
	Prefer not to say	14	1.4%

Source: Primary data

The gender distribution indicates that 50 percent of respondents are male and 48.7 percent are female. However, 1.4 percent of respondents were not interested in revealing their responses. These results highlight that the final data consists of male and female in proportion, which is a good indication of equal distribution of the respondents of the study based on gender

5.3.3 Education of the respondents

Table 5.3 represents the educational qualifications of the respondents. Education is grouped into primary/secondary, graduate, post-graduation and above.

Table 5.3: Education of the respondents

Demographic Profile	Category	Frequency	Percentage
Education	Primary/Secondary	2	0.2%
	Graduate	524	50.9%
	PG & above	503	48.9%

Source: Primary data

The educational qualifications of the respondents indicate that 50.9 percent are graduates, and 48.9 percent have either post-graduation or above post-graduation qualifications. It was found that very few respondents (0.2%) fall in the primary/secondary education category. The study area of this research consists of only tier 1 cities in south India. As a result, the sample taken for the study consisted of a well-educated group.

5.3.4 Occupation of the respondents

The occupation category of the respondents is presented in Table 5.4. The occupation category comprises four classes: student, employed, self-employed and others.

Table 5.4: Occupation of the respondents

Demographic Profile	Category	Frequency	Percentage
Occupation	Student	347	33.7%
	Employed	448	43.5%
	Self-employed	194	18.9%
	Others	40	3.9%

Source: Primary data

The sample's occupation data indicate that most of the study's respondents are employed 62.4 percent (employed 43.5% and self-employed 18.9 %). The sample also consists of 33.7 percent of students, whereas a small percentage of respondents (3.9 %) fall into the others category. The educational data indicated that most of the respondents are well educated, which is well reflected in the occupation category as most of the respondents fall in the category of employed and self-employed. These figures indicate that respondents' essential educational background with occupation results in more willingness to adopt new technologies such as AR.

5.3.5 Income of the respondents

The income of the respondents is presented in Table 5.5. The income category consists of 4 groups.

Table 5.5: Income of the respondents

Demographic Profile	Category	Frequency	Percentage
Income	Not applicable	261	25.36%
	Less than 3 Lakhs	156	15.16%
	3 Lakhs – 6 Lakhs	288	27.99%
	6 Lakhs – 10 Lakhs	211	20.51%
	Above 10 Lakhs	113	10.98%

Source: Primary data

The income data of the respondents indicate that 27.99 percent of the respondents fall in the income category of 3 lakhs-6 lakhs. It can be observed that 25.36 percent of the respondents fall in the category of not applicable. This is because they do not have a source of income other than the financial support offered by the family. 20.51 percent of the respondents fall in the income category of 6 lakhs-10 lakhs. 10.98 percent of the respondents earn an income above 10 lakhs, and 15.16 percent have an income below 3 lakhs. Using AR features in online shopping does not incur any extra cost; however, it is assumed that using AR can increase shopping behaviour in online shopping apps.

5.3.6 Location of the respondents

Table 5.6 indicates the respondents' location in the tier 1 cities of south India.

Table 5.6: Location of the respondents

Demographic Profile	Category	Frequency	Percentage
Location	Bangalore	358	34.80%
	Hyderabad	326	31.68%
	Chennai	345	33.52%

Source: Primary data

The location data of the respondents as per table 5.6 indicate that 358 respondents (34.80%) belong to Bangalore region, 345 (33.52%) respondents belong to Chennai and the remaining 326 (31.68%) respondents belong to Hyderabad. These results indicate that respondents from the three cities are almost proportionate to each other, giving a good insight into users in South India.

5.4 DESCRIPTIVE ANALYSIS OF LATENT VARIABLES

Descriptive statistics provide meaningful information as well as possible relationships between the variables of the study. It uses statistical and graphical techniques to analyse the nature of the variables in the study. This study has used statistical techniques, namely mean, standard deviation, skewness and kurtosis, as part of descriptive analysis. The mean is one of the measures of central tendency. Mean or average indicates the sum of all scores divided by the number of scores (Malhotra 2010). The mean calculation will demonstrate the central value around which other values are distributed. Standard deviation is a measure of dispersion that indicates the data's spread. When the mean value highlights the central value, the standard deviation indicates the level of data spread from the mean value (Malhotra 2010). The most commonly used measures of dispersion are variance and standard deviation. Variance indicates how each value is away from the mean value. It is computed by taking the square of the standard deviation. Variance is assumed to be low when the observed value is near the mean, whereas variance is considered high when the observed value is far from the mean. Standard deviation indicates the variation in the data values from the mean. It is computed by taking the square root of the variance.

Skewness and Kurtosis are measured to check the shape of the data distribution (Malhotra 2010). Skewness is the tendency of the data to deviate from the mean value,

creating a more extensive set of data in only one direction of the distribution. Skewed data indicate that the responses of the individuals are high towards one side of the measured scale. Kurtosis is a measure that checks the relative peakiness or flatness of the distribution curve, indicating whether the data is heavy-tailed or light-tailed in the distribution. Hence, a positive kurtosis value indicates more peakiness in the data, whereas a negative value indicates a flatter curve than the normal distribution. According to Sposito et al. (1983), the skewness and kurtosis values should not exceed 3.3 to confirm normality. Table 5.7 indicates the descriptive statistics of the measured latent variables (mean and standard deviation), skewness, and kurtosis.

Table 5.7: Descriptive analysis of latent variables

	Mean	**Standard Deviation**	**Variance**	**Skewness**	**Kurtosis**	**Level**	**Order**
PE	3.89	0.66	0.44	-0.989	2.245	High	4
EE	3.99	0.61	0.37	-0.585	0.733	High	1
SI	3.34	0.80	0.64	-0.409	0.021	Moderate	11
PI	3.77	0.63	0.40	-0.357	-0.054	High	6
HM	3.96	0.68	0.46	-0.527	0.350	High	3
FC	3.98	0.62	0.38	-1.124	2.711	High	2
IQ	3.67	0.64	0.41	-0.581	0.396	High	7
SQ	3.59	0.58	0.34	-0.176	0.219	High	8
TR	3.40	0.82	0.67	-0.158	-0.430	Moderate	10
PR	3.51	0.83	0.69	-0.217	-0.350	High	9
BI	3.85	0.70	0.49	-0.586	0.691	High	5

Note:

PE- Performance expectancy, EE-Effort expectancy, SI-Social influence,
PI-Personal innovativeness, HM-Hedonic motivation, FC-Facilitating conditions,
IQ-Information quality, SQ-System quality, TR-Trust, PR-Privacy risk,
BI-Behavioural intention

Source: Primary data

The results from Table 5.6 indicate the descriptive analysis of the latent variables. The mean values of the constructs range from 3.34 to 3.99. The construct trust had a minimum mean value (3.40), and effort expectancy had the maximum mean value (3.99). The standard deviation values of the constructs range from 0.58 to 0.83. The construct system quality (0.58) has the lowest standard deviation value, and privacy risk has the highest standard deviation (0.83). The skewness and kurtosis values are within the recommended levels (Sposito et al. 1983). The skewness values range from -0.158 to -1.124, and the kurtosis value ranges from -0.054 to 2.711. The table results indicate that all the values are within the recommended levels. The questionnaire items are measured using a 5-point Likert Scale (1- Strongly Disagree, 5- Strongly Agree). Hence, the level of the point measured in the scale was ascertained using the formula.

$$\text{Level} = \frac{(\text{Highest point in the scale} - \text{Lowest Point in the scale})}{\text{Number of levels in the scale}} = \frac{(5-1)}{5} = 0.80$$

Level 1-1.80 is considered “very low”, 1.81-2.60 is regarded as “low”, 2.61 – 3.40 corresponds to “moderate”, 3.41- 4.20 is regarded as “high”, and 4.21 – 5 corresponds to “very high”. The results indicate that based on the mean value of the constructs, performance expectancy, effort expectancy, personal innovativeness, hedonic motivation, facilitating conditions, information quality, system quality, privacy risk, and behavioural intention fall in the category of high level. In contrast, the constructs of trust and social influence fall in the category of moderate level.

5.5 DESCRIPTIVE ANALYSIS OF LATENT VARIABLES BASED ON REGION

The research has collected data from three cities in south India. Table 5.7 indicates the descriptive statistics of variables based on region. The results show that respondents of all three regions have a favourable attitude as the mean value falls in the “high” category. Meanwhile, respondents’ perceptions fall in the moderate category in trust (Chennai), social influence (Hyderabad), and privacy risk (Bangalore). The descriptive analysis also reflects that the Bangalore region has a higher mean on all variables other than privacy risk (moderate category). In contrast, the Chennai region had a lower mean score than the other areas. These details indicate that respondents have a favourable approach to the various factors; hence, examining these factors will help understand AR technology's acceptance in developing countries such as India.

Table 5.8: Descriptive Statistics of variables region wise

Constructs	Bangalore (358)		Level	Order	Chennai (345)		Level	Order	Hyderabad (326)		Level	Order
	Mean	SD			Mean	SD			Mean	SD		
PE	4.08	0.52	High	1	3.86	0.55	2	High	3.70	0.83	High	5
EE	4.00	0.57	High	2	3.90	0.58	1	High	4.08	0.66	High	1
SI	3.60	0.74	High	10	3.24	0.69	9	Moderate	3.16	0.91	Moderate	9
PI	3.94	0.63	High	6	3.62	0.53	6	High	3.74	0.69	High	3
HM	3.98	0.61	High	5	3.83	0.65	3	High	4.08	0.74	High	1
FC	4.00	0.53	High	3	3.86	0.63	2	High	4.08	0.67	High	1
IQ	3.92	0.54	High	7	3.42	0.61	8	High	3.66	0.67	High	6
SQ	3.75	0.54	High	9	3.44	0.50	7	High	3.59	0.66	High	7
TR	3.83	0.80	High	8	3.04	0.67	10	Moderate	3.29	0.77	Moderate	8
PR	3.21	0.84	Moderate	11	3.63	0.72	5	High	3.72	0.85	High	4
BI	4.10	0.63	High	4	3.66	0.66	4	High	3.78	0.74	High	2

Note:
PE- Performance expectancy, EE-Effort expectancy, SI-Social influence, PI-Personal innovativeness, HM-Hedonic motivation, FC-Facilitating conditions, IQ-Information quality, SQ-System quality, TR-Trust, PR-Privacy risk, BI-Behavioural intention

Source: Primary Data

5.6 EXPLORATORY FACTOR ANALYSIS

Factor analysis is a technique used to identify the relevant factors, eliminating and organising the items into specific variables or constructs of the study. Factor analysis, also called exploratory factor analysis (EFA), helps the researcher identify the relationships between the various items measured in the survey (Malhotra 2010). Further, it also helps to check the validity of the measures used in the research (Maskey et al. 2018). EFA aids in understanding the nature of the data set and helps ascertain the underlying factors. It offers valuable insights to the researcher in two key points. Firstly, the loadings of each item of the construct and the cross-loadings among the items of different constructs. The loadings of each item or factor loadings explain the correlation coefficient between the items and the construct. An item with good loading indicates its capacity to explain the construct. An item with a factor loading above 0.50 is considered ideal to be extracted (Grau et al. 2015). Secondly, EFA helps to identify the presence of cross-loadings exhibited by the factors. Cross loadings create instability in the factor structure, leading to misleading interpretations of constructs measured in the study. Cross loadings occur when an item loads on more than one component with a value of more than 0.32. Hence, cross-loaded items with more than 0.32 were removed from further analyses (Costello and Osborne 2005). Examining item loadings and removing cross-loaded items results in a clean matrix for further analysis.

Generally, EFA is computed when the researcher explores the underlying factors from the respondent's data. In contrast, confirmatory factor analysis is used when the items of the research instrument are adapted or adopted from existing literature. Hence, performing EFA is not required if the research study has used existing scales for data collection. However, it is recommended to perform EFA before CFA as it gives valuable insights on the factor loadings and cross-loadings, which can result in validity and reliability issues leading to unreliable results (Gerbing and Hamilton 1996; Walker and Maddan 2012). Hence, this study applied the EFA procedure to check the quality of the data collected before conducting the CFA technique.

Before performing EFA, it is essential to consider certain decision points, such as the extraction method, number of factors to be extracted, rotation method, and suppression of small coefficient based on absolute value. The study used principal component

analysis as the extraction method, which is considered the most potent factorization technique with the varimax rotation method (Ustun et al. 2023). The extraction of the factors was decided based on the eigenvalue. Several iterations were run to ensure that relevant items or factors were extracted to the constructs. The suitability of the sample to run the factor analysis needs to be examined by sampling adequacy test through the Kaiser-Meyer-Olkin (KMO) Test and Bartlett's Test of Sphericity. The KMO value should be greater than 0.50, and Bartlett's Test of Sphericity need to be large and significant (p-value ≤ 0.01), as reported by academicians (Malhotra 2010). The results of KMO and Bartlett's Test of Sphericity indicate that the variable has a minimum of two factors essential to run the factor analysis. The component matrix results were analysed to see the loading of factors on each component. The study considered all the items with more than 0.50-factor loading (Grau et al. 2015), whereas factors with cross-loadings were removed.

Following the criteria mentioned earlier, several iteration processes were run. The KMO value (0.902) and Bartlett's Test of Sphericity (p-value-.000) were within the recommended threshold levels in the final iteration process. All the items had 0.50 factor loadings. However, a few items were removed during the iteration due to cross-loadings and low loadings on the construct. The items removed during the iteration process include social influence (SI4), system quality (SQ1, SQ5, SQ6) and personal innovativeness (PI1, PI2). Hence, the obtained EFA results indicate that items measured by construct were well extracted through the research instrument. The matrix revealed the extraction of 11 factors with the respective items measured. The obtained data was further validated through CFA. This indicates that the data is suitable for further analysis. The final rotated component matrix obtained in the iteration is presented in Table 5.9.

Table 5.9: Final rotated component matrix

Rotated Component Matrix											
	Component										
	TR	**PR**	**PE**	**IQ**	**EE**	**FC**	**PI**	**SI**	**HM**	**BI**	**SQ**
TR3	.813										
TR2	.738										
TR1	.679										
TR4	.636										
PR3		.827									
PR2		.797									
PR4		.786									
PR1		.765									
PE2			.782								
PE1			.763								
PE3			.742								
PE4			.721								
IQ4				.738							
IQ3				.728							
IQ2				.689							
IQ1				.673							
EE3					.782						
EE2					.768						
EE1					.740						
EE4					.635						
FC1						.776					
FC3						.751					
FC2						.720					
FC4						.659					
PI4							.816				
PI3							.773				
PI5							.711				
SI2								.838			
SI3								.793			
SI1								.752			
HM2									.822		
HM1									.796		
HM3									.593		
BI1										.782	
BI2										.729	
BI3										.627	
SQ3											.817
SQ4											.795
SQ2											.505
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.											
Note: PE- Performance expectancy, EE-Effort expectancy, SI-Social influence, PI-Personal innovativeness, HM-Hedonic motivation, FC-Facilitating conditions, IQ-Information quality, SQ-System quality, TR-Trust, PR-Privacy risk, BI-Behavioural intention											

Source: Primary Data

5.7 ASSESSMENT OF MEASUREMENT MODEL

With the results of EFA, the next step involves the assessment of the measurement model. The measurement model, also the outer model, represents the relationship

between the observed and latent variables. Observed variables (observable or measured variables) are those the researcher measures through the data collection. For instance, the observed variable indicates each questionnaire item that measures a specific variable. Latent variables (factors or constructs) cannot be measured directly but are obtained through the items of the questionnaire (i.e. observed variables). The measurement model indicates how the latent variables and observed variables are related. It also shows how well the items have measured the construct. The assessment of the measurement model is performed using confirmatory factor analysis (CFA). CFA checks how well the latent and observed variables relate to the research data. The study has performed EFA to confirm the research instrument prepared for data collection. However, CFA checks how well the measured variables fit with the empirical data collected and the model fit. CFA is more theoretically driven, whereas EFA explores factors further assigned to the component. The study used the final matrix obtained in the iteration process (Table 5.9) for the CFA assessment. The measurement model was created using the pattern matrix plugin in Amos software. Once the measurement model is depicted, the next step involves the evaluation of it. The measurement model assessment comprises checking the validity, reliability, and goodness of fit measures (Malhotra 2010). The following section explains the assessment results.

5.7.1 Reliability Analysis

The reliability test measures the reliability of the research instrument. The research questionnaire consists of several items measuring the constructs, which are adapted based on the nature of the study. Hence, checking the reliability of the research instrument is essential. Reliability analysis checks the efficiency of the research instrument to provide consistent results even after repeated measurements are taken. Hence, a research instrument is highly reliable if it produces the same results in the data collection process. The assessment of the reliability analysis is measured through Cronbach Alpha, Composite Reliability, KMO, Bartlett's test and factor loadings.

5.7.1.1 Cronbach Alpha

Cronbach Alpha is a widely used test to measure the reliability of the research instrument. It is also known as coefficient alpha, which indicates how well the measured items represent the concerned construct (Malhotra 2010). It shows the degree to which

all items are closely related to each other, representing the measured construct. Cronbach's Alpha value ranges from 0-1. A high cronbach alpha indicates that items possess the characteristics of the measured construct. In contrast, a low cronbach alpha highlights that items do not possess the nature of the constructs and, hence, lack reliability. It is recommended to have a cronbach alpha value of 0.70 or above (Hair 2010). However, cronbach alpha values of 0.60 and above are also accepted (Malhotra 2010). The cronbach alpha value will be increased with the increase in the number of items used to measure the construct; hence, its value cannot be solely considered as an indication of reliability. Further, compared to cronbach alpha, composite reliability is regarded as a suitable measure as the constructs used in this study are reflective. However, the study used cronbach's alpha, a widely used conservative approach in assessing reliability. The cronbach alpha values are presented in Table 5.11.

