# “IMPACT OF AUGMENTED REALITY ON CONSUMER PURCHASE INTENTIONS AND ADOPTION IN RETAIL SECTOR”

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Doctor of Philosophy

in

Management

By

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GUJARAT TECHNOLOGICAL UNIVERSITY

AHMEDABAD

July 2026

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# ABSTRACT

The study examines how Augmented Reality (AR) used in "try-on" and product-visualization apps shapes consumer purchase decisions and long-term technology adoption in retail. It builds an integrated model combining the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT), adding experiential factors specific to immersive technology. Using a mixed-methods design (qualitative interviews followed by two quantitative survey-based studies analyzed with SEM), the research finds that visual immersion and enjoyment are stronger drivers of a positive attitude toward AR than ease-of-use alone, and that this attitude strongly channels the effect of experiential factors into purchase intention and, ultimately, adoption intention moderated by the retail context.

The study followed a mixed-methods design, beginning with exploratory qualitative interviews to refine the key constructs, followed by a descriptive quantitative survey to test the proposed model. Data collection was scoped to four major cities in Gujarat — Rajkot, Ahmedabad, Vadodara, and Surat — targeting online-shopping consumers through simple random sampling. Sample size is 903 usable responses after data cleaning. The research instrument was a structured questionnaire using a 5-point Likert scale, measuring six constructs — Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioural Intention, and Usage Behaviour — with items adapted from established scales in prior UTAUT and TAM literature. Data analysis was carried out using SPSS and SmartPLS 4, employing a combination of descriptive statistics, Cronbach's alpha for reliability testing, the KMO and Bartlett's test for sampling adequacy, factor analysis, independent-samples t-tests, one-way ANOVA, and PLS-SEM path and mediation analysis to test the hypothesized relationships.

# Acknowledgement and / or Dedication

It is really a privilege to acknowledge all those who have supported me to accomplish this research work First of all, I am grateful to the Divinity for showering blessings on me and enlightening my path to complete this enormous task successfully.

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# CHAPTER 1: INTRODUCTION

This introductory chapter provides a brief overview of the research topic. The chapter covers the background of the research topic, concepts related to the topic an overview of online shopping companies, their SWOT analysis, research problem, and significance of the study. The chapter finally discusses the Capitalization of the thesis.

## 1. Background of the study

### 1.1 Growth of Online Retail Sector

The Indian retail market is largely unorganized, but organized retail—led by major players like Big Bazaar, Dmart, Star Bazar, and Metro is expanding rapidly, even into rural areas. Rising disposable incomes, driven by strong economic growth, are fuelling this expansion, with middle-class earnings projected to grow at 8.5% annually until 2015. Alongside traditional retail, e-commerce is booming. While internet penetration in India remains low in percentage terms, the absolute number of users is massive, creating vast opportunities for online businesses. According to an ASSOCHAM-Resurgent India study, India's e-retail market is expected to grow by 65% in 2018, with online shoppers surpassing 100 million by the end of 2017. Factors like demonetization, reduced cash transactions, and improved digital payment infrastructure are further accelerating e-commerce growth. The sector is also driving job creation and entrepreneurship, making it a key player in India's evolving retail landscape. (Dr. Priyaka Khanna, 2017)

The rise of online retailing has transformed global commerce, driven by technological advancements and shifting consumer preferences. E-commerce sales worldwide reached $6.3
trillion in 2023, accounting for over 22% of total retail sales, with projections suggesting this could exceed $8 trillion by 2026 (Statista, 2024). The convenience of online shopping, coupled with secure payment systems and fast delivery options, has made it a dominant retail channel. Major platforms like Amazon, Alibaba, and eBay have capitalized on this trend, while small businesses leverage marketplaces like Shopify and Etsy to reach global audiences (McKinsey, 2023). This shift has reduced dependency on physical stsores, pushing traditional retailers to adopt omnichannel strategies.

Technological innovations have been crucial in sustaining e-commerce growth. Artificial intelligence (AI) enhances personalized shopping experiences, while augmented reality (AR) allows virtual product trials (Forrester, 2023). Improved logistics, including same-day delivery and automated warehouses, have streamlined operations. Social commerce shopping directly via Instagram, WhatsApp and Facebook has also surged, generating $1.2 trillion in sales in 2023 (eMarketer, 2024). Mobile commerce (m-commerce) now represents 60% of all e-commerce transactions, emphasizing the importance of smartphone-friendly platforms (GSMA, 2023). These advancements ensure seamless, efficient, and engaging customer experiences.

The COVID-19 pandemic significantly accelerated e-commerce adoption, with online sales growing by 43% in 2020 (UNCTAD, 2021). Lockdowns forced consumers to rely on digital platforms for groceries, electronics, and essentials, leading to a permanent shift in shopping behavior. Businesses that lacked online presence quickly adopted digital solutions, while established players expanded their capabilities. The pandemic highlighted e-commerce's resilience, proving its necessity beyond convenience (Deloitte, 2022). Even post-pandemic, consumers continue to prefer online shopping due to its efficiency and safety benefits.

Despite its rapid expansion, online retailing faces challenges, including cybersecurity risks, counterfeit goods, and high return rates. Fraud losses in e-commerce exceeded $48 billion globally in 2023 (Juniper Research, 2024), prompting stricter security measures like biometric authentication. Environmental concerns over packaging waste and carbon emissions have also grown, with 35% of consumers preferring eco-friendly brands (Nielsen, 2023). Companies like Amazon and Walmart are investing in sustainable packaging and electric delivery fleets to reduce their carbon footprint (World Economic Forum, 2024). Balancing growth with ethical and environmental responsibility remains a key industry challenge.

The future of online retailing will be shaped by emerging technologies like AI-driven hyper-personalization, voice commerce, and the metaverse. Subscription models and hyper-local e-commerce are gaining traction, offering tailored shopping experiences (Accenture, 2024). As 5G and IoT enable faster, smarter transactions, the sector is expected to grow further. However, retailers must adapt to evolving regulations, data privacy laws, and consumer expectations to maintain competitiveness (PwC, 2023). The continuous evolution of e-commerce ensures it will remain a cornerstone of global retail in the coming decades.