5.7.1.2 Composite reliability

Composite reliability also measures the internal consistency reliability of the research instrument. It indicates the total actual score variance with the total score variance. Composite reliability and Cronbach's alpha are similar reliability measures. However, composite reliability is preferred in SEM analysis, whereas Cronbach alpha is used more in EFA. The composite reliability value should be above 0.70 (Hair 2010). A composite reliability score between 0.60 and 0.70 is also acceptable (Malhotra 2010). However, it is recommended that constructs have a value above 0.70, as lower values may influence the validity of the SEM results. The composite reliability values are presented in Table 5.11.

5.7.1.3 KMO and Bartlett's Test

Kaiser-Meyer-Olkin (KMO) is measured to check the sampling adequacy. KMO indicate the proportion of variance in the constructs due to other factors. This statistic is noteworthy as it shows the data's suitability for factor analysis. A high KMO value (0.50-1.0) indicates that the data is suitable for factor analysis. However, a KMO value below 0.50 is not recommended (Malhotra 2010). Bartlett's test of sphericity is another measure used to check the appropriateness of the data. It tests the hypothesis, wherein it examines the null hypothesis that the correlation matrix is an identity matrix. This means that the variables measured are unrelated and unsuitable for factor analysis. An

identity matrix consists of 1 as the diagonal item and 0 as off diagonal item. If Bartlett's test of sphericity results in a higher value, then the null hypothesis will be rejected, indicating the variables are correlated with each other and the correlation matrix is not an identity matrix (Malhotra 2010). This shows that the data is reliable and suitable for factor analysis. The results indicate the sample obtained a KMO value of 0.902 above the recommended threshold levels. Furthermore, the result of Bartlett's test of sphericity is .000, leading to the rejection of the null hypothesis; hence, it is found that the correlation matrix is not an identity matrix, indicating that the data is suitable for further analysis. The results of KMO and Bartlett's test of sphericity are presented in Table 5.10

Table 5.10:KMO & Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.902**
Bartlett's Test of Sphericity	Approx. Chi-Square	15261.683
	Df	741
	Sig.	.000

Source: Primary data

5.7.1.4 Factor Loadings

Factor loadings indicate the correlation between the item or factor with the variable. A factor loading estimate elucidates the variance explained by the variable on a particular factor. A high factor loading is a good sign as it suggests that the concerned variable has explained the item well. It is an essential prerequisite that the factors have loadings above 0.70 for good results. However, factors with loading estimates above 0.50 are also accepted (Hair 2010). Hence, the results indicate that the study obtained the required factor loadings above 0.50. Table 5.11 shows the factor loading estimates obtained by the items. All the items have attained suggested factor loadings (0.50 and above). The factor loading estimates range from 0.521 to 0.817. The item SQ2 (system quality) obtained the lowest loading of 0.521, and the item SI2 (social influence) got the highest loading with 0.817. This indicates that the items have been able to extract the characteristics of the variable from the respondents. The reliability measures are comprised of Cronbach's alpha and composite reliability. All the constructs have attained the cronbach alpha ranging from 0.679 to 0.839 threshold levels (above 0.60).

The construct system quality has the lowest cronbach alpha (0.679), and the construct trust obtained the highest cronbach alpha (0.829). Likewise, the constructs have obtained composite reliability ranging from 0.701 to 0.841. The construct system quality attained the lowest composite reliability (0.701), whereas the construct trust got the highest composite reliability score (0.841). These results indicate that the constructs have attained good internal consistency reliability.

Table 5.11: Summary of factor loading estimates and reliability measures

Constructs	Items	Factor Loadings	Cronbach Alpha	Composite Reliability
Performance Expectancy (PE)	PE1	0.709	0.805	0.807
	PE2	0.765		
	PE3	0.710		
	PE4	0.676		
Effort Expectancy (EE)	EE1	0.674	0.774	0.777
	EE2	0.752		
	EE3	0.701		
	EE4	0.598		
Social Influence (SI)	SI1	0.743	0.813	0.816
	SI2	0.817		
	SI3	0.755		
Facilitating Condition (FC)	FC1	0.734	0.765	0.768
	FC2	0.733		
	FC3	0.679		
	FC4	0.539		
Hedonic Motivation (HM)	HM1	0.708	0.743	0.75
	HM2	0.759		
	HM3	0.653		
Personal Innovativeness (PI)	PI3	0.792	0.771	0.777
	PI4	0.796		
	PI5	0.603		
Information Quality (IQ)	IQ1	0.704	0.783	0.788
	IQ2	0.654		
	IQ3	0.671		
	IQ4	0.746		
System Quality (SQ)	SQ2	0.521	0.679	0.701
	SQ3	0.708		
	SQ4	0.742		
Privacy Risk (PR)	PR1	0.657	0.819	0.82
	PR2	0.758		
	PR3	0.791		
	PR4	0.711		
Trust (TR)	TR1	0.782	0.839	0.841
	TR2	0.802		

	TR3	0.771		
	TR4	0.661		
Behavioural Intention (BI)	BI1	0.670	0.749	0.758
	BI2	0.779		
	BI3	0.691		

Source: Primary data

5.7.2 Validity Analysis

Validity indicates the degree to which the survey instrument has measured what it was projected to measure. It is more focused on achieving accuracy in measurement. The validity of the research instrument is assessed using content validity, convergent validity and discriminant validity. The following sections discuss the validity measures adopted.

5.7.2.1 Content Validity

Content validity, also known as face validity, is a measure adopted to check the accuracy of the prepared research instrument (Malhotra 2010). The survey instrument is designed by adapting the prior literature studies, which have changed to suit the needs of the study. Hence, checking content validity will examine whether the items considered in the survey instrument can explain the construct in the best possible way. Content validity is the subjective measurement of the research instrument; hence, this research has consulted experts in academics and industries for expert opinions. The research instrument was given to the experts before the pilot study. Necessary changes were made to the questionnaire based on the expert's suggestions, and the research instrument was evaluated further for possible grammatical errors. A pilot study was conducted after revising research instruments. The content validity test is purely subjective; henceforth, constructive recommendations from experts and selected respondents play a significant role.

5.7.2.2 Convergent Validity

Items of the study need to correspond to the measured construct. Convergent validity measures how the items of the constructs adequately measure the constructs. It is the degree to which two or more items of the variables are correlated (Hair 2010). When convergent validity is high, it means that the indicators or items of the constructs are well correlated; hence, the items have measured the constructs in the way it is intended

to be measured. Factor loadings play a significant influence on convergent validity. Items of the construct with high factor loadings tend to converge to the intended concept. Likewise, low factor loadings of items result in poor convergent validity. Convergent validity is assessed by computing the Average Variance Extracted (AVE). AVE is "variance in the indicators or observed variables explained by the latent construct" (Malhotra 2010).

The AVE values should be more than 0.50 to establish convergent validity (Hair 2010). When AVE is more than 0.50, it can be implied that the variance due to measurement error is lower than the variance seized by the variable, which is a good indication. AVE is considered a strict measure in ascertaining the validity of the construct, which may be difficult in some circumstances. Hence, confirming the validity based on composite reliability is possible if the AVE values are below the recommended threshold levels (Malhotra 2010). However, constructs with low AVE values can be considered only when the corresponding constructs have composite reliability scores of 0.70 and above (Lam 2012). The convergent validity measures are presented in Table 5.12.

As per Table 5.12, all nine constructs possess the recommended threshold levels of average variance extracted. The remaining two constructs, information quality and system quality, obtained the AVE values below 0.50. A construct with low AVE values can be considered if the corresponding composite reliability is 0.70 and above (Lam 2012). Hence, the information quality and system quality constructs were considered for further analysis as they do not pose any convergent validity issues.

Table 5.12: Measures of average variance extracted (AVE Values) with composite reliabilities

Construct	Average variance extracted	Composite reliability
Performance Expectancy	0.512	0.807
Effort Expectancy	0.467	0.777
Social Influence	0.597	0.816
Facilitating conditions	0.457	0.768
Hedonic motivation	0.502	0.750
Personal innovativeness	0.541	0.777
Information quality	0.482	0.788
System quality	0.443	0.701
Privacy risk	0.534	0.820
Trust	0.571	0.841
Behavioural intention	0.511	0.758

Source: Primary data

5.7.2.3 Discriminant Validity

Discriminant validity measures the degree to which one construct is different or not related to other constructs of the study (Malhotra 2010). It indicates the lack of correlation among the other constructs. Discriminant validity of constructs can be measured by checking the cross-loadings and evaluating the square root of the average variance extracted of the constructs. The cross-loadings of the constructs are presented in Table 5.12. The discriminant validity is assessed by checking the factor loadings of the constructs with their cross-loadings on other constructs. A construct is said to be different from other constructs when the factor loadings of the items are higher than the cross-loadings on other items. The results show that the items are well-loaded on their respective components, and the cross-loadings are comparatively lower. The factor loadings are denoted in bold and italics in Table 5.13. Hence, based on the assessment of factor loadings and cross-loadings, it can be inferred that the constructs have attained discriminant validity.

The study also evaluated the square root of average variance extracted, known as the Fornell-Larcker criteria (Fornell and Larcker 1981), for discriminant validity assessment. The Fornell-Larcker criteria are the most widely used approach in checking the discriminant validity. This approach evaluates the discriminant validity by comparing the AVE of two variables to the shared variance between the two variables (Malhotra 2010). Hence, discriminant validity is established when the square root of AVE is higher than the correlation estimates with other variables. The results of the Fornell-Larcker criteria are presented in Table 5.14. The square root of AVE is denoted in bold and is indicated diagonally in the table. Thus, the results of the Fornell-Larcker criteria indicate that each construct is well-defined and different from the construct; hence, discriminant validity is established.

Table 5.13: Cross loadings of constructs

Rotated Component Matrix

	Component										
	TR	PR	PE	IQ	EE	FC	PI	SI	HM	BI	SQ
TR3	***.813***	-.116	.079	.149	.078	.068	.128	.087	.053	.113	.047
TR2	***.738***	-.166	.092	.210	.059	.032	.180	.134	.029	.144	.104
TR1	***.679***	-.177	.128	.214	.076	.070	.186	.129	-.002	.189	.115
TR4	***.636***	-.108	.127	.173	.074	.108	.048	.115	.105	.222	.070
PR3	-.088	***.827***	.008	.002	.007	.022	-.109	-.015	.017	-.043	-.011
PR2	-.110	***.797***	.003	-.008	.005	.082	-.097	-.005	.082	.012	.054
PR4	-.148	***.786***	-.026	.031	.036	-.001	-.029	-.037	.006	-.019	-.033
PR1	-.048	***.765***	.008	-.092	-.009	.088	.083	-.007	.062	-.039	.024
PE2	.037	.017	***.782***	.117	.064	.102	.016	.129	.083	.153	.044
PE1	.002	-.005	***.763***	.034	.107	.063	.082	.054	.152	.143	.066
PE3	.167	.001	***.742***	.063	.086	.021	.078	.180	.059	.033	.065
PE4	.142	-.023	***.721***	.069	.063	-.022	.034	.185	.055	.074	.098
IQ4	.158	.013	.063	***.738***	.124	.105	.155	.024	.040	.115	.179
IQ3	.140	.009	.071	***.728***	.065	.067	.162	.085	.132	.102	.032
IQ2	.174	.005	.056	***.689***	.163	.172	.009	.093	.066	.034	.120
IQ1	.216	-.125	.131	***.673***	.066	.108	.097	.125	.031	.163	.096
EE3	.029	-.013	.074	.072	***.782***	.085	.034	.021	.099	.072	.040
EE2	.096	.013	.032	.102	***.768***	.126	.042	.075	.131	.076	.071
EE1	.104	.034	.137	.091	***.740***	.152	-.018	.034	.092	.001	.019
EE4	.012	.005	.074	.110	***.635***	.085	.248	.094	.072	.098	.125
FC1	.007	.036	.019	.054	.102	***.776***	.111	-.014	.170	.047	.100
FC3	.023	.091	.079	.129	.080	***.751***	.068	.094	.093	.022	.009
FC2	.079	.070	-.009	.052	.193	***.720***	.241	-.010	.142	.035	.016

FC4	.139	.017	.066	.172	.104	***.659***	-.120	.068	-.009	.136	.059
PI4	.141	-.045	.035	.090	.088	.083	***.816***	.137	.042	.020	.033
PI3	.148	-.053	.071	.159	.067	.130	***.773***	.135	.007	.051	.029
PI5	.129	-.056	.084	.107	.077	.036	***.711***	.044	.083	.111	.032
SI2	.131	-.033	.158	.083	.091	.027	.124	***.838***	.058	.055	.009
SI3	.130	-.019	.217	.087	.031	.065	.024	***.793***	.078	.107	.076
SI1	.124	-.019	.187	.127	.096	.051	.202	***.752***	.032	.048	.067
HM2	.055	.053	.103	.080	.134	.146	-.005	.058	***.822***	.085	.103
HM1	.002	.061	.120	.034	.177	.127	.084	.054	***.796***	.067	.055
HM3	.145	.098	.161	.182	.118	.144	.092	.069	***.593***	.216	.133
BI1	.130	.011	.139	.117	.132	.125	.033	.039	.103	***.782***	.101
BI2	.253	-.060	.170	.166	.072	.061	.021	.114	.148	***.729***	.117
BI3	.283	-.084	.163	.132	.062	.065	.226	.097	.107	***.627***	.059
SQ3	.087	.072	.140	.090	.101	.045	.017	.046	.095	.105	***.817***
SQ4	.051	-.036	.127	.152	.089	.110	-.001	.049	.128	.134	***.795***
SQ2	.356	-.005	-.012	.276	.076	.033	.173	.087	.048	-.010	***.505***

Note: PE- Performance expectancy, EE-Effort expectancy, SI-Social influence, PI-Personal innovativeness, HM-Hedonic motivation, FC-Facilitating conditions, IQ-Information quality, SQ-System quality, TR-Trust, PR-Privacy risk, BI-Behavioural intention

Source: Primary data

Table 5.14: Fornell-Larcker criteria

	TR	PR	PE	IQ	EE	FC	PI	SI	HM	BI	SQ
TR	***0.756***										
PR	-0.348***	***0.731***									
PE	0.380***	-0.020	***0.716***								
IQ	0.642***	-0.087*	0.359***	***0.694***							
EE	0.311***	0.023	0.327***	0.421***	***0.684***						
FC	0.267***	0.140***	0.217***	0.418***	0.452***	***0.676***					
PI	0.496***	-0.162***	0.256***	0.449***	0.300***	0.337***	***0.736***				
SI	0.457***	-0.086*	0.527***	0.391***	0.285***	0.203***	0.405***	***0.773***			
HM	0.280***	0.151***	0.423***	0.387***	0.486***	0.486***	0.247***	0.289***	***0.708***		
BI	0.666***	-0.140***	0.518***	0.558***	0.367***	0.332***	0.352***	0.395***	0.498***	***0.715***	
SQ	0.448***	0.008	0.380***	0.548***	0.362***	0.302***	0.241***	0.290***	0.447***	0.481***	***0.664***

Note:

PE- Performance expectancy, EE-Effort expectancy, SI-Social influence, PI-Personal innovativeness, HM-Hedonic motivation, FC-Facilitating conditions, IQ-Information quality, SQ-System quality, TR-Trust, PR-Privacy risk,

BI-Behavioural intention

Source: Primary data

5.7.3 Common Method Bias

The research study used a survey questionnaire for data collection. This single survey questionnaire measures both independent and dependent variables together, which can lead to biases in the data. This issue is termed as common method bias. The problem of common method bias was identified by Campbell and Fiske (1959). When a single instrument is used for data collection, there is a high chance that the estimates of two or more constructs will be biased (Campbell and Fiske 1959). The presence of bias in the research data can lead to inaccurate variation in the findings. Furthermore, common method bias can adversely affect the validity measures and hypothesis testing, leading to inaccurate results (Podsakoff et al. 2003). Hence, it is essential to check the presence of common method bias before testing the proposed hypothesis. The common method bias was checked using Harman's one-factor test (Podsakoff et al. 2003).

5.7.3.1 Harman's one-factor test

Harman's one-factor test is the most widely used method proposed by Podsakoff et al. (2003) to check the presence of common method bias. This test checks common method bias through EFA procedures wherein all the items are extracted on one variable. The resulting total variance extracted by a single factor is evaluated. If the total variance extracted by the single factor exceeds 50 percent, then it is presumed the presence of common method bias (Podsakoff et al. 2003). Following the method, the study has performed EFA using principal component analysis with varimax rotation. Extracting a single factor is essential; hence, the number of factors to be extracted was set as 1. The Harman single factor test results indicate that the single factor extracted accounted for 22.529 percent, within the recommended threshold of less than 50 percent (Podsakoff et al. 2003).

5.7.4 Multicollinearity Tests

It is crucial to examine the relationship between two or more independent variables. Multicollinearity occurs when the data has two or more highly correlated predictors or independent variables (Kock and Lynn 2012). This poses challenges in data analysis as it creates difficulties in assessing the influence of predictor variables on dependent variables. Therefore, it is essential to identify the presence of multicollinearity as it can

adversely impact the model fit indices. The multicollinearity issue can be detected by computing the variance inflation factor (VIF). The VIF values should be less than 5, and the tolerance values should be above 0.20 or 0.10 (Hair 2010). Table 5.15 demonstrates the VIF values and tolerance values. The results indicate that the VIF and tolerance values have attained the recommended threshold levels. The trust reported the highest VIF value of 3.299; the lowest value was reported by privacy risk at 1.454. Further, privacy risk obtained the highest tolerance value of 0.688, and trust reported the lowest tolerance value of 0.303. Thus, the research data does not have any multicollinearity issues hence suitable for further analysis

Table 5.15:VIF & Tolerance values

Dependent variable	Independent variable	Collinearity Statistics	
		Tolerance	VIF
Behavioural intention	Performance Expectancy	0.501	1.995
	Effort Expectancy	0.547	1.830
	Social Influence	0.508	1.970
	Facilitating conditions	0.512	1.953
	Hedonic Motivation	0.428	2.337
	Personal Innovativeness	0.559	1.789
	Information Quality	0.307	3.261
	System Quality	0.457	2.186
	Privacy risk	0.688	1.454
	Trust	0.303	3.299

Source: Primary data

5.7.5 Confirmatory Factor Analysis (CFA)

The measurement model consists of all exogenous constructs irrespective of their actual nature (dependent or independent) without any structural relationships among them. The measurement model is validated through confirmatory factor analysis (CFA) (Malhotra 2010). CFA verifies the factor structure obtained in the EFA procedure. It is used in a measurement model to indicate which item represents the measured variable.

It also evaluates whether the number of variables and the loadings of the concerned indicators or factors confirm the theoretical aspect of the study. Furthermore, it validates how the items taken to measure the constructs are consistent with the actual construct taken from the theory. The CFA technique also checks the fit of the research data with the measurement model. Hence, it is considered more appropriate than performing EFA (Mueller and Hancock 2001). The pattern matrix obtained in the EFA iteration process was used through the pattern matrix plugin in IBM AMOS software to develop the path diagram for the measurement model. The ovals or circles indicate the constructs or variables of the study, and the measured variables or observed variables specify the items or indicators of the constructs represented as rectangles (Hair 2010). The correlation between the constructs is defined through curved arrows connecting with each of the constructs. While evaluating the CFA results, it is essential to check the item-wise loadings to the construct and the model fit of the measurement model.

5.7.5.1 Item-wise Loadings

Factor loadings indicate the item's capacity to explain the study's variable or construct. Each factor of the variable should have factor loadings of 0.50 and above (Hair 2010). However, any indicator with a factor loading of less than 0.50 must be removed from further analysis. The results obtained through validation of the measurement model using the CFA technique confirmed that all the indicators of the respective variables have obtained the recommended threshold levels for the factor loadings. The study has not removed any indicator, as it attained adequate factor loadings. The item SI2, belonging to the social influence variable, obtained the highest loading with a value of 0.817, whereas the item SQ2 of the system quality variable obtained the lowest loading with 0.521. Therefore, the results indicate that the items have successfully obtained the recommended threshold values. The indicators with factor loadings are presented in Table 5.16.

Table 5.16: Factor loading estimates

Constructs	Items	Factor Loadings
Performance Expectancy (PE)	PE1	0.709
	PE2	0.765
	PE3	0.710
	PE4	0.676

Effort Expectancy (EE)	EE1	0.674
	EE2	0.752
	EE3	0.701
	EE4	0.598
Social Influence (SI)	SI1	0.743
	SI2	0.817
	SI3	0.755
Facilitating Condition (FC)	FC1	0.734
	FC2	0.733
	FC3	0.679
	FC4	0.539
Hedonic Motivation (HM)	HM1	0.708
	HM2	0.759
	HM3	0.653
Personal Innovativeness (PI)	PI3	0.792
	PI4	0.796
	PI5	0.603
Information Quality (IQ)	IQ1	0.704
	IQ2	0.654
	IQ3	0.671
	IQ4	0.746
System Quality (SQ)	SQ2	0.521
	SQ3	0.708
	SQ4	0.742
Privacy Risk (PR)	PR1	0.657
	PR2	0.758
	PR3	0.791
	PR4	0.711
Trust (TR)	TR1	0.782
	TR2	0.802
	TR3	0.771
	TR4	0.661
Behavioural Intention (BI)	BI1	0.670
	BI2	0.779
	BI3	0.691

Source: Primary data

5.7.5.2 Assessment of Goodness of Fit of Measurement Model

With the evaluation of the factor loadings, the next step is to assess the goodness of fit of the measurement model. The goodness of fit is an essential criterion of any research model. The similarity of the estimated covariance matrix to the observed covariance matrix indicates the model fit of the measurement model. The estimated covariance matrix represents the theory, and the observed covariance matrix suggests the study's research data (Malhotra 2010). The research model obtains goodness of fit when the

value of the estimated covariance matrix (theory) and observed covariance matrix (actual data) is close to the matrix values. The model fit is assessed using absolute fit indices, incremental fit indices, and parsimony fit indices. Normed Chi-Square is calculated by taking the chi-square to the model's degrees of freedom. The recommended normed Chi-square value for a good model fit is less than 3; however, a value less than 5 is also acceptable. Absolute fit indices measure goodness of fit and badness of fit measures. It evaluates each model independently of others, indicating the degree to which the research data fit with the theory adopted, reflecting goodness of fit (Hair 2010).

The goodness of fit measures consists of GFI (Goodness-of-fit index) and AGFI (Adjusted goodness-of-fit index). The GFI examines the data's degree of variance and covariance, which the hypothesized model describes. The recommended GFI value ranges from 0 to 1, wherein a high value indicates a better model fit. GFI value above 0.90 is the recommended threshold level (Hair 2010). AGFI consider the degrees of freedom in the model. Hair (2010) suggested an AGFI value of 0.90 and above, representing a good model fit. In contrast to GFI, Badness-of-fit indices indicate the deviation. The badness of fit indices consists of $\chi 2$, Standardized root mean square residual (SRMR), and Root mean square error of approximation (RMSEA). Standardized root mean square residual (SRMR) is the standardized value of the root mean square residual. SRMR is computed by dividing the fitted residuals by the residual standard error. It aids with the comparison of fit among different models. A lower SRMR indicates a good model. Dash and Paul (2021) suggested any SRMR should be below 0.05 to demonstrate a good model fit. However, an SRMR value up to 0.08 is also accepted.

Steiger and Lind (1980) conceptualised the Root mean square error of approximation (RMSEA). This measure evaluates how well the proposed model fits with the study population rather than the sample (Steiger and Lind 1980). RMSEA estimates the difference between the actual and the predicted covariance, representing the square root of the mean of the squared residuals. Hence, RMSEA checks how much difference exists between the hypothesised and perfect models. When the difference is low, it

indicates a perfect fit; therefore, it is recommended that the RMSEA value should be 0.07 or less to demonstrate a good model fit (Dash and Paul 2021).

Incremental fit indices consist of measures which check how well the estimated research model fits with the baseline model or the null model. The null model follows the assumption wherein all observed variables are uncorrelated. The most commonly used measures in incremental fit indices are the Tucker-Lewis Index (TLI) and the Comparative Fit Index (CFI) (Hair 2010). TLI evaluates the proposed research model to a model with no interrelationships among any items. It compares the normed chi-square values of the proposed model and the null model. TLI is also the non-normed fit index (NNFI) (Bentler 1990). The proposed model fits well if the TLI is close to one. Hair (2010) suggested a TLI value of 0.90 and above, which indicates a good model fit. Comparative Fit Index (CFI) is another measure under incremental fit indices that compares the proposed model fit with the null or independent model. CFI focus mainly on the latent factors or variables of the study rather than the items or indicators. Hair (2010) suggested a CFI value of 0.90 and above to attain a good model fit. Furthermore, CFI is least influenced by the sample size of the research data and the model complexity; hence, it is recommended as a widely used index (Fan et al. 1999; Hair 2010).

Parsimony fit indices consist of measures which give information on the best model among the competing models based on its fit relative to the complexity of other models (Hair 2010). The parsimony goodness-of-fit index (PGFI) estimates the goodness of fit based on the ratio between degrees of freedom used by the proposed model and the total degrees of freedom available. The parsimony fit indices comprise the goodness-of-fit (PGFI) and the normed fit Index (PNFI). While evaluating the model fit measures, it is recommended to report at least one of the measures in absolute fit indices and incremental fit indices along with the chi-square value with degrees of freedom (Hair 2010). Hence, this study has evaluated the model fit measures, namely GFI, AGFI, chi-square, SRMR, RMSEA, CFI and TLI. The results of the model fit indices indicate that the measurement model has obtained the recommended threshold levels. The results of the measurement model fit are presented in Table 5.17. Figure 5.1 shows the measurement model with factor loading estimates.

The present data has computed EFA to confirm the accuracy of the items taken for the research instrument. With the EFA results, the measurement model was formed using the pattern matrix model builder plugin in AMOS software. Further, the validity and reliability measures of the data were evaluated. The results indicated that the research data had obtained the recommended validity and reliability levels. In addition to these tests, the study has also conducted tests to identify the presence of common method bias and multicollinearity. Hence, the measurement model was further validated using confirmatory factor analysis. The results indicate that the model has attained the recommended goodness of fit indices and is, therefore, suitable for further structural model assessment analysis.

Table 5.17: Goodness-of-Fit Statistics of measurement model

Type	Index	Ideal Threshold Levels	Measurement Model Values
Absolute Fit Indices	Chi-square of the estimated model	p-value >0.05	.000
	Normed chi-square CMIN/df	< 3 or < 5	2.133
	Goodness of fit index (GFI)	>0.90 or >0.95	0.933
	Root Mean Square Error of Approximation (RMSEA)	<0.08	0.033
	Standardized Root Mean Residual (SRMR)	<0.05 or < 0.08	0.0421
	Adjusted Goodness of Fit Index (AGFI)	>0.90 or >0.95	0.919
Incremental Fit Indices	Tucker Lewis Index (TLI)	>0.90	0.943
	Comparative Fit Index (CFI)	>0.90	0.950

Source: Primary data

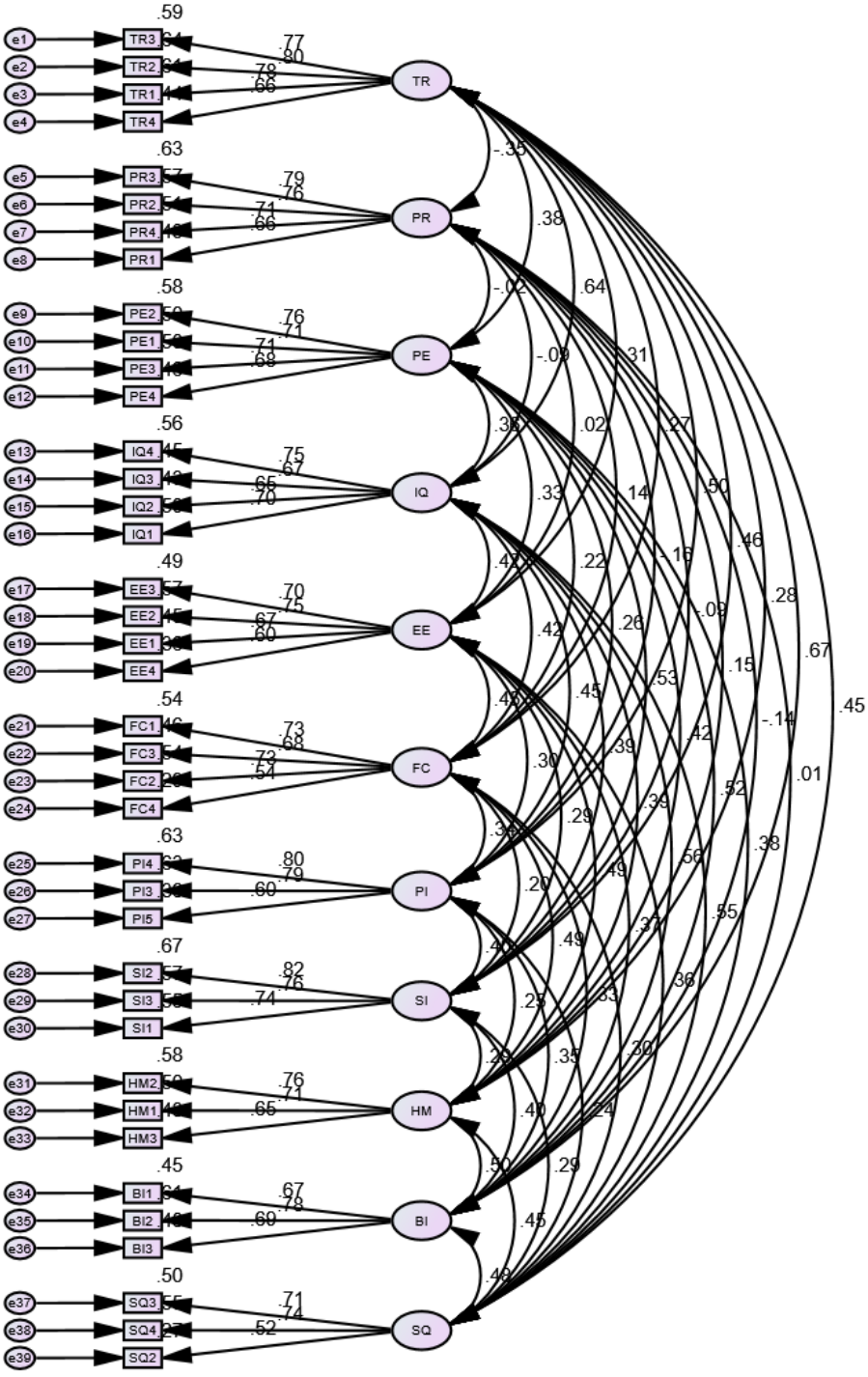

Figure 5.1: Measurement model
Source: Primary data

5.8 ASSESSMENT OF STRUCTURAL MODEL

The measurement model has obtained acceptable threshold levels of validity, reliability and model fit indices. Hence, the next phase involves the assessment of the structural model. The structural model indicates the path analysis connecting the independent and dependent variables. Path analysis estimates the strength of the relationship between the independent variables (exogenous variables) and dependent variables (endogenous variables). An arrow is drawn from one variable to another to indicate the proposed hypothesis in the study (Hair 2010). The structural model consists of variables and the items taken to measure the variables. The ovals or circles represent the variable of the study, whereas the squares indicate the items brought to measure the variable. Curved arrows represent the correlational relationship between the independent or exogenous variables. The structural model assessment of the research model is performed by computing the following tests.

i. Performing the path analysis to assess the proposed hypothesis
ii. Examining the coefficient of determination (R^2)
iii. Assessing the model fit indices to determine the goodness of fit of the proposed research model.

Each proposed hypothesis of the study is assessed through the path analysis, which is further examined with the prior research studies. The standardised path coefficient or beta coefficient indicates the strength of the relationship between the independent and dependent variables. The beta coefficient can be interpreted as small, medium and large effects. The beta coefficient with absolute values less than 0.10 indicates a small effect, 0.30 indicates a medium effect, and 0.50 indicates a large effect (Kline 2004). The proposed hypothesis is accepted or rejected based on the critical ratio or P value. A hypothesis is accepted when the t-value is above 1.96 and the p-value is below 0.05 (5%). Likewise, the path analysis with a t-value of 2.576 and a p-value less than 0.01 (1%), a t-value of 3.291 and a p-value less than 0.001 (0.1%) are also accepted. The following sections examine the testing of the proposed hypothesis. Figure 5.2 indicates the model showing the results of SEM for direct paths (structural model assessment).

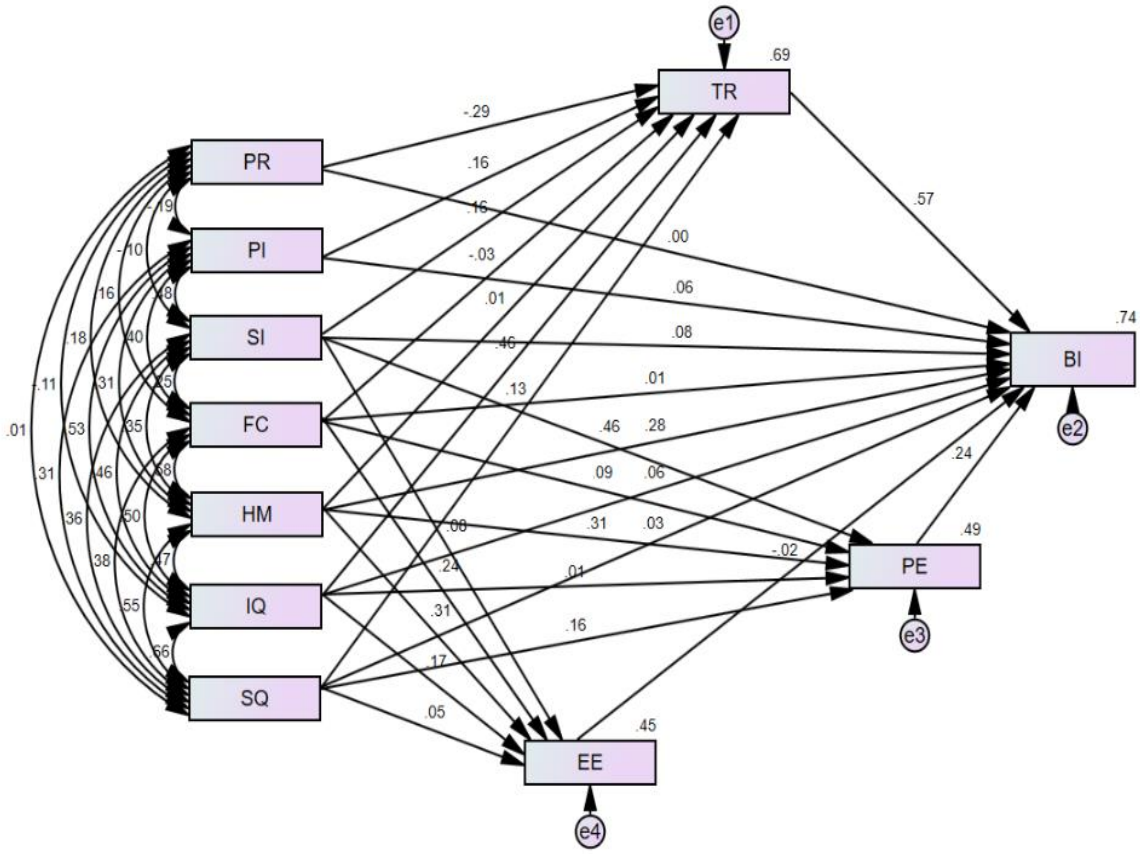

Figure 5.2: Model showing the results of SEM for direct paths (structural model assessment)
Source: Primary data

5.8.1 Path Analysis

Path analysis is used to investigate the relationships between independent variables and dependent variables. It examines the proposed hypothesis of the study, resulting in the acceptance or rejection of the hypothesis based on p-value or critical value. The following sections describe the hypothesis testing results with the supporting literature studies.