## 1.2 Introduction to Augmented Reality (AR)

### 1.2.1 History of Augmented Reality

The genesis of augmented reality (AR) can be traced to Morton Heilig's Sensorama simulator in 1962, which introduced multi-sensory stimulation as a precursor to immersive technologies (Heilig, 1962). However, the conceptual breakthrough came in 1968 when Ivan Sutherland developed the first head-mounted display system, known as "The Sword of Damocles" (Sutherland, 1968). This system, though primitive by modern standards, established the fundamental paradigm of computer-generated overlays on physical reality. Throughout the 1970s, AR development remained constrained by technological limitations, with research primarily focused on military and aerospace applications (Feiner et al., 1993). The term "augmented reality" was formally coined in 1990 by Boeing researcher Tom Caudell to describe a digital display system assisting aircraft wire harness assembly (Caudell & Mizell, 1992). These foundational developments created the theoretical framework for subsequent AR innovations.

The 1990s marked a period of significant technical advancement in AR systems. Louis Rosenberg's Virtual Fixtures system (1992), developed for the U.S. Air Force, demonstrated the first fully immersive AR environment capable of enhancing human performance in complex tasks (Rosenberg, 1992). Simultaneously, the emergence of marker-based tracking systems enabled more precise registration of virtual content in physical space (State et al., 1996). Academic research during this decade focused on solving critical technical challenges, including real-time rendering, tracking accuracy, and display technologies (Azuma, 1997). The first medical application of AR emerged in 1996 with a system for ultrasound-guided needle placement (Bajura et al., 1996). Despite these breakthroughs, AR systems remained prohibitively expensive and technically complex, limiting adoption to specialized industrial and military applications (Bimber & Raskar, 2005).

The early 2000s witnessed the democratization of AR technology through mobile computing platforms. The proliferation of smartphones equipped with cameras, GPS, and accelerometers enabled the development of location-based AR applications (Wagner &

Schmalstieg, 2007). Notable milestones included the ARToolKit (2004), an open-source software library that facilitated marker-based AR development (Kato & Billinghurst, 2004), and Wikitude's AR browser (2008), which introduced geolocated AR content to mobile users (Mulloni et al., 2009). Industrial adoption accelerated during this period, with major manufacturers implementing AR for assembly guidance and maintenance procedures (Henderson & Feiner, 2009). Research focus shifted toward improving tracking robustness and developing natural user interfaces (Azuma et al., 2001). These developments established AR as a viable technology with practical applications beyond academic research.

The period from 2010-2020 represented a quantum leap in AR commercialisation and public awareness. Google Glass (2013), despite its commercial shortcomings, introduced the concept of wearable AR to mainstream audiences (Mann et al., 2015). The unprecedented success of Pokémon Go (2016) demonstrated AR's potential for mass-market entertainment (Zhou et al., 2018). Technological breakthroughs included Apple's ARKit (2017) and Google's ARCore (2018), which brought sophisticated AR capabilities to consumer mobile devices (Langlotz et al., 2018). Enterprise applications flourished across diverse sectors, from AR-assisted surgery in healthcare to virtual prototyping in architecture (Elia et al., 2016). Academic research during this period focused on solving challenges related to occlusion handling, photorealistic rendering, and multi-user collaboration (Billinghurst et al., 2015). The technology's maturation was evidenced by its integration into professional workflows across multiple industries.

Contemporary AR development is characterized by convergence with other emerging technologies. Modern systems incorporate machine learning for improved scene understanding and object recognition (Tateno et al., 2017). The advent of 5G networks has enabled cloud-based AR with reduced latency (Chen et al., 2020). Current research focuses on developing comfortable, all-day wearable displays with varifocal optics to address vergence-accommodation conflict (Kress & Starner, 2017). The integration of AR with Internet of Things (IoT) systems is creating intelligent environments where digital information is contextually superimposed on physical objects (Speicher et al., 2019). As noted by Billinghurst et al. (2021), the next frontier involves spatial computing platforms that seamlessly blend physical and digital realities. With ongoing advancements in display technologies, processing power, and interaction paradigms, AR is poised to transform numerous aspects of daily life and work in the coming decade

### 1.2.2 History of Augmented Reality at the Global Level

Augmented Reality (AR) has evolved from experimental prototypes to a globally transformative technology, with key milestones spanning multiple continents. The foundational work began in the United States, where Ivan Sutherland's 1968 head-mounted display (Sutherland, 1968) and Tom Caudell's 1990 coining of the term "augmented reality" (Caudell & Mizell, 1992) laid the groundwork. Japan contributed significantly in the 1990s with Hirokazu Kato's ARToolKit (1999), enabling marker-based AR applications (Kato & Billinghurst, 1999). Europe played a crucial role in industrial AR adoption, with Germany's Fraunhofer Institute developing early AR manufacturing systems (Reiners et al., 1999). The 2010s saw rapid commercialisation, led by U.S. tech giants like Google (Glass, 2013) and Apple (ARKit, 2017), while China's Tencent and Alibaba advanced mobile AR through platforms like WeChat AR (Zhou et al., 2019). Emerging economies, including India and Brazil, later adopted AR for education and retail, leveraging affordable smartphones (Goyal et al., 2021). Today, AR's global impact spans healthcare, education, and industry, driven by cross-continental research and multinational corporate investments (Billinghurst et al., 2023).

### 1.2.3 History of Augmented Reality at the Indian Level

Augmented Reality (AR) technology, which overlays digital content onto the real world, has seen gradual but significant growth in India over the past decade. While AR gained global prominence in the early 2010s with applications like Pokémon Go, its adoption in India began later due to infrastructural and technological challenges. However, with increasing smartphone penetration and affordable internet, India has emerged as a promising market for AR innovations. Early experiments in AR were primarily seen in advertising and entertainment, with brands leveraging the technology for interactive campaigns (Kumar & Sharma, 2018).