5.8.1.1 Effect of Performance Expectancy (PE) on Behavioural Intention (BI)

This hypothesis discusses the effect of performance expectancy on behavioural intention (Table 5.18)

Table 5.18: Hypothesis testing: The effect of PE on BI

Hypothesized paths	Direction	Beta (β) estimate	Critical Ratio	Decision
H_1:PE → BI	+	0.243***	10.785	Supported

Source: Primary data

Performance expectancy has prognosticated the user behavioural intention (β=0.243, p-value < .001). Therefore, hypothesis 1 is supported. Prior research has found performance expectancy to be a critical predictor of user behavioural intention towards accepting a new technology (Abed 2021; Jajic et al. 2022). Thus, it can be concluded from hypothesis H_1 that performance expectancy significantly influences users' behavioural intention towards adopting AR technologies in e-commerce apps.

5.8.1.2 Effect of Effort Expectancy (EE) on Behavioural Intention (BI)

Table 5.19 exhibits the results of hypothesis testing on the effect of effort expectancy on behavioural intention.

Table 5.19: Hypothesis testing: The effect of EE on BI

Hypothesized paths	Direction	Beta (β) estimate	Critical Ratio	Decision
H_2: EE → BI	+	-0.025	-1.147	Rejected

Source: Primary data

This hypothesis examines the influence of effort expectancy on the user behavioural intention (β=¯0.025, p-value =0.251). However, the results indicate effort expectancy as an insignificant predictor of user behavioural intention. These results aligned with prior studies (Paulo et al. 2018; Saprikis et al. 2021), which reported the trivial role of effort expectancy towards adopting AR technology in e-commerce apps. Hence, the proposed hypothesis is rejected.

5.8.1.3 Effect of Trust (TR) on Behavioural Intention (BI)

Table 5.20 exhibits the results of hypothesis testing on the effect of trust on behavioural intention.

Table 5.20: Hypothesis testing: The effect of TR on BI

Hypothesized paths	Direction	Beta (β) estimate	Critical Ratio	Decision
H_3: TR → BI	+	0.575***	19.845	Supported

Source: Primary data

The hypothesis results indicate that trust significantly predicts the user behavioural intention (β=0.575, p-value < .001). Hence, the proposed hypothesis is accepted. These results were in line with prior studies, which have proved the significant role of trust in users' behavioural intentions (Kang et al. 2023; Li et al. 2022). Thus, it can be concluded that trust is an essential predictor in influencing the user's adoption intention.

5.8.1.4 Effect of Social Influence (SI) on Behavioural Intention (BI)

The results of the proposed hypothesis examining the impact of social influence on behavioural intention are presented in Table 5.21

Table 5.21: Hypothesis testing: The effect of SI on BI

Hypothesized paths	Direction	Beta (β) estimate	Critical Ratio	Decision
H_4: SI → BI	+	0.076	3.379***	Supported

Source: Primary data

The proposed hypothesis (H_4) investigated the impact of social influence on user behavioural intention and was found to be significant (β=0.076, p-value < .001). These results are validated by prior research findings, which have found social influence to significantly predict user behavioral intention (Abed 2021; Faqih 2022). Thus, it can be presumed that the role of peer groups and friends is a significant predictor in influencing the user's choice towards using AR features in e-commerce apps.

5.8.1.5 Effect of Facilitating Conditions (FC) on Behavioural Intention (BI)

Table 5.22 indicates the hypothesis testing results examining the influence of facilitating conditions on behavioural intentions.

Table 5.22: Hypothesis testing: The effect of FC on BI

Hypothesized paths	Direction	Beta (β) estimate	Critical Ratio	Decision
H_5: FC→ BI	+	0.007	0.296	Rejected

Source: Primary data

The proposed hypothesis examines the impact of facilitating conditions on user behavioural intention towards adopting AR technologies in e-commerce apps. The results indicate facilitating conditions as an insignificant predictor influencing the user behavioural intention (β=0.007, p-value = 0.767). These results aligned with previous studies (Mutterlein et al. 2019; Saprikis et al. 2021) that highlighted the insignificant role of facilitating conditions. Hence, the proposed hypothesis is rejected, indicating the trivial role of supporting systems and resources.

5.8.1.6 Effect of Hedonic Motivation (HM) on Behavioural Intention (BI)

Hypothesis H_6 examines the role of hedonic motivation on user behavioural intention.

Table 5.23: Hypothesis testing: The effect of HM on BI

Hypothesized paths	Direction	Beta (β) estimate	Critical Ratio	Decision
H_6: HM→ BI	+	0.283***	11.548	Supported

Source: Primary data

Table 5.23 indicates the hypothesis testing results investigating the influence of hedonic motivation on behavioural intention. The results indicate hedonic motivation as a significant predictor of behavioural intention (β=0.283, p-value < .001). These results align with the findings of prior research investigations suggesting hedonic motivation as a substantial factor (Abed 2021; Jajic et al. 2022). Hence, based on the hypothesis testing result, it can be inferred that hedonic motivation significantly influences the user's behavioural intention towards using AR technologies in e-commerce apps.

5.8.1.7 Effect of Personal Innovativeness (PI) on Behavioural Intention (BI)

Table 5.24 indicates the examination of personal innovativeness on user behavioural intention.

Table 5.24: Hypothesis testing: The effect of PI on BI

Hypothesized paths	Direction	Beta (β) estimate	Critical Ratio	Decision
H_7: PI→ BI	+	0.06**	2.789	Supported

Source: Primary data

The results of Table 5.24 indicate the hypothesis testing results which demonstrate the significant influence of personal innovativeness on user behavioural intention (β=0.060, p-value = p-value < .01). These results confirm the prior research findings, which identified a significant role of personal innovativeness on influencing the users' behavioural intention towards adopting a technology (Abed 2021; Faqih 2022). Hence, it can be encapsulated that personal innovativeness is a significant predictor influencing users' behavioural intention towards using a technology.

5.8.1.8 Effect of Information Quality (IQ) on Behavioural Intention (BI)

This hypothesis investigates the influence of information quality on users' behavioral intention.

Table 5.25: Hypothesis testing: The effect of IQ on BI

Hypothesized paths	Direction	Beta (β) estimate	Critical Ratio	Decision
H_8: IQ→ BI	+	0.063*	2.19	Supported

Source: Primary data

Table 5.25 indicates the hypothesis suggesting that information quality significantly predicts user behavioural intention (β=0.063, p-value < 0.05). These results align with the studies (Chiu et al. 2021; Oyman et al. 2022). Henceforth, it can be summed up that the information quality of AR technology significantly influences the users' decisions.

5.8.1.9 Effect of System quality (SQ) on Behavioural Intention (BI)

Hypothesis H_9 examines the role of system quality on a user's behavioral intention towards a technology.

Table 5.26: Hypothesis testing: The effect of SQ on BI

Hypothesized paths	Direction	Beta (β) estimate	Critical Ratio	Decision
H_9: SQ→ BI	+	0.034	1.427	Rejected

Source: Primary data

Table 5.26 indicates the results of hypothesis testing. The results show that system quality does not influence the user's behavioural intention (β=0.034, p-value < 0.154). These results concur with prior studies on mobile commerce adoption in Oman (Chan et al. 2022; Tarhini et al. 2019). Hence, it can be concluded that system quality is not a significant predictor of user behavioral intention.

5.8.1.10 Effect of privacy risk (PR) on Behavioural Intention (BI)

This hypothesis investigates the influence of privacy risk on behavioral intention presented in Table 5.27

Table 5.27: Hypothesis testing: The effect of PR on BI

Hypothesized paths	Direction	Beta (β) estimate	Critical Ratio	Decision
H_{10}: PR→ BI	-	0.001	0.071	Rejected

Source: Primary data

The results of Table 5.27 suggest that the privacy risk does not negatively influence the users' behavioral intention (β=0.001, p-value=0.943). These results align with the prior research findings (Rauschnabel et al. 2017; Vimalkumar et al. 2021), highlighting the absence of the negative influence of privacy risk of technology on user behavioural intention. Hence, it can be inferred that the negative influence of privacy risk does not influence the user's behavioural intention towards any technology.

The hypothesis testing results of direct effects are presented in Table 5.28

Table 5.28: Summary of the hypothesis testing results to direct paths

Hypothesised Path	Std Estimate	C.R.	P value	Result
H_1:PE --> BI	0.243	10.785	***	Supported
H_2: EE --> BI	-0.025	-1.147	0.251	Not supported
H_3: TR --> BI	0.575	19.845	***	Supported
H_4: SI--> BI	0.076	3.379	***	Supported
H_5: FC --> BI	0.007	0.296	0.767	Not supported
H_6: HM--> BI	0.283	11.548	***	Supported
H_7: PI--> BI	0.06	2.789	0.005**	Supported
H_8: IQ--> BI	0.063	2.19	0.029*	Supported
H_9: SQ--> BI	0.034	1.427	0.154	Not supported

H_{10}:PR--> BI	0.001	0.071	0.943	Not supported

Note:

Significance level - *p<0.05 (5%) t value > 1.96; **p<0.01 (1%) t value >2.576; ***p<0.001 (0.1%) t value >3.291

Source: Primary data

5.8.2 Coefficient of determination (R^2)

The coefficient of determination (R^2) is a measure which assesses the predictive power of the structural model. It explains the proportion of variance the independent variable explains on a dependent variable (Hair 2010). R^2 is computed considering the squared correlation between the actual and predicted values of the outcome variable. The coefficient of determination ranges from 0 to 1. A higher R^2 shows the model's high explanatory power, indicating that the proposed model is good. The model's explanatory power is classified as weak, moderate and substantial. Hair (2010) suggested that R^2 values of 0.25, 0.50, and 0.75 indicate the model's weak, moderate, and substantial explanatory power. Furthermore, R^2 values of 0.10 are also accepted in some research studies (Hair Jr et al. 2021). The number of predictors in the research model highly influences the R^2 value. Therefore, the R^2 value increases with the increase in the number of variables; henceforth, the model's explanatory power should be interpreted based on the complexity of the research (Hair Jr et al. 2021). This research has examined the coefficient of determination (R^2).

Firstly, the structural model with variables PE, EE, SI, FC, HM, and PI on BI resulted in 0.52 (52%), indicating the model's explanatory power with moderate influence. In addition, the model was extended to include trust, privacy risk, and information quality. The constructs of trust, performance expectancy and effort expectancy were considered as mediators in the research. Including new constructs has increased the explanatory power from 0.52(52%) to 0.74 (74%) on BI, indicating moderate explanatory power. The model's explanatory power has increased by 22%, which is remarkable. Furthermore, adding trust, performance expectancy and effort expectancy resulted in 0.69(69%), 0.49(49%) and 0.45(45%), which exhibited moderate explanatory power of the model. The coefficient of determination value of the proposed model has moderate

explanatory power in predicting the users' behavioural intention towards using AR technologies in e-commerce apps.

5.8.3 Goodness of Fit Indices

With the assessment of the structural model, the next phase is to check the model fit indices of the structural model. The goodness of fit of the research model is assessed by evaluating the estimated covariance matrix with the observed covariance matrix (Hair 2010). The research has evaluated the goodness of fit of the structural model through the Chi-square of the estimated model, Normed chi-square CMIN/df, Goodness of fit index (GFI), Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Residual (SRMR), Adjusted Goodness of Fit Index (AGFI), Tucker Lewis Index (TLI), Comparative Fit Index (CFI). The results of the goodness of fit indices of the structural model are presented in Table 5.29, indicating the attainment of the recommended model fit indices (Dash and Paul 2021; Hair 2010). Table 5.29 illustrates that the Chi-square value is .000, and the normed chi-square value CMIN/df is 2.814, within the acceptable limits. In addition, other measures such as GFI=0.997 and RMSEA=.042, SRMR=.0090, AGFI=0.968, TLI=0.984, and CFI=0.998 are within the threshold levels recommended in previous research studies.

Table 5.29: Goodness-of-Fit Statistics of Structural Model

Type	Index	Ideal Threshold Levels	Structural Model Values
Absolute Fit Indices	Chi-square of the estimated model	p-value >0.05	.000
	Normed chi-square CMIN/df	< 3 or < 5	2.814
	Goodness of fit index (GFI)	>0.90 or >0.95	.997
	Root Mean Square Error of Approximation (RMSEA)	<0.08	.042
	Standardized Root Mean Residual (SRMR)	<0.05 or < 0.08	.0090
	Adjusted Goodness of Fit Index (AGFI)	>0.90 or >0.95	.968

Incremental Fit Indices	Tucker Lewis Index (TLI)	>0.90	.984
	Comparative Fit Index (CFI)	>0.90	.998

Source: Primary data

5.9 MEDIATION ANALYSIS

Mediation analysis is a technique used to analyse the influence of variables between the independent and dependent variables. The mediation effect occurs when a variable other than the independent and dependent variables intervene in the relationship (Hair 2010). These variables are termed as mediators. When an independent variable affects a dependent variable, it is called a direct effect. Figure 5.3 indicates the direct model. In this direct model, *X* is the independent or exogenous variable, and *Y* is the dependent or endogenous variable. The arrow connecting from *X* to *Y* is ***a,*** which indicates the direct effect.

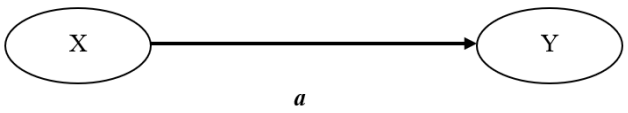

Figure 5.3: Direct model
Source: Secondary data

Mediation occurs when a variable intervenes in the relation between *X* and *Y* constructs. The presence of a mediating variable creates an indirect effect connecting the independent or exogenous variable to the dependent or endogenous variable. Figure 5.4 indicates a mediated model. Here, *X* is the independent variable, *Y* is the dependent variable, and *M* is the mediating variable. The direct effect of *X* on *Y* is denoted as ***a***. The impact of the independent variable *X* on a dependent variable *Y* with mediating variable *M* indicates the indirect effect, represented as ***c***; *X→M→Y*. The presence of a mediating variable in a structural model with good model fit indices indicates mediation's presence (Hair 2010).

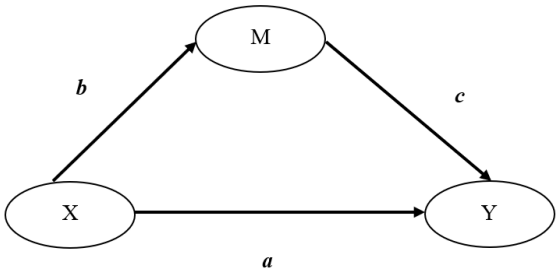

Figure 5.4: Mediated model
Source: Secondary data

The study followed the mediation approach developed by Zhao et al. (2010) using the bootstrapping approach. The mediation process is undertaken through a series of analysis. As per this approach, the first step is to check the indirect effect (***b.c),*** i.e., X→M→Y. If the indirect effect is insignificant, then it is concluded that M does not mediate the relation between the *X* (independent variable) and *Y* (dependent variable). If the direct effect (***a)*** is significant, but the indirect effect (***b.c)*** is insignificant, then there is only a direct effect (no mediation). Furthermore, If the direct effect (***a)*** and indirect effect (***b.c)*** are insignificant, then there is no effect (no mediation). These were the cases of mediation when the indirect effect was insignificant. When the indirect effect (***b.c)*** is significant, the next step is to check the significance of the direct effect (***a)***. If the indirect effect (***b.c)*** is significant and the direct effect (***a)*** is insignificant, then it indicates the presence of indirect only (full mediation).

Full mediation is a kind of mediation wherein the mediator (***M***) completely mediates the relation between X and Y. This means that the direct effect is insignificant without the mediator. In other cases, partial mediation occurs when the indirect effect ***(b.c)*** is significant, and the direct effect ***(a)*** is also significant. Partial mediation is a situation where the mediator mediates only a part of the effect on X→Y. Two kinds of partial mediation exist: Complementary and Competitive (Hair Jr et al. 2021; Zhao et al. 2010). Complementary mediation is a situation where both direct effect (***a)*** and indirect effect (***b.c)*** are positive. i.e., the product of both direct and indirect effects is positive. Conversely, suppose either direct effect ***(a)*** or indirect effect ***(b.c)*** have different signs; then, the product of direct and indirect effect will give negative results. This is a

situation of competitive mediation or inconsistent mediation. Here, the mediator acts as a suppressor effect, reducing the total impact of *X* on *Y*.

The mediation process is analysed using the bootstrapping procedure. Bootstrapping procedures do not follow any assumptions of sample distribution and are considered suitable even with a small sample size (Hair Jr et al. 2021). The bootstrapping procedure was performed in Amos 23.0 with 2,000 subsamples and a 95 percent confidence interval. The bias-corrected confidence intervals of the lower and upper bound must be checked along with the p-value. Suppose the bias-corrected confidence intervals do not include 0 with the same sign directions (i.e., either the upper and lower bound are positive or negative). In that case, the indirect effect is significant, indicating the presence of mediation (Hair Jr et al. 2021). Figure 5.5 shows the mediation analysis procedure adopted.