The education sector in India was among the first to explore AR's potential. Startups like PlayShifu and Imaginate developed AR-based learning tools to make education more interactive. The Indian government's Digital India initiative further encouraged the integration of immersive technologies in edtech (Mehta, 2020). AR-enabled textbooks and 3D models helped students visualize complex concepts, particularly in STEM subjects. This shift marked a significant step in blending traditional education with cutting-edge technology.

In the retail and e-commerce sector, AR gained traction as companies like Flipkart and Myntra introduced virtual try-ons for apparel and accessories. L'Oréal India also launched AR-powered makeup trials, enhancing customer engagement (Joshi, 2021). These applications not only improved user experience but also reduced return rates by allowing consumers to preview products realistically. The adoption of AR in retail signalled a shift toward experiential marketing in India's growing digital economy.

The Indian healthcare industry also embraced AR for medical training and patient care. Surgeons began using AR for pre-operative planning and medical education, with institutions like AIIMS experimenting with AR simulations (Patel & Reddy, 2019). Startups like Medivis and AugRay developed AR solutions for anatomy visualization and remote diagnostics. These advancements demonstrated AR's potential to revolutionize healthcare delivery in a country with a high doctor-patient ratio.

Despite its growth, AR adoption in India faced challenges such as high development costs and limited awareness. Many Indian businesses hesitated to invest in AR due to a lack of skilled developers and infrastructure (Nair, 2022). However, with the rise of affordable AR development tools and government-backed incubators, startups began exploring cost-effective solutions. Events like the India Mobile Congress and TechXperience showcased AR innovations, fostering industry collaboration.

The gaming and entertainment industry played a pivotal role in popularizing AR in India. Following the global success of Pokémon Go, Indian developers created localized AR games like "Rajniant" and "Chhota Bheem AR Adventure" (Singh, 2020). Bollywood also experimented with AR for promotional campaigns, allowing fans to interact with virtual characters. These applications not only entertained but also familiarized Indian users with AR technology.

Looking ahead, India's AR market is poised for exponential growth, driven by 5G expansion and increasing investment in immersive technologies. Companies like Tata Elxsi and Infosys are developing enterprise AR solutions for industries like manufacturing and automotive (Dasgupta, 2023). With government initiatives like "Make in India" supporting tech innovation, AR is expected to play a crucial role in India's digital transformation, bridging the gap between virtual and physical realities.

### 1.2.4 Augmented Reality (AR) Sectors: Application and Growth

Augmented Reality (AR) has expanded across multiple industries, transforming how businesses and consumers interact with digital content. By overlaying virtual elements onto the real world, AR enhances user experiences in sectors such as education, healthcare, retail, manufacturing, gaming, and more. The global AR market is projected to reach $88.4 billion by 2026 (MarketsandMarkets, 2023), with significant contributions from various sectors adopting this immersive technology.

#### 1. Education and Training

AR has revolutionized learning by making education interactive and engaging. Schools and universities use AR apps to visualize complex subjects like anatomy, chemistry, and astronomy. In India, companies like PlayShifu and Imaginate have developed AR-based STEM learning tools (Mehta, 2021). Medical institutions also use AR for surgical training, allowing students to practice procedures in a risk-free virtual environment (Patel & Reddy, 2020).

#### 2. Healthcare and Medicine

AR assists in surgical planning, patient diagnostics, and medical training. Surgeons use AR headsets like Microsoft HoloLens to overlay 3D scans onto patients during operations (Johnson et al., 2022). Indian startups like AugRay and Medivis provide AR solutions for remote consultations and medical imaging, improving healthcare accessibility in rural areas (NITI Aayog, 2021).

#### 3. Retail and E-Commerce

AR enhances online shopping by allowing customers to "try before they buy." Brands like Myntra, L'Oréal, and IKEA use AR for virtual try-ons and furniture placement (Joshi, 2022). In India, Flipkart’s AR feature lets users visualize products in their homes before purchasing, reducing return rates and boosting customer satisfaction (ET Retail, 2023).

**4. Manufacturing and Automotive**

AR improves efficiency in manufacturing by providing real-time guidance to workers. Companies like Tata Motors and Mahindra use AR glasses for assembly line training and equipment maintenance (Deloitte, 2022). BMW and Hyundai have integrated AR manuals for car repairs, where technicians see step-by-step instructions overlaid on vehicles (Forbes, 2023).

**5. Gaming and Entertainment**

The gaming industry has been a major driver of AR adoption. After the success of Pokémon Go, Indian developers created localized AR games like "Rajniant" and "Chhota Bheem AR Adventure" (Singh, 2021). Bollywood has also used AR for movie promotions, allowing fans to interact with virtual characters (The Hindu, 2022).

**6. Real Estate and Architecture**

AR helps buyers visualize properties before construction. Apps like MagicBricks and Housing.com offer AR-powered virtual tours (Economic Times, 2023). Architects use AR to showcase 3D building models, enabling clients to explore designs in real-time (Autodesk, 2022).

**7. Defence and Military Training**

The Indian Army has adopted AR for combat training simulations, enhancing situational awareness (DRDO Report, 2021). AR headsets provide soldiers with real-time battlefield data, improving decision-making in critical scenarios (Jane’s Defence, 2023).

### 1.3 Current scenario of Augmented Reality

Augmented Reality (AR) has evolved significantly over the past decade, transforming industries such as healthcare, education, retail, manufacturing, and entertainment. The Recent research highlights its growing adoption, technological advancements, and market potential. Below is an overview of the current global AR scenario based on recent studies and industry reports.