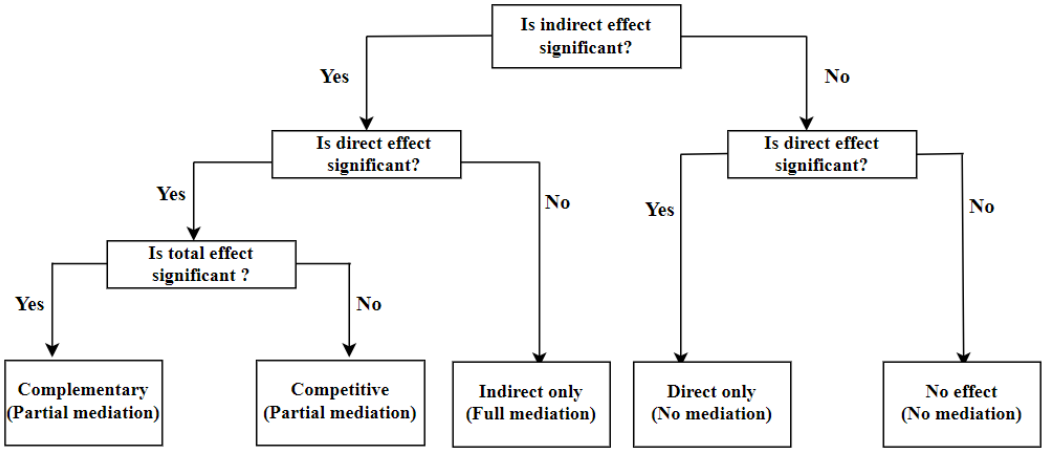

Figure 5.5: Mediation Analysis
Source: (Hair Jr et al. 2021; Zhao et al. 2010)

The study has investigated the role of performance expectancy, effort expectancy and trust as mediators in the proposed model using the mediation analysis. The mediating variables' role and impact on dependent variables are analysed. Following are the cases discussing the mediation paths.

5.9.1 Indirect Effect of Social Influence

The study has examined the indirect effect of social influence on behavioural intention through the mediator's performance expectancy, effort expectancy and trust. The results

indicated the significance of performance expectancy and trust as mediating variables between social influence and behavioural intention. These results confirm the previous research findings (Fagan 2019; Mostafa and Kasamani 2021). Thus, the hypothesis H4a and H4c are accepted (Figure 5.6 and Figure 5.8). However, effort expectancy did not mediate the relationship between social influence and behavioural intention, indicating the presence of only direct effect. These results aligned with the studies (Chen and Aklikokou 2020), showing the presence of a direct effect only. Hence, hypothesis H4b was rejected (Figure 5.7). Therefore, it can be concluded that performance expectancy and trust are crucial in influencing the indirect effect of social influence on behavioural intention. The results examining the indirect effect of social influence are presented in Table 5.30.

Table 5.30: Indirect effect of social influence

Direct without mediator

Parameter	Estimate	C.R.	P	Result
SI--> BI	0.076	3.379	***	S

Indirect with mediator

Parameter	Estimate	Lower CI	Upper CI	P Value	Result Indirect Path	Final Conclusion
SI --> PE --> BI	0.070	0.054	0.088	0.001	S	Complementary (Partial mediation)
SI --> EE --> BI	-0.001	-0.005	0.001	0.21	NS	Direct only (No mediation)
SI --> TR --> BI	0.057	0.041	0.075	0.001	S	Complementary (Partial mediation)

Source: Primary data

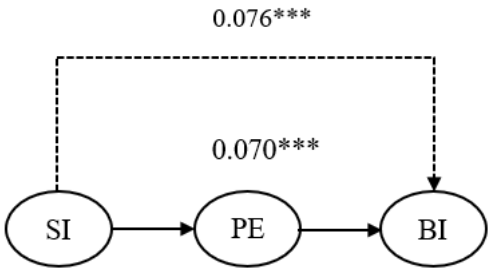

Figure5.6: Indirect effect of SI on BI through PE
Source: Primary data

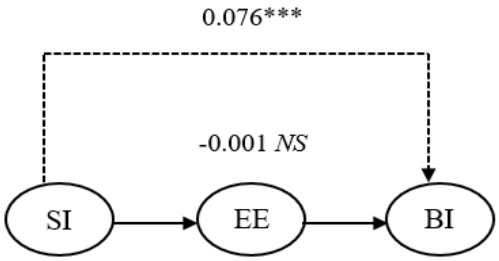

Figure 5.7: Indirect effect of SI on BI through EE
Source: Primary data

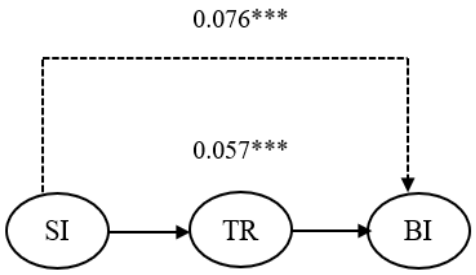

Figure 5.8: Indirect effect of SI on BI through TR
Source: Primary data

5.9.2 Indirect Effect of Facilitating Conditions

The indirect effect of facilitating conditions on behavioural intention in the presence of mediators, namely performance expectancy, effort expectancy and trust, was investigated in this study. The mediation results indicate the insignificant role of mediators in influencing the direct effect of facilitating conditions on behavioural intention. The mediation results of performance expectancy and effort expectancy align with the findings of prior studies (Sulaiman et al. 2023). Similarly, the indirect effect of facilitating conditions through trust was insignificant. These results contradict the previous research findings (Enaizan et al. 2020). Hence, the hypotheses H5a, H5b and H5c are rejected as there is no effect (no mediation). Table 5.31 and Figure 5.9-5.11 present the indirect effect of facilitating conditions.

Table 5.31: Indirect effect of facilitating conditions

Direct without mediator

Parameter	Estimate	C.R.	P	Result
FC--> BI	0.007	0.296	0.767	NS

Indirect with mediator

Parameter	Estimate	Lower CI	Upper CI	P value	Result Indirect Path	Final Conclusion
FC --> PE --> BI	-0.021	-0.037	-0.007	0.004	-0.021	No effect (No mediation)
FC --> EE --> BI	-0.005	-0.017	0.005	0.27	NS	No effect (No mediation)
FC --> TR --> BI	-0.014	-0.043	0.018	0.428	NS	No effect (No mediation)

Source: Primary data

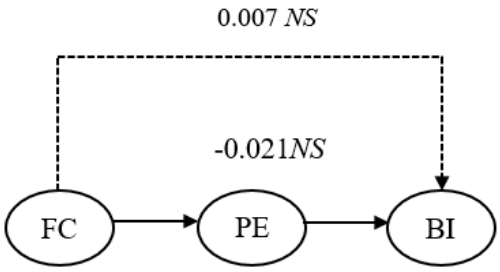

Figure 5.9: Indirect effect of FC on BI through PE
Source: Primary data

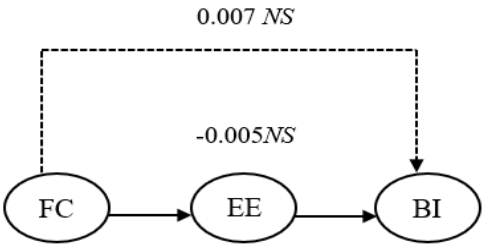

Figure 5. 10: Indirect effect of FC on BI through PE
Source: Primary data

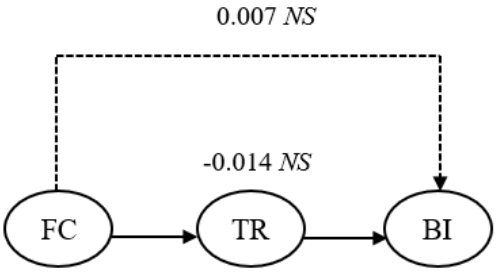

Figure 5.11: Indirect effect of FC on BI through TR
Source: Primary data

5.9.3 Indirect Effect of Hedonic Motivation

The research has investigated the indirect effect of hedonic motivation on user behavioural intention through the proposed mediators. The mediation results indicate that performance expectancy significantly influences the indirect impact of hedonic motivation on user behavioural intention. These results were in line with the prior studies of Fagan (2019), which reported the presence of full mediation. Hence the hypothesis H6a is accepted. On the contrary, effort expectancy and trust were found to be insignificant mediators on the influence of hedonic motivation on user behavioural intention. These agree with previous studies (Enaizan et al. 2020; Fagan 2019), rejecting the H6b and H6c hypotheses. The mediation results with effort expectancy and trust indicate the presence of direct effect only (no mediation). The results of the indirect effect are presented in Table 5.32 and illustrated in Figure 5.12-5.14.

Table 5.32: Indirect effect of hedonic motivation

Direct without mediator

Parameter	Estimate	C.R.	P	Result
HM--> BI	0.283	11.548	***	S

Indirect with mediator

Parameter	Estimate	Lower CI	Upper CI	P value	Result Indirect Path	Final Conclusion
HM --> PE --> BI	0.064	0.046	0.083	0.001	S	Complementary (Partial mediation)
HM --> EE --> BI	-0.007	-0.02	0.006	0.271	NS	Direct only (No mediation)
HM --> TR --> BI	0.005	-0.023	0.034	0.767	NS	Direct only (No mediation)

Source: Primary data

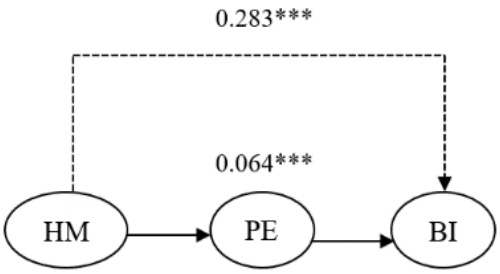

Figure 5.12: Indirect effect of HM on BI through PE
Source: Primary data

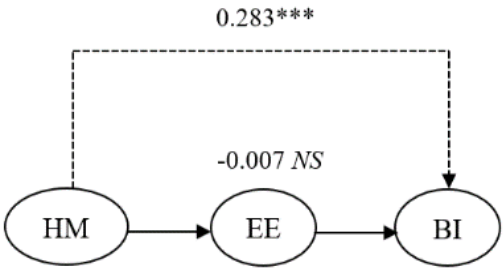

Figure 5.13: Indirect effect of HM on BI through EE
Source: Primary data

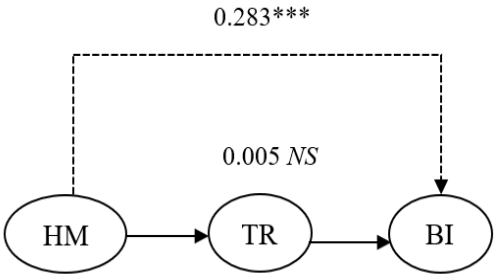

Figure 5.14: Indirect effect of HM on BI through TR
Source: Primary data

5.9.4 Indirect Effect of Personal Innovativeness

This research has analysed the indirect effect of personal innovativeness on user behavioural intention through trust. The mediation results indicate that trust is a significant mediator in the indirect influence of personal innovativeness on user behavioural intention. The mediation analysis found partial mediation (complementary) in the indirect effect (Figure 5.15). These results align with prior research investigations (Rouibah et al. 2016). However, these results contradict previous studies (Chan and Lee 2021). Hence the hypothesis H7a is accepted. Table 5.33 indicates the mediation results.

Table 5.33: Indirect effect of personal innovativeness

Direct without mediator

Parameter	Estimate	C.R.	P	Result
PI--> BI	0.060	2.789	0.005**	S

Indirect with mediator

Parameter	Estimate	Lower CI	Upper CI	P value	Result Indirect Path	Final Conclusion
PI --> TR --> BI	0.059	0.041	0.078	0.001	S	Complementary (Partial mediation)

Source: Primary data

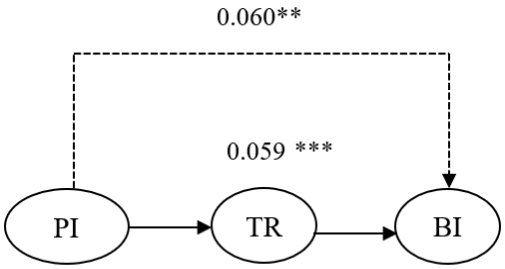

Figure 5.15: Indirect effect of PI on BI through TR
Source: Primary data

5.9.5 Indirect Effect of Information Quality

The research has investigated the indirect effect of information quality on user behavioural intention with the mediator's performance expectancy, effort expectancy and trust. The results indicate the presence of partial mediation (complementary mediation) in indirect effect with trust as a mediator; hence, H8c is accepted. However, these results contradict previous studies' results (Handarkho 2020). On the contrary, the mediation results indicate that performance expectancy and effort expectancy do not influence the indirect effect of information quality on behavioural intention; hence, there is only a direct effect. The mediation results have also reported the insignificant influence of indirect effect through effort expectancy, which agrees with prior studies (Lee et al. 2019; Sulaiman et al. 2023). Similarly, the insignificant mediating results of performance expectancy contradict the previous research findings (Lee et al. 2019; Sulaiman et al. 2023). Hence, the hypothesis H8a and H8b are rejected. The results of the indirect effect are presented in Table 5.34 and Figure 5.16-5.18.

Table 5.34: Indirect effect of information quality

Direct without mediator

Parameter	Estimate	C.R.	P	Result
IQ--> BI	0.063	2.19	0.029*	S

Indirect with mediator

Parameter	Estimate	Lower CI	Upper CI	P value	Result Indirect Path	Final Conclusion
IQ --> PE --> BI	0.003	-0.011	0.019	0.673	NS	Direct only (No mediation)
IQ --> EE --> BI	-0.004	-0.012	0.003	0.225	NS	Direct only (No mediation)
IQ --> TR --> BI	0.228	0.193	0.266	0.001	S	Complementary (Partial mediation)

Source: Primary data

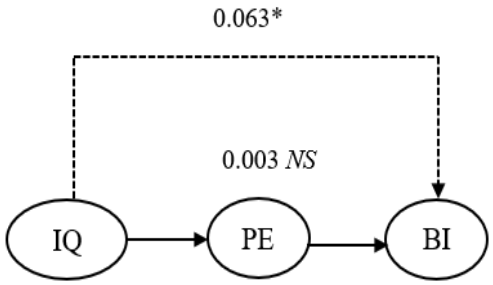

Figure 5.16: Indirect effect of IQ on BI through PE
Source: Primary data

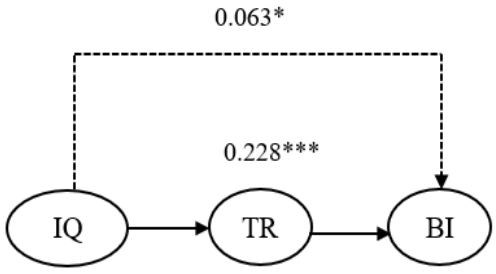

Figure 5.17: Indirect effect of IQ on BI through EE
Source: Primary data

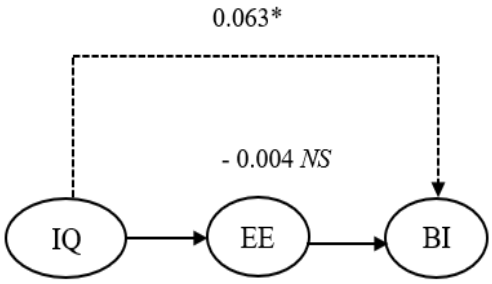

Figure 5.18: Indirect effect of IQ on BI through TR
Source: Primary data

5.9.6 Indirect Effect of System Quality

The indirect effect of system quality was investigated to examine the mediating role of performance expectancy, effort expectancy and trust. The results indicate that the indirect effect of system quality on behavioural intention through mediators' performance expectancy and trust was statistically significant. The results of the indirect effect through performance expectancy indicated full mediation, contrary to the prior findings (Sulaiman et al. 2023), which reported an insignificant mediating role of performance expectancy. Furthermore, the mediation analysis indicated trust as a significant mediator exerting full mediation. These results concurred with earlier research findings (Chiu et al. 2017). Therefore, the hypothesis H9a and H9c were accepted. On the contrary, effort expectancy was an insignificant mediator in the indirect influence on the user's behavioural intention. The results of earlier studies (Yang et al. 2017) were consistent with these insignificant results. Hence the hypothesis H9b was rejected. Table 5.35 and Figure 5.19-5.21 indicate the indirect effect of system quality.

Table 5.35: Indirect effect of system quality

Direct without mediator

Parameter	Estimate	C.R.	P	Result
SQ--> BI	0.034	1.427	0.154	NS

Indirect with mediator

Parameter	Estimate	Lower CI	Upper CI	P value	Result Indirect Path	Final Conclusion
SQ --> PE --> BI	0.036	0.021	0.056	0.001	S	Indirect only (Full mediation)

SQ --> EE --> BI	-0.001	-0.007	0.001	0.181	NS	No effect (No mediation)
SQ --> TR --> BI	0.07	0.041	0.104	0.001	S	Indirect only (Full mediation)

Source: Primary data

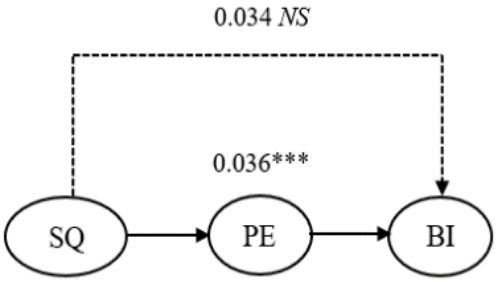

Figure 5.19: Indirect effect of SQ on BI through PE
Source: Primary data

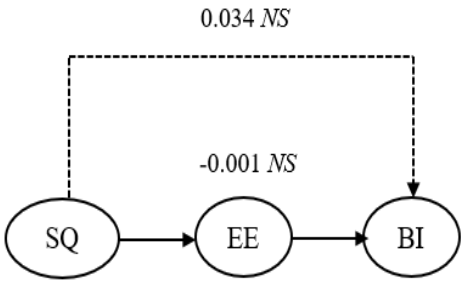

Figure 5.20: Indirect effect of SQ on BI through EE
Source: Primary data

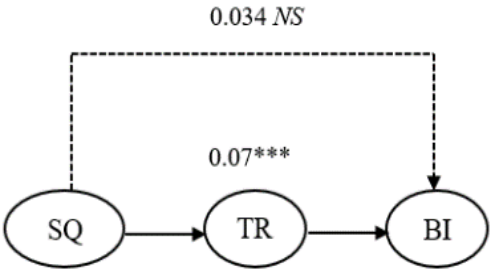

Figure 5.21: Indirect effect of SQ on BI through TR
Source: Primary data

5.9.7 Indirect Effect of Privacy Risk

The indirect effects of privacy risk on the user's behavioural intention through trust were analysed. The results demonstrated the indirect effect of privacy risk as statistically significant, exercising full mediation in influencing the relation between privacy risk and user behavioural intention. Prior studies reported similar results (Liu

and Tao 2022; Waung et al. 2021). Furthermore, the studies of Enaizan et al. (2020) have found trust influences a partial mediation on the indirect effect of privacy risk on behavioural intention. Thus, the hypothesis H10a is accepted. The results of the indirect effect of privacy risk are presented in Table 5.36 and Figure 5.22.