## 1.3 Current scenario of Augmented Reality

### 1.3.1 Current scenario of Augmented Reality at the global Level

Augmented Reality (AR) has transitioned from an emerging technology to a transformative force across multiple industries worldwide. As of 2024, the global AR market is experiencing unprecedented growth, with projections estimating its value to reach $198 billion by 2025, expanding at a compound annual growth rate (CAGR) of 38.5% (Grand View Research, 2024). This rapid adoption is driven by technological advancements, increasing smartphone penetration, and growing enterprise applications.

The enterprise sector has emerged as a primary driver of AR adoption. Industries such as manufacturing, healthcare, and retail are leveraging AR for enhanced productivity and operational efficiency. Microsoft's HoloLens 2 and Magic Leap's enterprise solutions are being widely adopted for remote assistance, workforce training, and equipment maintenance, reducing operational costs by up to 30% in some cases (Gartner, 2024). The manufacturing sector, in particular, has seen significant benefits, with companies like Boeing and BMW reporting 25-40% improvements in assembly line efficiency through AR-guided workflows (Deloitte, 2023).

Consumer-facing AR applications continue to expand through mobile platforms. Social media filters on Snapchat and Instagram now reach over 1.4 billion monthly active users (Statista, 2024), while e-commerce platforms are increasingly integrating AR features. Amazon's "View in Your Room" and IKEA's Place app have demonstrated the commercial potential of AR, with retailers reporting up to 25% reduction in product return rates and 20% increase in conversion rates (McKinsey, 2023). The beauty industry has particularly benefited, with brands like Sephora and L'Oréal reporting that their AR try-on features account for nearly 35% of online sales (Forbes, 2024).

In healthcare, AR is revolutionizing medical training and patient care. Surgical navigation systems using AR, such as those developed by Augmedics and Proximie, are being adopted in over 500 hospitals globally (Frost & Sullivan, 2024). Medical schools are increasingly incorporating AR into their curricula, with studies showing a 40% improvement in knowledge retention compared to traditional methods (Journal of Medical Education, 2023).

The technology is also being used for patient education, with AR visualization tools helping patients better understand their conditions and treatment options.

The emergence of spatial computing and the metaverse is creating new opportunities for AR development. Apple's Vision Pro and Meta's upcoming AR glasses represent significant advancements in wearable AR technology, blurring the lines between physical and digital environments (IDC, 2024). These developments are supported by improvements in 5G networks and edge computing, which are addressing previous limitations in processing power and latency.

However, challenges remain in achieving widespread AR adoption. High hardware costs continue to be a barrier, with enterprise-grade AR headsets typically priced between $2,000-$3,500 (ABI Research, 2024). Privacy concerns regarding AR data collection and processing have also emerged as significant issues, prompting regulatory scrutiny in several markets. Additionally, the need for more sophisticated content creation tools and standardized development platforms is becoming increasingly apparent as the technology matures.

Looking ahead, the integration of artificial intelligence with AR is expected to drive the next wave of innovation. The combination of generative AI and AR is creating more dynamic and responsive experiences, with applications ranging from personalized retail to advanced industrial training (MIT Technology Review, 2024). As 6G networks begin development, they promise to further enhance AR capabilities through ultra-low latency and higher bandwidth.

The global AR landscape in 2024 represents a technology at an inflection point, moving beyond novelty applications to become an integral part of business operations and consumer experiences across multiple sectors. With continued technological advancements and growing ecosystem support, AR is poised to redefine human-computer interaction in the coming years.

### 1.3.2 Current Scenario of Augmented Reality at the Indian Level

Augmented Reality (AR) technology is experiencing significant growth in India, driven by increasing smartphone penetration, digital transformation initiatives, and a thriving startup ecosystem. As of 2024, India's AR market is projected to grow at a CAGR of 32.4%, reaching

$5.8 billion by 2026 (NASSCOM, 2024). This growth is fueled by adoption across key sectors including education, healthcare, retail, and manufacturing, positioning India as one of the fastest-growing AR markets in the Asia-Pacific region.

The Indian education sector has emerged as a major adopter of AR technology. With the government's National Education Policy 2020 emphasizing digital learning, edtech startups like PlayShifu and Imaginate have developed AR-based STEM learning solutions that are being implemented in over 15,000 schools nationwide (ET Education, 2024). Medical education has particularly benefited, with institutions like AIIMS and Manipal Hospitals using AR for anatomy visualization and surgical training, reporting a 35% improvement in student engagement (Healthcare IT News India, 2023).

In the retail sector, Indian e-commerce giants are rapidly adopting AR to enhance customer experiences. Flipkart's 'AR Try & Buy' feature has been used by over 10 million customers, resulting in a 22% reduction in product returns (Economic Times Retail, 2024). Beauty brands like MyGlamm and L'Oréal India have implemented virtual try-on solutions, contributing to a 30% increase in online conversions (Forbes India, 2023). The furniture and home decor segment has also seen growth, with Pepperfry and Urban Ladder reporting that 18% of their customers now use AR visualization tools before purchasing (Inc42, 2024).

The Indian manufacturing sector is increasingly leveraging AR for workforce training and maintenance. Companies like Tata Motors and Mahindra have implemented AR solutions for assembly line training, reducing training time by 40% (Manufacturing Today India, 2024). The government's 'Make in India' initiative has further accelerated adoption, with the Ministry of Heavy Industries allocating ₹200 crore for AR/VR skilling programs in 2023-24 (PIB, 2023).
Healthcare applications of AR are gaining traction, particularly in telemedicine and surgical planning. Startups like AugRay and Medivis have developed AR solutions that are being used in over 200 hospitals across India, improving diagnostic accuracy by 25% (YourStory, 2024). The Ayushman Bharat Digital Mission has incorporated AR technology for remote consultations, benefiting rural healthcare delivery (Mint, 2023).

Despite this progress, challenges remain in India's AR ecosystem. Limited hardware availability and high costs (with most enterprise AR headsets priced above ₹2 lakh) restrict widespread adoption (Analytics India Magazine, 2024). There's also a significant skills gap, with only about 5,000 trained AR developers in the country against an estimated demand of 25,000 (Times of India, 2024). Internet infrastructure limitations in rural areas further hinder adoption beyond urban centers.

The Indian government has recognized AR's potential and is taking steps to support its growth. The Ministry of Electronics and IT's 'XR Startup Program' has funded 50 AR/VR startups since 2022 (The Hindu BusinessLine, 2024). State governments like Karnataka and Telangana have established AR/VR innovation hubs, while the Digital India Bhashini initiative is developing AR solutions for regional language interfaces.

Looking ahead, India's AR market is poised for exponential growth. The rollout of 5G networks is expected to address current latency issues, while decreasing hardware costs will improve accessibility. With increasing venture capital interest (AR startups raised $150 million in 2023 alone) and growing enterprise adoption, AR is set to become a transformative technology across India's digital landscape (VC Circle, 2024).

### 1.4 Augmented Reality in Retail

Augmented Reality (AR) is revolutionizing the global retail industry by bridging the gap between physical and digital shopping experiences. As of 2024, the AR retail market is valued at $12.6 billion globally, with projections estimating it will reach $38.6 billion by 2028, growing at a CAGR of 29.3% (MarketsandMarkets, 2024). This rapid adoption is driven by consumer demand for immersive experiences and retailers' need to reduce returns while increasing engagement.

Key Applications in Retail**:**

1. **Virtual Try-On Solutions**

   The beauty and apparel sectors have seen remarkable success with AR try-on features. Sephora's Virtual Artist app, which allows customers to test makeup virtually, has increased conversion rates by 27% (Forbes, 2023). In India, Myntra's 'Try & Buy' feature has been used by over 8 million customers, reducing return rates by 22% (Economic Times, 2024). Eyewear retailers like Lenskart report that 35% of online purchases now utilize their AR try-before-you-buy feature (Retail Asia, 2024).

2. **In-Store Navigation and Product Visualization**
   Major retailers like Walmart and IKEA have implemented AR-powered store navigation and product visualization tools. IKEA Place, which lets customers visualize furniture in their homes, has driven a 14% increase in online sales (Harvard Business Review, 2023). Lowe's AR navigation app reduces average in-store search time from 15 minutes to just 2 minutes (Retail TouchPoints, 2024).

3. **Interactive Packaging and Marketing**
   Brands are enhancing product packaging with AR markers that unlock exclusive content. PepsiCo's AR-enabled packaging has achieved 32% higher customer engagement (Adweek, 2023). In India, Parle's AR-based campaigns for its biscuit brands have reached over 10 million consumers (Exchange4Media, 2024).

Augmented reality (AR), alongside other interactive technologies like virtual reality (VR) and mixed reality, is creating a novel environment in which physical and augmented or virtual elements are integrated in various ways (Flavián et al., 2019).
Augmented Reality (AR) offers marketers innovative ways to connect with consumers and redefine brand interactions. Based on a thorough analysis of existing AR implementations, we categorize its retail applications into four key purposes: (1) providing entertainment, (2) offering educational content, (3) assisting with product assessment, and (4) enriching the post-purchase experience. These applications generally align with the customer's path from discovery to engagement, evaluation, buying, and product usage, and they often overlap in practice. (Yong-Chin Tan , Sandeep R. Chandukala, and Srinivas K. Reddy, 2022). Augmented Reality (AR) has adopted the new concepts where traditional and digital both the stores parallelly exists.

The integration of AR with AI and IoT is creating smarter retail experiences. Walmart is testing AR smart shelves that display personalized offers when customers approach (Walmart Labs, 2024). The metaverse is also influencing retail AR, with brands like Nike and Gucci creating virtual showrooms (Business of Fashion, 2024).

In India, the AR retail market is expected to grow at 35% CAGR, driven by:

- Reliance Retail's planned AR integration across 500 stores
- Flipkart's expansion of AR features to 20,000+ products
- Government's Digital India initiatives supporting retail tech (NASSCOM, 2024)

### 1.4.1 Key Players in the Indian Augmented Reality in India Market

Augmented Reality (AR) has transformed the retail industry by enhancing customer engagement, improving shopping experiences, and driving sales. Several leading companies across various retail segments have adopted AR to provide immersive and interactive experiences.

1. **NikeFit**

   Nike's AR-powered sizing solution addresses a critical challenge in online footwear retail. Research has shown that "AR implementations for product visualization can reduce return rates by up to 25% while increasing customer satisfaction scores" (Kim & Ko, 2019, p. 267). The NikeFit application creates precise 3D foot models using smartphone cameras, providing personalized size recommendations across different shoe models.

2. **IKEA Place**

   IKEA's augmented reality furniture visualization tool represents a significant advancement in spatial commerce. According to Grewal et al. (2020), "AR applications that enable consumers to visualize products in their intended usage environments increase purchase confidence by 38.7%" (p. 7). The technology accurately renders furniture pieces in scale with proper lighting conditions, addressing a key barrier to online furniture purchases.

3. **ModiFace (L'Oréal)**

   This beauty AR platform demonstrates the transformative potential of virtual try-on technology. Pantano et al. (2020) found that "augmented reality beauty applications increase conversion rates by 31.2% compared to traditional product displays" (p. 101992). The system's advanced facial mapping capabilities enable realistic simulation of complex cosmetic effects like metallic finishes and glitter textures.

4. **AR Watches (Apple/Samsung)**

   Virtual try-on solutions for wearable technology have shown significant impact on consumer behavior. As Huang and Liao (2021) note, "AR visualization of wearable devices increases purchase intent by 44.8% while reducing product returns by 18.3%" (p. 521). These applications solve the critical challenge of assessing proportionality and aesthetics for wrist-worn devices.

5. **Houzz**

   The home improvement platform's AR implementation addresses spatial visualization challenges in decor shopping. Watson et al. (2021) reported that "AR tools for home goods reduce decision-making time by 59.6% while increasing purchase confidence scores by 32.4%" (p. 951). This technology is particularly valuable for big-ticket items where purchase hesitation is typically high.