Table 5.36: Indirect effect of privacy risk

Direct without mediator

Parameter	Estimate	C.R.	P	Result
PR--> BI	0.001	0.071	0.943	NS

Indirect with mediator

Parameter	Estimate	Lower CI	Upper CI	P value	Result Indirect Path	Final Conclusion
PR --> TR --> BI	-0.105	-0.123	-0.087	0.001	S	Indirect only (Full mediation)

Source: Primary data

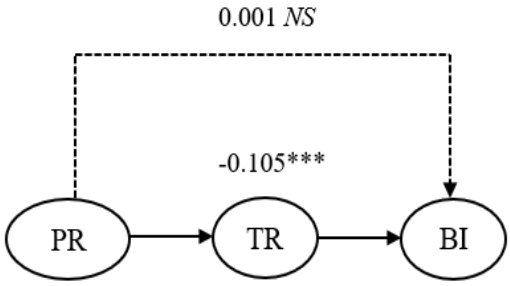

Figure 5.22: Indirect effect of PR to BI through TR
Source: Primary data

5.10 CHAPTER SUMMARY

This chapter, titled Data Analyses and Interpretations, explains the statistical tools and techniques used in the data analysis procedure in this research study. The data screening was done to identify the outliers, unengaged responses and missing data, resulting in the final data of 1029 responses. The descriptive analysis of the demographic data and latent variables was performed to analyse the distribution of the research data. The chapter also explains the exploratory factor analysis performed to confirm the accuracy of the research instrument. Common method bias, multicollinearity, and validity and reliability of the measurement model were all examined and explained. Furthermore, validation of the measurement model through confirmatory factor analysis was presented. The results of the proposed hypothesis were justified in the path analysis of

the structural model assessment. The research has also elucidated the various indices used to assess the model fit of the measurement model and structural model. Further, the study has illustrated mediation analysis to examine the role of performance expectancy, effort expectancy and trust as mediators. The next chapter will provide a detailed discussion of the findings obtained in the data analysis, its implications, and the limitations of the research, with recommendations for future studies.

CHAPTER 6

FINDINGS, RECOMMENDATIONS AND CONCLUSION

6.1 INTRODUCTION

This chapter outlines the discussions with theoretical and practical implications based on the study's findings. The results obtained are discussed to explore their relevance to the study area. Moreover, the results are connected with supporting literature for validation. The chapter includes the study's findings, implications, conclusions and limitations. The findings section explains the results of each hypothesis, indicating their significance or insignificance along with the prior literature in technology adoption studies in various contexts. The findings section summarizes the socio-demographic information and the research hypothesis, which examines the factors influencing the users' behavioral intention towards using AR technology in e-commerce apps. The following section discusses the significant implications of the research in two subsections: theoretical implications and practical implications. Theoretical implications examine the theoretical framework of the study. Here, inferences are made to discuss the validity of the theory adopted in the research and the contribution of the theoretical framework to the literature. The next section of the implication part discusses the research study's practical or managerial implications. The practical implications summarize the various suggestions and recommendations offered by the study's results, which will help policymakers and practitioners attain effectiveness and efficiency in managerial decision-making. Even though this research has well-defined theoretical and practical implications, it has certain limitations that can be taken as an opportunity for future research. Hence, the following section indicates the study's limitations and offers recommendations for future research. Finally, the entire chapter summary is well presented in the conclusion section at the end.

6.2 FINDINGS

The findings section discusses the results obtained in the study. The research study explores the various drivers towards user behavioral intention of AR technology in e-commerce apps. The study used the UTAUT3 model with constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, personal innovativeness and behavioral intention. In addition to the UTAUT3 constructs, the other context-specific variables such as privacy risk, trust and quality dimensions were added to the research model. These context-specific variables

were added to attain a higher predictive power for the research model. Based on the research gap identified, the study has proposed research objectives. With the research objective and supporting literature, the research has attempted to examine direct and indirect path analysis. The direct path analysis was tested through ten hypotheses, and the indirect analysis (mediation analysis) was tested through seventeen sub-hypotheses. The research study has adopted a systematic methodology for achieving research objectives. The study followed a quantitative approach with a cross-sectional design. A questionnaire survey method was used to collect data from tier 1 cities in South India. This collected data was further analysed using SPSS software, and structural equation modelling was performed using AMOS software. The proposed model has attained the recommended model fit indices, resulting in 73.6 percent predictive power. The following sections discuss the proposed hypothesis results with supporting literature. The findings section also discusses the respondents' socio-demographic information, as discussed in the section below.

6.2.1 The Socio-Demographic Information

It is essential to examine the socio-demographic information of the study respondents. The study area is limited to the tier 1 cities in South India, namely Bangalore, Chennai and Hyderabad. The final sample taken for the study consists of 1029 respondents from these cities. The study has obtained more than the minimum number of respondents required to be approached from each city. The research data consists of 34.52 percent of respondents from Bangalore, 33.52 percent of respondents belong to Chennai and 31.69 percent from Hyderabad. This indicates that the respondents from three regions are proportionately distributed, which has given a broader perspective towards consumer choices and technology adoption. The gender-wise distribution shows a proportionate distribution of male and female groups. Most respondents (88.8 percent) are between 18 and 38. Furthermore, the respondents belong to a well-educated and qualified group. The majority of the respondents belong to Generation Z and millennials, who are primarily tech-savvy and use more technology and apps in gadgets for daily activities (Jayathilaka and Sachitra 2023). As AR is a new technology, the opinion of this age group gives more insights into the user perspective towards AR technology. Most respondents (62.4) belong to a working group (employed and self-

employed) compared to students and others. The income category of the research data also indicates that 15.16 percent of the respondents fall in the income group of less than three lakhs, 27.99 percent of the respondents fall in the income group between three lakhs to six lakhs and 25.36 percent fall in the non-applicable group. However, 20.51 percent of the respondents fall in the income group between six lakhs and ten lakhs, and 10.98 percent belong to the income group above ten lakhs. The income category of the respondents is a significant indicator of purchasing power. When users try out the AR feature of online shopping apps, they will be more willing to purchase the product as they have a virtual representation of the product, which is more value-added than the 2d images and video demonstration. The demographic data of the study indicates that the investigation has successfully collected respondents belonging to diverse categories that show a good representation of the data.

6.2.2 Factors Influencing Behavioural Intention

The research investigates the factors influencing users' behavioural intention to adopt AR technology in e-commerce apps. The factors were analysed using the SEM technique with the AMOS software. The proposed hypothesis was analysed through the path analysis, and further, the indirect effect through the mediators was evaluated using the bootstrapping procedure. The following sections describe the results connecting with the prior research studies.

6.2.2.1 Influence of Performance Expectancy on Behavioural Intention.

Performance expectancy is the individual's belief towards the usefulness of the technology offered to the users. It significantly predicts user behavioural intention (Venkatesh et al. 2003). The findings of this research study have identified performance expectancy as a significant factor in influencing consumer's intention to use AR technologies in e-commerce apps. For instance, prior studies (Alesanco-Llorente et al. 2023) have reported performance expectancy as the most influencing factor affecting the user's intention to use mobile augmented reality technologies at physical stores. Consumers prefer to use technology when it offers efficiency and effectiveness in their activities, enhancing higher productivity. A prior study found that consumers highly prioritise the usefulness of technology, and hence, it emerged as the most significant factor in the research (Alam et al. 2021).

Furthermore, Abed (2021) proved the significant role of performance expectancy on user behavioural intention towards accepting AR technology in Saudi Arabia. These results are congruent with other research studies conducted in developing countries in the area of smart mobile tourism apps in Malaysia (Sia et al. 2023), education sector in Turkey (Ates and Garzón 2023) and metaverse platforms in Vietnam (Lee et al. 2023). These results indicate that consumers accept technologies when it is assumed to improve their activities in the best possible ways. With AR features, consumers can get a virtual experience of the products, which aids in quickly comparing the product dimensions in a preferred space. This feature of AR technology influences the intention to use the technology in e-commerce apps.

6.2.2.2 Influence of Effort Expectancy on Behavioural Intention.

Effort expectancy indicates the degree to which a system is easily used without any operational difficulties. Venkatesh et al. (2003) found effort expectancy as a significant construct influencing user behavioural intention. When a technology is simple and can be quickly learned, it increases the likelihood of increasing the usage intention. Prior studies have reported effort expectancy as a significant predictor of user behavioural intention. For instance, prior research (Chan et al. 2023) examined the usage intention of prospective users of virtual reality-based telerehabilitation services. The study found effort expectancy as a significant predictor as users prioritised ease of schedule flexibility offered by the system and were willing to receive treatment online owing to potential health risks. However, this research has found a contradictory finding, as effort expectancy was an insignificant predictor of user behavioural intention. Prior studies have reported findings similar to these conflicting results. For instance, the research conducted in Saudi Arabia by Altalhi (2021) on the acceptance of massive open online courses (MOOC) proved effort expectancy as an insignificant predictor as users found that features of MOOC technology are similar to the currently used technologies.

Furthermore, the current research findings were in line with the similar results demonstrated in the context of the mobile payment system in Jordan (Al-Okaily et al. 2023), building information modelling (BIM) (Xue et al. 2023) in general and in the context of AR (Paulo et al. 2018; Saprikis et al. 2021). A possible explanation for this insignificant result could be the users' experience using AR features on social media

platforms. Furthermore, most respondents are more technologically inclined as they are more frequently encountered with technology. Users are accustomed to the availability of AR features on social media platforms. Thus, users of e-commerce apps expect fewer problems and can quickly learn to use AR features in online shopping apps. Therefore, focusing on the simplicity involved in AR features will not exclusively motivate the consumers to use the technology as they are well versed in using it.

6.2.2.3 Influence of Trust on Behavioural Intention.

Trust is a significant predictor influencing the adoption of a new technology. When a consumer perceives a technology as trustworthy and reliable, it increases the intention to use it. Furthermore, trust in technology forms a favourable attitude, which surges the intention to use the technology. Some studies have found trust to be a significant predictor of behavioural intention than the perceived usefulness of the technology. For instance, a prior survey by Parayil Iqbal et al. (2023) found trust to be the most influential factor, rather than effort expectancy, in the context of m-banking adoption among Islamic banking customers. The results of this study indicated the significant positive influence of trust on user behavioural intention towards the use of AR technology. Furthermore, trust emerged as the most important factor influencing user behavioural intention. However, Jajic et al. (2022) examined the adoption of AR in supermarkets among students in Croatia have reported the insignificant role of trust in influencing the adoption intention.

Prior research has testified to the insignificant influence of trust in mobile banking in India (Singh and Srivastava 2018). The study indicated that mobile banking is a service of the banking sector where customers consider banks to be the most trusted institutions; as a result, trust does not play a significant role in the adoption intention. The significant role of trust observed in this study is consistent with the prior research studies in mobile commerce (Sarkar et al. 2020) and voice-based assistants (Pitardi and Marriott 2021). The research by Kang et al. (2023) investigated AR adoption among mobile users in the USA and found users with high trust in AR apps influence user intention, which further increases the online and offline store patronage intention. Similarly, prior research has investigated the adoption of AR head-up displays among drivers, highlighting trust as an essential factor influencing users' intention to adopt

technology, even though risk factors are associated (Li et al. 2022). Henceforth, companies and developers need to focus on enhancing security policies and strengthening trust towards AR-powered e-commerce apps.

6.2.2.4 Influence of Social Influence on Behavioural Intention.

The opinions of peer groups and friends highly influence consumer decision-making. They often search for ideas and recommendations for any new product or service. Social influence significantly predicts technology adoption (Venkatesh et al. 2003). The present investigation examined the role of social influence on users' behavioural intention and discovered a noteworthy positive correlation between social influence and adoption intention. This indicates that social influence impacts the decision to adopt AR technology in e-commerce apps. These results were contrary to the results reported by prior studies. For instance, Paulo et al. (2018) demonstrated the insignificant role of social influence on the adoption of AR by tourists in Portugal. Jajic et al. (2021) also observed the presence of an insignificant role of social influence on the adoption of AR technology in supermarkets and hypermarkets among students in Croatia. The positive results observed in this study agreed with the prior technology adoption studies. For instance, prior research has reported social influence as a significant predictor of behavioural intention among Hong Kong students to use discussion forums on electronic learning platforms (Wut and Lee 2022).

Likewise, research has reported social influence as a significant predictor influencing retailers in Egypt to use m-payment (Esawe 2022). In the context of AR, Abed (2021) demonstrated the significant role of social influence on user behavioural intention among consumers in Saudi Arabia. Mutterlein et al. (2019) conducted research amongst students in Germany and emphasized the significant role of social influence on the acceptance of AR apps with gaming and location guides. Prior studies in the area of technology adoption in the Indian context have demonstrated a positive role of social influence (Dogra and Kaushal 2021; Patil et al. 2020; Vimalkumar et al. 2021). The research findings of this study indicate that Indians give high priority to social groups. People who are important to an individual play a significant role in the decision-making process, especially when they look forward to get acceptance from others while adopting a new technology. Hence, the opinions and suggestions of peer groups,

friends, and family members significantly influence consumers' choices and preferences.

6.2.2.5 Influence of Facilitating Conditions on Behavioural Intention

Resources in terms of support systems, knowledge, and availability of gadgets play a significant role in technology adoption and are hence considered to be a critical factor in influencing the intention to adopt technology (Venkatesh et al. 2003). Facilitating conditions indicate the availability of resources that help individuals use the technology without difficulties. Hence, users look forward to the availability of infrastructural support, technical support from companies, or help from friends in case of hindrances while using the technologies. Prior studies in the area of information systems (Dogra and Kaushal 2021; Vimalkumar et al. 2021) in general and in the context of AR (Abed 2021; Paulo et al. 2018) have reported the significant role of facilitating conditions on the technology adoption. However, the findings of this study have reported an insignificant role in facilitating conditions on behavioural intention. These insignificant results corroborate with prior research studies in the Indian context. For instance, prior research have emphasised the insignificant role of facilitating conditions on the behavioural intention of Indian customers towards online banking adoption (Kaur and Arora 2020). Likewise, in social media applications, Alvi (2021) also proved that facilitating conditions have no impact on the behavioural intention of university students in India to use social networking tools.

Research studies conducted in AR also observed the lack of influence of facilitating conditions. For instance, Saprikis et al. (2021) found the insignificant role of facilitating conditions on students' behavioural intention towards using mobile AR apps in shopping malls. Similar findings were reported in the research investigation on the behavioural intention amongst students in Germany to use mobile AR apps (Mutterlein et al. 2019). A possible validation for these insignificant results is the experience of using AR on social media platforms. Users might have tried out the AR feature in social media apps, which has made them more familiar with its functioning in general, even though they might not have experienced it in e-commerce apps. Users consider themselves self-learners and prefer browsing the internet and QnA portals to solve

queries on any operational difficulties. Hence, the results of this investigation indicate the absence of a positive role in facilitating conditions for users of e-commerce apps.

6.2.2.6 Influence of Hedonic Motivation on Behavioural Intention

Hedonic motivation indicates the fun, enjoyment or pleasure experienced by individuals while using the technology. Venkatesh et al. (2012) have pointed out the significant role of hedonic motivation. When technology offers a pleasurable experience, it increases users' behavioral intention towards technology. The statistical analysis of this research has found the significant influence of hedonic motivation on behavioural intention to use AR technology in e-commerce apps. Hedonic motivation was the most influential factor among the UTAUT factors in this research study. These significant results corroborate prior research findings in the Indian context. Using thematic analysis, prior research (Menon and Shilpa 2023) found hedonic motivation as the highest influencing predictor of user intention to use AI-enabled voice-based assistants among high school students in India. Vimalkumar et al. (2021) found a significant relationship between hedonic motivation and user behavioural intention in using voice-based digital assistants among students in India. However, a study by Mishra et al. (2023) investigated cryptocurrency adoption in the Indian context found the insignificant role of hedonic motivation on user behavioural intention.

The significant role of hedonic motivation was observed in prior studies in AR. Abed (2021) highlights the significant influence of hedonic motivation to use AR technology in Saudi Arabia. Saprikis et al. (2021) investigated the adoption of mobile AR in shopping malls found enjoyment and pleasure experienced from mobile AR increase the intention to use it further. Paulo et al. (2018) concluded the significant role of hedonic motivation in influencing tourists to use mobile AR apps during trips in Portugal. Henceforth, the statistical results indicate that hedonic motivation is a crucial factor influencing user intention.

6.2.2.7 Influence of Personal Innovativeness on Behavioural Intention

Personal innovativeness indicates the desire to try new technology; hence, it is important in determining technology adoption. Farooq et al. (2017) extended the UTAUT 2 theory by including personal innovativeness. The results of this study have

observed the significant influence of personal innovativeness on user behavioural intention. These results are in agreement with the prior research findings. For instance, prior research have indicated the prominent role of personal innovativeness in technology adoption found personal innovativeness to be a significant predictor of virtual communication technology adoption (Gupta et al. 2023). Similarly, Abed (2021) highlighted the significant role of personal innovativeness in adopting AR technology in Saudi Arabia. Faqih (2022) found a substantial role in innovativeness on user behavioral intention to use mobile AR games among students in Jordan. However, the study by Maisha and Shetu (2023) found personal innovativeness in information technology as an insignificant predictor of e-learning system adoption among students in Bangladesh. Similarly, Jajic et al. (2022) demonstrated the insignificant role of personal innovativeness on students' intention to use AR in Croatia. These insignificant results reported by prior studies (Jajic et al. 2022; Maisha and Shetu 2023) were contrary to the results obtained in this study. AR is a novel technology; hence, the results of this study indicate that users' desire to try new technology will increase their intention to try AR technology in e-commerce apps.