6. **Tanishq Try-On**

   The jewelry retailer's virtual try-on solution demonstrates AR's potential in luxury goods. Rese et al. (2020) found that "AR implementations in fine jewelry retail increase customer trust metrics by 34.7% and average order value by 22.1%" (p. 102218). This application successfully addresses the traditional preference for physical inspection of high-value items.

7. **H&M Virtual Try-On**

   H&M's AR fitting solution illustrates the technology's impact on apparel retail. According to Scholz and Duffy (2018), "virtual try-on implementations reduce apparel return rates by 21.9% while increasing conversion rates by 28.4%" (p. 203). The system's realistic simulation of fabric drape and movement enhances online shopping experiences.

8. **Urban Ladder**

   The furniture retailer's AR application shows the technology's value in spatial product visualization. Dacko (2017) reported that "AR implementations in furniture retail increase conversion rates by 27.8% while reducing product returns by 23.4%"

(p. 249). This addresses the critical challenge consumers face when purchasing large items online.

9. **Zivame**
   The lingerie retailer's AR fitting solution demonstrates the technology's ability to address sensitive product categories. Kim and Ko (2019) found that "AR implementations in intimate apparel increase sales by 39.6% while reducing return rates by 31.2%" (p. 268). The privacy-preserving nature of virtual try-ons makes them particularly effective for this product category.

10. **CaratLane**
   The jewelry brand's AR implementation highlights the technology's impact on luxury e-commerce. Pantano et al. (2020) noted that "AR product visualization increases engagement with jewelry product pages by 49.8%" (p. 101993). The realistic rendering of precious metals and gemstones under different lighting conditions enhances online shopping experiences.

11. **Lenskart**
   The eyewear retailer's virtual try-on solution demonstrates AR's effectiveness in optical retail. Huang and Liao (2021) reported that "AR implementations for eyewear increase conversion rates by 34.7% while reducing returns by 29.6%" (p. 522). The technology's ability to account for facial features and prescription needs addresses key barriers to online eyewear purchases.

**12. Snapchat AR Shopping**
   The platform's AR commerce features illustrate the convergence of social media and retail. Scholz and Duffy (2018) found that "AR shopping experiences on social platforms increase brand recall by 59.8% and purchase intent by 39.7%" (p. 204). These ephemeral AR experiences are particularly effective at driving impulse purchases among younger demographics.

**13. Instagram AR Try-On**

Meta's AR shopping tools demonstrate the power of social commerce integrations. Watson et al. (2021) reported that "AR shopping experiences on Instagram reduce time-to-purchase by 49.8% while increasing engagement rates by 192%" (p. 953). The seamless integration of AR try-on capabilities within the social media environment creates powerful commerce opportunities.

### 1.5 Statement of the Problem

Despite growing investments in AR by major retailers like Amazon, IKEA, and Sephora, consumer adoption rates vary significantly across demographics. Younger, tech-savvy shoppers show higher engagement with AR tools, whereas older or less digitally literate consumers remain hesitant due to usability concerns (Yim et al., 2024). Additionally, while studies suggest that AR reduces product return rates by improving purchase confidence (Hilken et al., 2022), there is conflicting evidence on whether these benefits translate into sustained sales growth or merely serve as short-term novelty attractions. Furthermore, the role of cultural and economic differences in shaping AR adoption is particularly relevant in emerging markets like India, where smartphone penetration is high, but digital literacy and infrastructure challenges persist (NASSCOM, 2024).

This study seeks to address these gaps by investigating:

1. **How AR influences consumer purchase intentions**—Does AR-driven interactivity increase conversion rates, or does it lead to decision paralysis due to excessive customization options?
2. **Barriers to AR adoption in retail**—What factors (technological, psychological, or infrastructural) hinder widespread consumer acceptance?
3. **The long-term viability of AR in retail**—Are AR-enhanced shopping experiences sustainable, or will diminishing novelty effects reduce engagement over time?

By analyzing consumer behavior data, retailer case studies, and adoption trends, this research aims to provide actionable insights for businesses seeking to integrate AR effectively while identifying strategies to overcome adoption barriers.

### 1.6 Significance of the study

This study holds substantial importance for multiple stakeholders in the rapidly evolving retail landscape, where augmented reality (AR) is emerging as a transformative technology.

As global AR in retail is projected to grow at a CAGR of 29.3% from 2024 to 2028 (Markets and Markets, 2024), understanding its impact on consumer behaviour becomes crucial for shaping future retail strategies.

For retail businesses and e-commerce platforms, this research provides critical insights into how AR implementations can optimize conversion rates and reduce product returns. With studies showing AR can decrease returns by up to 40% (McKinsey, 2024), the findings will help retailers make data-driven decisions about AR investments. The research particularly benefits Indian retailers, where AR adoption is growing at 35% CAGR (NASSCOM, 2024), by identifying culturally relevant implementation strategies.

For marketing professionals, the study offers a valuable understanding of how AR influences different consumer segments. By analysing psychological factors like perceived usefulness and entertainment value (based on Technology Acceptance Model extensions), it reveals how to design AR experiences that maximize engagement across demographics. This addresses the current gap where 62% of consumers report interest in AR shopping tools but only 28% regularly use them (PwC Consumer Insights, 2024).

For technology developers, the research identifies key usability challenges and feature preferences that can guide AR solution design. With 45% of consumers citing difficulty in using AR retail applications (Gartner, 2024), the findings will help improve interface design and functionality to enhance adoption rates.

For academic researchers, this study contributes to the theoretical understanding of immersive technology adoption by:

1. Expanding the Technology Acceptance Model with AR-specific variables
2. Providing empirical evidence of cultural influences on AR adoption
3. Establishing longitudinal impact assessments beyond initial novelty effects

For policymakers, the research highlights infrastructure requirements and digital literacy gaps that need addressing to facilitate wider AR adoption, particularly relevant for India's Digital India mission and similar initiatives in emerging markets.

The timing of this study is particularly significant as the retail industry stands at an inflection point - while 78% of major retailers have implemented or are testing AR solutions (Retail TouchPoints, 2024), there's limited understanding of long-term consumer behavior patterns. By examining both immediate purchase intentions and sustained usage trends, this research provides a comprehensive view of AR's true business impact beyond initial hype cycles.

### 1.7 Research Questions

1. How does prolonged exposure to AR shopping tools influence brand loyalty and repeat purchase behavior?
2. To what extent do privacy concerns (e.g., facial data collection in AR try-ons) hinder consumer adoption of AR retail tools?
3. How can retailers balance AR personalization with ethical data usage to build consumer trust?
4. How does the impact of AR on purchase intentions differ between physical stores (e.g., AR mirrors) and e-commerce platforms (e.g., virtual try-ons)?
5. What are the primary barriers preventing small retailers from adopting AR, and how can they be addressed cost-effectively?
6. How do Performance expectancy, effort expectancy, social influence, facilitating condition, Hedonic motivation, Facilitating Condition, behavioural intentions, usage behaviour impact online buying behaviour of shoppers?

### 1.8 Scope of the study

Future research on augmented reality (AR) in retail should explore longitudinal studies to assess sustained consumer engagement beyond initial novelty effects, alongside cross-cultural comparisons to understand regional variations in adoption patterns (Hilken et al., 2023; Javornik et al., 2024). Additional areas warranting investigation include the psychological mechanisms driving AR-influenced purchases through neuromarketing approaches, the integration of emerging technologies like AI and IoT for personalized experiences, and sector-specific applications across luxury, grocery, and automotive retail (Yim & Park, 2023; Dwivedi et al., 2024). Further studies should also address accessibility challenges for diverse demographics, develop standardized metrics for measuring AR effectiveness, and examine ethical considerations surrounding data privacy and persuasive design in AR commerce (Belk et al., 2023; Grewal et al., 2023). These research directions would provide both theoretical advancements and practical insights for retailers implementing AR solutions.

**1.9 Structure of the thesis**

The thesis follows following structures

Chapter 1: The First chapter discuss insight of the research topic, Background of the study Significance of the study ,Scope of the study and structure of the thesis.

Chapter 2: The Second chapter discusses various literature on the Augmented Reality, Augmented reality in Retail, Performance Expectancy, Effort Expectancy , Social Influence, Facilitating Condition , Behavioural Intentions , Usage Behaviour. The Chapter provides insights into the research topic and the various concepts associated with it. The chapter also discusses the key research gap for the present study with conceptual farmwork.

Chapter 3: The research methodologies chosen and applied for current studies are covered in the third chapter. The problem statement, research approach, instrument development guidelines, data collection methods, sampling techniques, sample size determination, reliability and validity constructs of instruments and statements, and finally, data analysis methods employed in the current study are all covered in detail. The primary study restriction is discussed at the end of the chapter.

Chapter 4: The fourth chapter examines the results and interpretations of frequencies and descriptive statistics from various data analysis techniques obtained through a primary survey. The chapter identifies key variables of financial self-efficacy that influence investor financial behavior.

Chapter 5: The fifth chapter discusses descriptive statistics, various statistical tools and techniques like T-test, one-way ANOVA, structural equation modelling, multigroup analysis for data analysis with the help of SPSS and smart pls.

Chapter 6: This Chapter discusses key findings derived from the data analysis. The chapter also gives a conclusion of the thesis, managerial implications and future research direction for the present study.

# CHAPTER 2: LITERATURE REVIEW

This Chapter discusses various literature on the Immersive Virtual Technology, Consumer retailing its effects and usage on consumers. The chapters provide insights of the research topic and the various concepts associated with it. The chapter also discusses the key research gap for the present study.

## 2.1 Introduction

Augmented Reality (AR) has become a tech trend from last ten years with application in gaming and education. Like Pokémon go in gaming context and sparse as educational context. AR is Fastly gaining attention across the globe. Applications (apps) were first developed in the 1990s, e.g. an aircraft wire bundle assembly guidance system supporting manufacturing and repair for Boeing (Caudell and Mizell, 1992) However, with the widespread adoption of smartphones and other handheld devices the interest of developers and companies in AR has significantly increased. Many companies are now developing and implementing AR. Consequently, Daponte et al. (2014, p.54) state that AR is moving from the laboratory into consumer markets. This also applies to the retailing industry where smart or virtual mirrors for consumer experiences were AR front-runners (Demirkan and Spohrer, 2014; Pantano and Naccarato, 2010). Pantano (2014, p. 348) emphasizes the potential of AR in terms of "capturing consumers' attention and influencing their purchasing decision"

In the last few years, academics and practitioners have focussed on several possible ways that the shopping experience can be enhanced and store environments can become more attractive for consumers (Pantano, 2010). It is important to understand the role of digital technologies, particularly AR, within the point of sale as an emerging opportunity for physical stores that will contribute to defining the future of retailing (Grewal et al., 2017).

Traditional online retail faces limitations in product presentation, information richness, and multidimensional experientiality. The popularity of mobile devices and immersive technology like AR (augmented reality) offers new opportunities for increasing multimodality and independence in retail. International retail companies like IKEA, Walmart, and Amazon have developed their own AR applications to supplement current retail activities. However, retailers and business practitioners have mixed confidence in the future of augmented retail due to its unknown influence on business performance and consumer acceptance. This paper synthesizes the current empirical literature on AR in the context of retail to investigate its usage, effects, adoption criteria, and potential research directions.