6.2.2.8 Influence of Information Quality on Behavioural Intention

Information quality is an essential requirement for successful technology adoption. The accuracy of the information is necessary as it creates trust towards the system. The statistical results of this study have found a significant influence of information quality on user behavioural intention. Prior studies have found the significant impact of information quality on the acceptance of technology in the Indian context. For instance, prior research investigating telehealth by healthcare practitioners in rural India found the significant role of information quality in the use of technology (Rana et al. 2023). Likewise, Sharma et al. (2023) found information quality to be a determinant of the continuous use intention of news apps in major metropolitan cities in India. The information quality received from AR technology plays a significant role in accepting the technology for future use. For instance, in the context of AR-based mobile apps, Oyman et al.(2022) concluded that users expect accurate and high-quality information from AR-based apps, reflecting the significant role of information quality on the behavioral intention of app users. Likewise, Chiu et al. (2021) found that the user's

intention to continue using AR in retail applications is highly influenced by the quality of information offered by the AR app. These results indicate the significant role of information quality in technology adoption. Hence, it is crucial to ensure that quality information is delivered to the users of AR technology.

6.2.2.9 Influence of System Quality on Behavioural Intention

System quality indicates the technical aspects of the information system that influence its performance. A high-performance system suggests the presence of all essential aspects of system quality; hence, it directly affects the user's behavioural intention to use the system. The significant role of system quality on user behavioural intention was proved in prior studies. For instance, Anand et al. (2023) examined the acceptance of AR-based apps in smart tourism in the Indian context and found the significant role of system quality in influencing user satisfaction, creating a reuse intention of the AR app. Likewise, Chiu et al. (2021) proved the significant role of AR-based apps' system quality on the customer's intention to use the app further in food chain outlets in China. However, the results of this study have found the role of system quality to be insignificant. These results were in agreement with the findings of other studies. For instance, Yoo (2020) found the insignificant role of system quality in enhancing cosmetic shoppers' satisfaction using AR technology in South Korea. Tseng et al. (2021), in the context of mobile shopping apps in Taiwan, reported the insignificant role of system quality in enhancing users' satisfaction towards the app.

Chan et al. (2022) examined the adoption of mobile shopping among users in Malaysia reported the insignificant role of system quality on the user's adoption intention. Similarly, Tarhini et al. (2019), in the context of mobile commerce adoption among Omani customers, also reported the insignificant role of system quality on customer's technology adoption behaviour. System quality is highly essential for the app's performance. Henceforth, emphasising the AR app's system quality attributes may not be a predictor towards using the app. This may be because users expect the system quality attributes to be present and do not consider them to be the extra quality of the app. Therefore, the findings of this research have established the insignificant role of system quality on customers' intention to use AR technology in online shopping apps.

6.2.2.10 Influence of Privacy Risk on Behavioural Intention

Privacy risks influence technology adoption. It indicates the loss caused as a result of misuse of information. The study has proposed investigating the negative influence of privacy risk on user behavioural intention. The statistical results demonstrated the insignificant negative influence of privacy risk on user behavioural intention. The findings of this research are in agreement with the prior research studies. For instance, Vimalkumar et al. (2021) examined the adoption of voice-based digital assistants among students in India and reported that the negative effect of privacy risk does not influence the behavioural intention to use the technology. Prior research on the adoption of mobile AR games among Germans found the insignificant role of the negative influence of privacy risk in reducing user adoption intention (Rauschnabel et al. 2017). Prior research has reported the user's willingness to use metaverse education applications in Henan despite the negative impact of privacy risk (Wang and Shin 2022). However, the findings of this research were found to be contrary to prior studies. For instance, Faqih (2022) reported the negative influence of privacy risk and hence was reluctant to adopt mobile AR games among university students in Jordan. Harborth and Pape (2021) have confirmed the negative impact of privacy concerns on the user's intention to download MAR apps in Germany. Prior research has demonstrated that privacy risks negatively influence user's intention to continue using augmented reality-based services (Yin and Hsu 2023). The insignificant results indicate a positive approach towards accepting AR technology despite privacy risks. Hence, based on the supporting results, the negative influence of privacy risk does not influence the behavioural intention towards AR technology in e-commerce apps.

6.2.3 The Mediation Analysis Results

The preceding section discussed the direct effect of various factors on user behavioural intention. The results of direct effects indicate the significant and insignificant factors in the adoption of AR technology. Besides investigating direct effects, the current study has examined the indirect influence of factors on user behavioural intention through the mediator's performance expectancy, effort expectancy and trust. The study followed the mediation analysis proposed by Zhao et al. (2010) using the bootstrapping procedure with 2000 bootstrap estimations with 95% bias-corrected confidence intervals (CI).

When the confidence intervals (upper bound and lower bound) do not include zero, the indirect influence is presumed to be significant. The research has examined the indirect effect of social influence, facilitating conditions, personal innovativeness, information quality, system quality, trust, and privacy risk. The following sections discuss the results of the mediation analysis.

6.2.3.1 The Indirect Effect of Social Influence

The present study has examined the indirect effect of social influence through performance expectancy, effort expectancy and trust on behavioural intention towards AR technology. The results indicate social influence's positive and significant role on user behavioural intention (β=0.076, p-value=<.001) to use AR technology in e-commerce apps. Furthermore, the indirect effect of social influence was investigated through performance expectancy, effort expectancy and trust. The results indicate the significance of indirect paths with performance expectancy (SI→PE→BI; β=0.070, p-value=<.001) and trust (SI→TR→BI; β=0.057, p-value=<.001) as mediators. The presence of partial mediation was confirmed as the direct effects and indirect effects are significant. These results are in line with prior research studies. For instance, Fagan (2019) highlighted that performance expectancy has fully mediated the effect of social influence on user behavioural intention towards using technology among students in Texas. Similarly, the results have confirmed full mediation's presence in the indirect path of social influence and user behavioural intention through trust. These results were in line with the results in the area of social media learning in Bangladesh (Rahman et al. 2021). However, the results have highlighted the absence of the indirect effect of social influence on user intention through effort expectancy (SI→EE→BI; β=-0.001, p-value=0.21). These results were in line with the studies by Chen and Akilkokou (2020) in the area of e-government adoption in Tongo, which reported the absence of mediation in the indirect effect of social influence on behavioural intention through effort expectancy. Therefore, the relationship between social influence and behavioural intention is partially mediated by performance expectancy and trust. In contrast, effort expectancy does not mediate between social influence and behavioural intention.

6.2.3.2 The Indirect Effect of Facilitating Conditions

The research findings have found the insignificant role of facilitating conditions on user behavioural intention to use technology. However, the research has investigated the role of performance expectancy, effort expectancy and trust on the indirect path of facilitating conditions on user behavioural intention. The results of the indirect path have demonstrated an insignificant influence, reflecting the absence of mediating effects. The indirect influence of facilitating conditions on behavioural intention through effort expectancy (FC→EE→BI; β=¯0.005, p-value=0.27) reported an insignificant indirect effect, which was contrary to the research findings demonstrated by Chen and Aklikokou (2020) in the area of e-government adoption. Furthermore, the insignificant indirect influence (FC→PE→BI; β=-0.021, p-value=0.004) of performance expectancy were in line with the studies by Sulaiman et al. (2023) conducted in Iraq. The study has also reported the insignificant indirect influence (FC→TR→BI; β=-0.014, p-value=0.428) through trust, found to be contrary to the results of Enaizan et al. (2020) in the area of electronic medical records system in Malaysia. Hence, the statistical results indicate the absence of mediation effect of performance expectancy, effort expectancy and trust in the relationship between facilitating conditions and behavioural intention.

6.2.3.3 The Indirect Effect of Hedonic Motivation

Hedonic motivation is the most influencing factor among the UTAUT factors (β=0.283, p-value=<.001). The study has also investigated the indirect influence of hedonic motivation on user behavioural intention through mediators. The result of mediation analysis indicates the significance of indirect path (HM→PE→BI; β=0.064, p-value=<.001) with partial mediation effect. These results agreed with the prior studies by Fagan (2019) on the acceptance of mobile learning by students in Texas with a full mediation effect. However, the indirect path of hedonic motivation on behavioural intention through effort expectancy (HM→EE→BI; β=-0.007, p-value=0.271) was found insignificant, indicating the presence of direct effect only. These results were contradictory to the prior studies (Fagan 2019). Similarly, the insignificant indirect path with trust (HM→TR→BI; β=0.005, p-value=0.767) was also observed, indicating the

presence of direct effect only. These results were contrary to the research findings of Enaizan et al. (2020). Henceforth, the mediation analysis suggests the lack of mediating effect by effort expectancy and trust on the direct impact of hedonic motivation on behavioural intention. In contrast, the relationship between hedonic motivation and user behavioural intention is partially mediated by performance expectancy.

6.2.3.4 The Indirect Effect of Personal Innovativeness

Personal innovativeness is a significant predictor of technology adoption. The direct effect of personal innovativeness on user behavioural intention was significant (PI→BI; β=0.06, p-value<0.05). The study has also investigated the indirect influence of personal innovativeness on user behavioural intention through trust. The results of mediation analysis indicate the presence of a partial mediating effect of trust (PI→TR→BI; β=0.059, p-value<0.001). These results were in line with the preceding studies (Rouibah et al. 2016), which reported the significant influence of personal innovativeness on behavioural intention through trust, indicating the presence of a mediating effect. Meanwhile, these results did not agree with the study by Chan and Lee (2021) in the area of autonomous vehicle acceptance, indicating the lack of a mediating effect by trust. Therefore, this study has established the existence of a partial mediation effect of trust on the indirect effect of personal innovativeness on user behavioural intention towards adopting AR technology.

6.2.3.5 The Indirect Effect of Information Quality

Information quality is a crucial factor in the acceptance of technology. The current study has reported the significant influence of information quality on behavioural intention to use the technology (IQ→BI; β= 0.063, p value<.05). Further, the study has also investigated the indirect influence of information quality on user behavioural intention through performance expectancy, effort expectancy and trust. The indirect path of information quality on behavioural intention through performance expectancy (IQ→PE→BI; β=0.003, p-value=0.673) was reported to be insignificant. Hence, the absence of a mediation effect was reported. These results were confirmed by prior research investigations (Lee et al. 2019; Sulaiman et al. 2023). The current study has also demonstrated the insignificant mediating effect of effort expectancy on the indirect

path of information quality on user behavioural intention (IQ→EE→BI; β=-0.004, p-value=0.225), which align with the results of prior studies (Lee et al. 2019; Sulaiman et al. 2023). The study has also evaluated the mediation effect of trust. The mediation results indicated the presence of indirect influence (IQ→TR→BI; β= 0.228, p-value<0.001) indicating trust as a partial mediator. However, these results were found to be contrary with Handarkho (2020) in the area of social commerce. Hence, it can be concluded that trust is a mediator in the indirect path of information quality to user behavioural intention. In contrast, performance expectancy and effort expectancy do not play a mediating role in the indirect path.

6.2.3.6 The Indirect Effect of System Quality

System quality is a significant factor influencing the user's technology adoption decision. However, the results of this research have observed an insignificant direct effect of system quality on user behavioural intention. This research has investigated the indirect effect of system quality on behavioural intention through the mediator's performance expectancy, effort expectancy and trust. The mediation analysis found the insignificant indirect path of system quality (SQ→EE→BI, β= -0.001, p-value=0.181). This insignificant mediating effect of effort expectancy may be due to the insignificant direct effect of system quality on user behavioural intention. The indirect path of system quality through the mediator effort expectancy was found to agree with the results observed in the study by Yang et al. (2017) in the area of MOOCs. However, these results contradicted prior studies (Rahi et al. 2019; Sulaiman et al. 2023). The indirect path of system quality through the mediator performance expectancy demonstrated the presence of full mediation (SQ→PE→BI, β= 0.036, p-value=0.001). These results contradict those of Sulaiman et al. (2023) in Middle Eastern countries. Similarly, the results have also observed the significance of the indirect path with trust as mediator (SQ→TR→BI; β= 0.070, p-value=0.001) indicating the presence of full mediation. This result corroborates with the results in mobile banking (Chiu et al. 2017). Henceforth, performance expectancy and trust significantly mediate the indirect path of system quality and user behavioural intention towards AR technology.

6.2.3.7 The Indirect Effect of Privacy Risk

The research has found an insignificant negative influence of privacy risk on user behavioural intention. It indicates that users are least concerned about the negative influence of privacy risk in the technology and would use it despite the risk involved. The current study has examined the indirect influence of privacy risk on user behavioural intention through trust. It was found that trust fully mediates the relationship between privacy risk and user behavioural intention (PR→TR→BI, β=-0.105, p-value=0.001). The results of this research are consistent with prior research studies. For instance, Liu and Tao (2022) reported that trust fully mediated the privacy risk and user behavioural intention towards the acceptance of smart healthcare services in China. Hence, users with great concerns about the privacy risks of technology are less likely to trust the technologies, reducing their intention to accept the technology. Furthermore, a study by Enaizan et al. (2020) on electronic medical records demonstrated the presence of trust as a partial mediator in the relationship between privacy risk and user intention. Similarly, prior research has demonstrated the partial mediation effect of trust in the area of autonomous vehicles (Waung et al. 2021). Thus, companies should focus on increasing the users' behavioural intention towards AR technology by lowering the customers' concern towards privacy risk and enhancing trust by introducing customer confidentiality policies.

6.3 IMPLICATIONS

The research study has examined the various factors influencing the user acceptance of AR technology in e-commerce apps. The relationships between the factors were explored to determine the strength of the influence and the relevance of the factors in influencing the user's behavioural intention. The section discusses the contributions of the research study in expanding the literature on technology adoption. It helps industry practitioners develop promotion policies and programs for the most effective and efficient acceptance of AR technology in e-commerce apps.

6.3.1 Theoretical Implications

The research study examined the adoption of AR technology in e-commerce apps. The study has investigated the various technology adoption theories to explore and discuss

the factors influencing customers or users to use AR technology while using e-commerce apps. Research in AR technology is novel and needs to be explored in developing countries like India. Furthermore, research in AR technology in the Indian context is minimal; hence, the results of this study have a significant contribution to the literature. This research has explored the various factors influencing the adoption of AR technology using the UTAUT3 theory. Although the theory constructs can explain the user behavioural intention, the research has also included a few context-specific variables such as trust, privacy risk, and quality dimensions (information quality and system quality), which gave more insights into the behavioural intention towards technology adoption. Hence, integrating UTAUT3 with some additional variables gave an overview of the user perspective towards adopting AR technology in the Indian context. Prior research studies indicated a dearth of studies examining the role of trust in adopting novel technologies such as AR. As a result, trust was included as one of the context-specific variables along with the other UTAUT factors. The study results revealed trust as the most significant factor influencing user behavioural intention. These results indicate that when users have higher trust levels towards the AR feature of the app, their intention to use the feature is strongly increased. The study has also found information quality superseding the role of system quality on the user behavioural intention. Furthermore, the insignificant role of privacy risk indicates that users are more open to accepting technologies even though they have potential risks and threats to privacy.

AR features offer a virtual product experience, resulting in a pleasurable user experience. This was proved as hedonic motivation emerged as the significant factor among the UTAUT factors considered in the study. The research has also found effort expectancy, facilitating conditions, system quality, and privacy risk to be insignificant predictors of the acceptance of AR technologies. Although these results contradict the prior research findings, they paved the way for further validation in other research studies. Apart from examining the direct effect of factors influencing the user's behavioural intention, this research has also explored the indirect effect of performance expectancy, effort expectancy, and trust on behavioural intention. These results are significant contributions not yet explored in AR studies in the e-commerce sector.

Henceforth, discussing and investigating these factors and their relationships offered more in-depth perspectives towards user adoption behaviour in India.

6.3.2 Managerial Implications

This research has observed significant findings in customers' perception of using AR technology in online shopping platforms. AR technology offers numerous benefits to the users. Understanding the factors influencing the user's intention to use AR technology will help companies and policymakers have a good execution plan to ensure its rapid penetration into the e-commerce market as an indispensable tool in online shopping activities. The study has formulated a comprehensive AR technology model considering the UTAUT 3 factors and other constructs such as quality dimensions, trust and privacy risk. A critical examination of these factors will help the companies upgrade their online shopping portals with AR and further enable them to use the technology that benefits both customers and companies.

This current research offers a holistic understanding of the factors inducing people to use AR technology to aid their online shopping activities and provides valuable practical implications for companies. For instance, trust emerged as a significant factor influencing the user's behavioral intention toward using AR technology. This indicates that companies need to be more transparent in their activities, which creates awareness of AR technology usage. Companies and app developers should give clear information on how AR technology works in online shopping portals and how it helps customers have a better shopping experience. App developers should include detailed instructions with tutorial videos that enable the customers to understand the technology's usefulness. In addition to highlighting the benefits the technology offers, it is also recommended to specify the instances where the AR feature may not give the desired output, making users more aware of the probable results. AR technology works on sensors that capture information through camera, location, etc., which can create privacy risk concerns. Therefore, companies need to inform users about why camera access is required to use the AR technology and what information is captured, processed and kept in the database. Although data is essential to companies for future purposes, they can allow customers to access details on the information gathered through the AR feature and

delete those data from the company database. When companies are transparent in functioning, users will be more confident using the technology.

The study has also observed the significant role of hedonic motivation as it emerged as an important factor among other UTAUT factors. This significant impact of hedonic motivation on user behavioral intention indicates that companies and app developers should enhance the AR feature of online shopping apps to offer customers a more pleasurable experience. App developers should ensure that the virtual representation of the product is highly realistic and provides the experience of the product within the user's environment. Customers will experience pleasure in using the technology when the technical features of the app function in the most appropriate way. For instance, the app needs to adjust its AR output based on the lighting conditions. Furthermore, the app's response time in generating the AR output also influences the users' satisfaction. Therefore, developers must ensure that the app responds quickly when the AR option is activated. Similarly, the quality of the virtual elements display also motivates the users to try out more products with AR features, which can create a product purchase intention. The pleasure experienced by virtual representation may vary with the product type. Hence, companies must undertake qualitative assessments through interviews and discussions to reveal customers' expectations towards each product type while using the AR feature. Companies can also incentivise users to share their AR experience with others on social media platforms. Such initiatives can increase users' interest in trying the features repeatedly and spark interest among prospective users.

The study has also found the significant influence of performance expectancy on the user adoption of AR technology. Companies should focus on promoting the usefulness of AR technology in better shopping in advertisement campaigns. Consumers focus on the level of benefit that AR technology can offer to the users through its adoption in online shopping apps. Marketers must undertake a study to explore customers' expectations through AR technology. Along with promoting the usefulness of the technology, companies should also emphasise the value addition of the AR technology towards improvising the user activity in the app. For instance, companies should make customers aware of the benefits of AR technology by contrasting traditional and AR-powered online shopping. With these inputs, marketers and app developers should

develop an app interface that can offer an enriched virtual experience, resulting in a delightful customer experience.

Social influence was found to be a significant predictor of user behavioral intention. This positive and significant impact of social influence indicates that companies should focus more on improving the effect of peer groups, family, and recommendations, which will influence the user's intention to use AR technology. As social groups highly influence users, companies need to make strategies focusing on social groups. For instance, companies can highlight the number of users who have used the AR feature to place an order. Creating endorsements with influencers will be an added advantage for the companies. Influencers are more connected with people than celebrities, and people consider the influencer's recommendations more trustworthy than traditional advertisements and celebrity endorsements. Furthermore, the customers can easily relate to the advice of influencers, which will increase their interest in using AR while placing an order. Hence, companies need to consider influencers to promote the AR feature of online shopping apps. Furthermore, they can also encourage individuals to share their experience of using AR features on online shopping apps and social media platforms by offering exclusive discounts and early access during special sales.

The results have also proved the significant role of information quality on user behavioral intention. When the information provided by the AR feature is accurate and reliable, it will directly influence the intention to use the AR feature. Companies need to focus on enhancing the quality of inputs offered by the technology, which will help in better and more efficient use of technology. For instance, AR features offer virtual elements to the user environment, which requires proper focus on the space of the physical environment. App developers should design the AR feature, which will give appropriate instructions on how to focus the area where the virtual product will appear and how the measurements of the products should be indicated. Furthermore, app developers should give clear instructions to help users use the AR feature more effectively. When users receive clear instructions on using AR features and easy tips on every stage of usage, it will gradually increase their trust towards the technology, leading to positive word-of-mouth communication.

Finally, this study reported personal innovativeness's positive and significant influence on user behavioral intention towards AR technology. Companies should focus on early adopters of technology as other adopters highly regard their opinions. Hence, marketers should identify and focus on these early adopters, as they are the initial customers of new technologies and are considered influencers in social circles. The opinions of these innovative customers will help other customers to be more assured of being free from any risk involved with the technology. When the AR features are updated regularly, highly innovative customers will be delighted with the app's functionality, inspiring them to share their experiences on social media platforms. This positive feedback will encourage other users with varied innovativeness to adopt AR features in online shopping apps.

6.3.3. Limitations of The Study and Future Research Directions

The studies in AR technology are in the nascent stage. Henceforth, this research has offered several contributions to adopting AR technology in the e-commerce sector in an Indian context. Despite the insightful contributions, this research is also subject to shortcomings and limitations, which can be considered opportunities for future research studies. The study area of this research focuses on Tier 1 cities of South India as they have the highest market share in the e-commerce market. As a result, tier 2 cities and tier 3 cities were excluded from the study. Tier 2 and 3 cities are also emerging markets in the e-commerce sector. Henceforth, it would be helpful for future studies to consider tier 2 and 3 cities, which will also help compare with the results of this study. Secondly, this research followed a cross-sectional design where data was collected only once from the respondents. The collected data reflects respondents' perceptions while responding to the research questionnaire. Hence, there is a need to perform a longitudinal study that may help reveal the users' real perspectives towards adopting the technology. Third, this research has focused on a quantitative approach wherein a structured questionnaire was used in data collection. A structured questionnaire restricts respondents' opinions within the specified options (strongly agree- strongly disagree, 5-point Likert scale). Focus group discussions and one-on-one interviews will offer more insightful views on user acceptance of technologies. Therefore, future studies can use a mixed approach with both quantitative and qualitative approaches. Fourth, India is a diverse country with

varied cultures, tastes and preferences. Cultural factors play a critical role in customers' choices, which was overlooked in this research study. Furthermore, the cause of insignificant relationships may result from ignoring cultural factors. Therefore, future studies can incorporate the cultural factors to understand user adoption behaviour in-depth. The current research has used UTAUT3 constructs with other context-specific variables. This study can be further explored by including variables like customer engagement, attitude, and brand loyalty to examine the role of these factors on the behavioural intention to use. The proposed model of this research study can be used to investigate the adoption of technologies such as virtual reality, artificial intelligence and voice-based digital assistants.

6.4 CONCLUSION

India is the second largest country contributing to the global e-commerce market (Coppola 2023). Furthermore, it is the only country with the highest product returns in e-commerce platforms. The user penetration rate in the AR market is estimated to grow from 65.8 percent to 85.5 percent in 2028 (Statista 2023). These estimates have reflected the potentiality of AR technology in the Indian market, especially in e-commerce platforms, as it will help tackle the issue of product returns to a certain extent. However, research examining AR technology adoption in e-commerce apps remains unexplored in the Indian scenario. This study has attempted to investigate this new area by examining the factors influencing AR technology adoption using the UTAUT 3 theory with other context-specific variables among customers in tier 1 cities. Following the cross-sectional design, the empirical investigation has resulted in the following conclusions:

- The study's first objective is to explore and identify the significant factors influencing the user adoption of AR technology in e-commerce apps. Based on the literature review on technology adoption studies, the study has considered factors from UTAUT 3 theory: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, personal innovativeness and behavioral intention to use technology. Apart from the UTAUT constructs, the study has included context-specific variables such as trust, privacy risk, information quality and system quality. The significant

factors that drive the user adoption of AR technology in e-commerce apps are performance expectancy, social influence, hedonic motivation, personal innovativeness, information quality and trust.

- The study's empirical analysis identified the significant drivers of AR technology adoption in e-commerce platforms. Trust is one of the context-specific variables included in the research study, which emerged as the most decisive factor influencing the user adoption of AR technology with a beta coefficient value of 0.575. Among the UTAUT factors, hedonic motivation is the second factor strongly influencing user adoption, with a beta coefficient 0.283.
- The proposed model of this research study has attained the recommended model fit indices exhibiting good model fit. The coefficient of determination (R^2) value resulted in a 0.74 percent prediction of the user's behavioural intention. The R^2 value indicated the model has attained moderate explanatory power in predicting the user behavioural intention.
- The mediation analysis using the bootstrapping procedure revealed the strength of the mediators in the indirect path. Effort expectancy was found to be an insignificant mediator; hence, the indirect influence of social influence, facilitating conditions, hedonic motivation, personal innovativeness, information quality and system quality on user behavioural intention was found to be insignificant. Performance expectancy significantly mediates the indirect influence of social influence, hedonic motivation and system quality on user behavioral intention. Furthermore, trust was an essential mediator in the indirect influence of social influence, personal innovativeness, information quality and system quality on user behavioral intention.

In summary, the present study makes a value-added contribution to the technology adoption studies through the application of UTAUT3 theory and the inclusion of context-specific variables. The findings of this study can be taken as a guideline by academic practitioners and policymakers for the successful development of promotional campaigns, which will help in better penetration of the technology among the e-commerce platform customers. Furthermore, focusing on the influential drivers

of AR technology adoption will help companies enhance the technology and motivate users to use technology as an inevitable tool during online shopping. Consistent usage of AR before placing orders in online shopping will eventually reduce the problem of online product returns, significantly contributing to helping the country attain the objective of carbon neutrality.

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APPENDICES

APPENDIX I: QUESTIONNAIRE

Dear respondent

I am Komal Anand, Research Scholar pursuing Ph.D. at the School of Humanities, Social Sciences and Management, National Institute of Technology Karnataka, Surathkal. As part of my research work, I am investigating the factors influencing the behavioral intention of users to adopt Augmented Reality (AR) technologies in online shopping apps as a tool in the purchase process. The use of AR features in online shopping apps will present the virtual presentation of the products, which will help in assessing the products in a better way. I kindly request you fill out this questionnaire and help me pursue my research work successfully. The information you provide will be used only for academic purposes and kept confidential. Your participation is valuable but voluntary; hence, you can withdraw anytime. Please contact me at komal.inbox@gmail.com if you have any queries or need clarification.

I agree to participate in this survey.

Yes ( ) No ( )

SECTION I

Tick (✓) anyone from the options of your choice

1. I believe using AR features in online shopping apps would be useful when browsing these sites.
   Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

2. I believe using AR features in online shopping apps will help me accomplish my tasks more quickly.
   Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

3. I believe that using the AR feature in online shopping apps will help me shop more productively.
   Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

4. I believe using AR features in online shopping apps will help me shop quickly.
   Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

5. It will be easy for me to learn to use AR features in online shopping apps.
   Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

6. Using AR features in online shopping apps will be clear and understandable.
   Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

7. It will be easy for me to use the AR feature in online shopping apps.
   Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

8. It will be easy for me to become skilful in using the AR feature in online shopping apps.
   Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

9. I feel that people who influence my behavior will think that I should use the AR feature in online shopping apps.
   Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

10. I believe that people close to me will think I should use the AR features in online shopping apps.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

11. People whose opinions I respect will prefer that I use AR features in online shopping apps.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

12. I believe that If I use AR features in online shopping apps, it can boost my self-esteem.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

13. I am more interested in trying new technologies than known technologies.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

14. I like learning about new technologies.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

15. I know more than others about the latest technologies.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

16. I try new technologies before my friends and relatives.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

17. I am willing to give up existing technologies to accommodate new innovative technologies.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

18. I believe using AR features in online shopping apps would be fun.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

19. I believe using AR features in online shopping apps would be very entertaining.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

20. I can try out products in an enjoyable way with the AR feature in online shopping apps.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

21. I have the necessary resources to use the AR feature in online shopping apps.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

22. I have the knowledge necessary to use AR features in online shopping apps.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

23. I believe the AR feature in online shopping apps is compatible with the other technologies I use.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

24. I think I will get help from others when I have difficulties using AR features in online shopping apps.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

25. The use of AR features in online shopping apps will provide accurate information.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

26. The information offered through the AR feature of online shopping apps would be easy to understand.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

27. The AR feature of online shopping apps will give me personalised information.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

28. Using the AR feature of the online shopping apps will give me relevant information.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

29. I feel that the AR feature in online shopping apps will promptly respond to my requests, offering good results.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

30. The AR feature in online shopping apps will perform its functions quickly and efficiently.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

31. I feel that AR features in online shopping apps are reliable
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

32. The AR feature in online shopping apps will provide precise services matching the apps' purpose.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

33. I feel that there won't be any problems while using the AR feature in online shopping apps.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

34. The AR feature of the online shopping app will work and fully meet my needs.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

35. I believe the AR feature of online shopping apps would be trustworthy.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

36. I feel that the legal and technological aspects of the AR feature of online shopping apps will protect me from problems.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

37. I believe that the AR feature of the shopping apps will keep its promises and commitments.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

38. I would trust the AR feature of online shopping apps as it will keep users' interests in mind.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

39. Without my permission, the AR feature of the online shopping app may share data with unidentified people or companies.
Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

40. I am concerned about the security of my interactions with online shopping apps with AR features.

Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

41. I am concerned that the AR feature of the online shopping apps may collect too much information about me.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

42. Personal data stored in the AR-enabled online shopping app could be misused.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

43. I intend to use the AR feature of online shopping apps in future.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

44. I will recommend that my friends and family use the AR feature of online shopping apps.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

45. I plan to use the AR feature of online shopping apps frequently.
    Strongly Disagree ( ) Disagree ( ) Neutral ( ) Agree ( ) Strongly Agree ( )

SECTION II

Please provide your personal details

Gender	Male ( ) Female ( )
Age	18-24yrs ( ) 25-31yrs ( ) 32-38yrs ( ) 39-45yrs ( ) Above 45yrs ( )
Education (Please mark the highest level)	Not professionally educated ( ) Primary/ Secondary ( ) Graduate ( ) Post Graduation and above ( )
Occupation	Employed ( ) Student ( ) Self-employed business ( ) Others ( )
Annual Income	Less than Rs.3,00,000 ( ) Rs3,00,000-Rs.6,00,000 ( ) Rs.6,00,000-Rs.10,00,000 ( ) More than Rs.10,00,000 ( ) Not Applicable ( )
Location	Bangalore ( ) Hyderabad ( ) Chennai ( )

APPENDIX II: List of Publications based on Ph.D. Work

Sl. No.	Title of the paper	Authors (in the same order as in the paper. Underline the scholar's name)	Name of the Journal/ Conference/ symposium, Vol., No., Pages	Month & Year of Publication	Category
1.	Quality Dimensions of Augmented Reality-based Mobile Apps for Smart-Tourism and its Impact on Customer Satisfaction & Reuse Intention	Komal Anand Vikas Arya Sheena Suresh Anshuman Sharma	Tourism Planning & Development Vol.20, Issue 2 236-259	October 2022 (Published)	1
2.	An Empirical Investigation on The Influence of Quality Factors Of AR-based mobile Apps and Its Role on Enhancing Satisfaction and Reuse Intention Behaviour	Komal Anand Dr. Sheena Suresh	International Journal of Business Innovation and Research DOI: 10.1504/IJBIR.2022.100500 63	Not yet published 2022 (Accepted)	1
3.	An Empirical Examination of AR Technology Adoption-Extending UTAUT with Trust	Komal Anand Dr. Sheena Suresh	ISDSI-Global Conference 2021-IIM Nagpur	December 27-30,2021	4
4.	An Empirical Investigation on the Acceptance of Augmented Reality on Online Shopping Apps	Komal Anand Dr. Sheena Suresh	Management Doctoral Colloquium (SHODH SAMAGAM) – IIM Visakhapatnam	December 09-10,2021	4

5.	Impact of Dimensions of Quality on Customer Satisfaction using Augmented Reality Applications	Komal Anand Dr. Sheena Suresh	International E-Conference on The Age of Digital Transformation: Impact of Emerging Technologies in Marketing – IMS Unison University, Dehradun	December 18-19,2020	4

*** Category:**

1: Journal paper, full paper reviewed, 2: Journal paper, Abstract reviewed, 3: Conference/Symposium paper, full paper reviewed, 4: Conference/Symposium paper, abstract reviewed, 5: others (including papers in Workshops, NITK Research Bulletins, Short notes etc.) (If the paper has been accepted for publication but yet to be published, the supporting documents must be attached.)

Komal Anand
Research Scholar

Dr. Sheena
Research Guide

APPENDIX III: Curriculum Vitae

Komal Anand

Anand Sadan
Near Sadananda Mermaid Flats
Padannapalam
Kannur-670014
Kerala
Email Id: komal.inbox@gmail.com

Educational Background

Ph.D. (Thesis Submitted)	National Institute of Technology Karnataka
UGC Net Lectureship in Management	UGC
MBA (Marketing & HR)	Department of Management Studies, Kannur University Kerala
BBM (Marketing)	Chinmaya Arts & Science College, Kannur, Kannur University

Professional Experience

- Worked as an Assistant Professor for more than five years at the Centre for Management Studies, Kannur University Kerala.
- Worked as Assistant Director in charge at Centre for Management Studies, Kannur University Kerala, for six months.
- Worked as Assistant Professor for 2 years at the Institute of Technology Mayyil, Kannur University, Kerala.

Skill Set

- MS Word, MS Excel, SPSS, AMOS, Smart PLS

Roles and Responsibilities

- Subjects handled: Principles of Management, Marketing Management, Training and Development.
- Examiner for the valuation of answer scripts of Kannur University, Kerala

Research Publications

- Komal Anand, Vikas Arya, Sheena Suresh & Anshuman Sharma (2023) Quality Dimensions of Augmented Reality-based Mobile Apps for Smart-Tourism and

its Impact on Customer Satisfaction & Reuse Intention, Tourism Planning & Development, 20:2, 236-259, DOI: 10.1080/21568316.2022.2137577

- Komal Anand & Sheena Suresh. The Influence of Quality Factors on AR-Based Mobile Apps and Its Role in Enhancing Satisfaction and Reuse Intention Behaviour-An Empirical Investigation, International Journal of Business Innovation and Research, DOI:10.1504/IJBIR.2022.10050063 (In press)

Papers Presented

- Presented a paper titled "An Empirical Examination of AR Technology Adoption-Extending UTAUT with Trust" at ISDSI-Global Conference 2021-IIM Nagpur on December 27-30, 2021.
- Presented a paper titled "An Empirical Investigation on the Acceptance of Augmented Reality on Online Shopping Apps" at Management Doctoral Colloquium (SHODH SAMAGAM) – IIM Visakhapatnam December 09-10, 2021.
- Presented a paper titled "Impact of Dimensions of Quality on Customer Satisfaction using Augmented Reality Applications" at International E-Conference on The Age of Digital Transformation: Impact of Emerging Technologies in Marketing – IMS Unison University, Dehradun, December 18-19, 2020

Workshops Attended

- National Level Five Days Hands-on Training Program on SPSS and SPSS AMOS held from 27th May-31st May 2019 at Welcomgroup Graduate School of Hotel Administration (WGSHA), Manipal Academy of Higher Education, Manipal.
- Three days Workshop on Case Study Approach on Research Paper Writing Skills held from 8th May-10th May 2019 at the Department of Commerce, PG and Research Centre, Manipal Academy of Higher Education, Manipal.
- 2 Days E-Workshop on "Questionnaire Designing" held from 15th-16th May 2021, organized by Research Smiths.
- 2 Days International E-Conference on The Age of Digital Transformation: Impact of Emerging Technologies in Marketing held from 18th - 19th December

2020 organized by the School of Management (SoM), IMS University, Dehradun.