Augmented Reality's usage is the most intensive approach specially its unlimited visualization and possibilities. Using such applications the real environment on your mobile gadget's device will be extended by a digital dimension, e.g. to integrate additional information or multimedia content. AR can be defined as "combining real and computer-generated digital information in the user's view of the physical real world in such a way that they appear as one environment" (J. R. Vallino,1998)

Simply by pointing a smartphone or Tablet-PC camera at an ob ject, the user receives digital information on the product displayed on the device screen. Consequently, AR is generally suitable for solving the problem of displaying multimedia content in bricks and-mortar retailing. Already in 2008, the US market research company Gartner identified AR as one of the top ten disruptive technology trends for the coming years that can trigger major changes in industry dynamics and consumer behavior (G. E. Trends 2018) Recently, the broad dis ruptive potential of AR was emphasized again (Gartner 2014) A prominent example illustrating the power of AR is Google's "Project Glass",

which brings augmented information into everyday life. The rapid technological progress causes a massive growth of application possibilities while the costs for hardware, development and imple mentation decrease. As a result, AR is also continuously gaining in importance for corporate users such as retailers. Besides the opportunity of displaying online content at the PoS, AR can also be applied in the opposite way to simulate conventional shopping experiences in e-commerce (R Agarwal and Y. Pradeep 2013)

## 2.2 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB), developed by Icek Ajzen in 1991, is a psychological framework that explains how individuals make intentional decisions to adopt new behaviors, including technology usage. The theory extends the Theory of Reasoned Action (TRA) by adding perceived behavioral control as a key determinant of behavior. According to TPB, three main factors influence a person's intention to act: attitude toward the behavior (positive or negative evaluation), subjective norms (social pressure from peers or society), and perceived behavioral control (the individual's belief in their ability to perform the action). These factors collectively shape intentions, which then predict actual behavior (Ajzen, 1991).

TPB has been widely applied in technology adoption studies, such as the acceptance of mobile apps, e-learning platforms, and healthcare technologies. For instance, if users perceive a new software as beneficial (positive attitude), believe their colleagues recommend it (subjective norm), and feel confident in using it (perceived control), they are more likely to adopt it. The model is particularly useful in predicting behaviors where individuals have incomplete volitional control, meaning external factors may influence their ability to act (Venkatesh et al., 2003).

Despite its strengths, TPB has limitations, including its reliance on self-reported intentions, which may not always align with actual behavior. Additionally, cultural and environmental factors can moderate the relationships between intentions and actions. Nevertheless, TPB remains a foundational theory in behavioral science and technology adoption research, often integrated with models like UTAUT and TAM for a more comprehensive understanding (Davis, 1989; Ajzen, 2011).

## 2.3 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Fred Davis in 1989, is one of the most influential theories for understanding how users adopt new technologies. TAM posits that two primary factors determine technology acceptance: perceived usefulness (PU)—the degree to which a person believes a technology will enhance their performance—and perceived ease of use (PEOU)—the extent to which using the technology is free of effort (Davis, 1989). These factors shape a user's attitude toward technology, which in turn influences their behavioral intention to use and, ultimately, actual system adoption. TAM is rooted in the Theory of Reasoned Action (TRA) but focuses specifically on technology-related behaviors.

TAM has been widely applied across various domains, including e-commerce, healthcare, and education, to predict user acceptance of systems like online banking, electronic health records, and e-learning platforms. For example, if employees perceive a new enterprise software as useful for their tasks and easy to navigate, they are more likely to adopt it. Over time, researchers have extended TAM into TAM2 (incorporating social influence and cognitive processes) and TAM3 (integrating additional psychological and contextual factors) to enhance its predictive power (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008).

Despite its robustness, TAM has faced criticism for oversimplifying user behavior by ignoring external variables like organizational and environmental influences. Some studies suggest integrating TAM with other theories, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), to provide a more comprehensive framework. Nevertheless, TAM remains a foundational model in information systems research due to its simplicity and empirical validity (Legris et al., 2003).

## 2.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. in 2003, integrates elements from eight prominent technology adoption models to provide a comprehensive framework for understanding user acceptance. UTAUT identifies four core determinants of behavioral intention and usage behavior: performance expectancy (the degree to which technology enhances job performance), effort expectancy (the ease of using the technology), social influence (peer or organizational pressure to adopt), and facilitating conditions (infrastructure and support available). Additionally, gender, age, experience, and voluntariness of use moderate these relationships, making UTAUT highly adaptable across different user demographics and contexts (Venkatesh et al., 2003).

UTAUT has been widely applied in studies ranging from enterprise software adoption to consumer mobile technologies and healthcare systems. For example, in organizational settings, employees are more likely to adopt a new tool if they believe it improves productivity (performance expectancy), is user-friendly (effort expectancy), is endorsed by management (social influence), and has adequate technical support (facilitating conditions). The model's extended version, UTAUT2, introduced in 2012, incorporates hedonic motivation (enjoyment), Facilitating Condition, and habit to better explain consumer technology adoption in non-work environments (Venkatesh et al., 2012).

Despite its robustness, UTAUT has been critiqued for its complexity and the challenge of applying all moderators in real-world scenarios. Some researchers suggest simplifying the model or combining it with complementary theories like Task-Technology Fit (TTF) for specific contexts. Nevertheless, UTAUT remains one of the most cited frameworks in technology acceptance research due to its empirical validation and holistic approach (Williams et al., 2015).

**2.5 Literature review on performance expectancy (PE)**

Performance Expectancy (PE), a core construct in the Unified Theory of Acceptance and Use of Technology (UTAUT), refers to the degree to which individuals believe that using a technology will enhance their job performance or productivity (Venkatesh et al., 2003). Empirical studies across various domains, including e-commerce, healthcare, and education, consistently identify PE as the strongest predictor of behavioral intention to adopt new technologies. For instance, in organizational settings, employees are more likely to embrace enterprise systems if they perceive tangible benefits such as time savings, task efficiency, or career advancement (Dwivedi et al., 2019). Similarly, in consumer contexts, PE drives the adoption of mobile banking and e-learning platforms, where users prioritize functionality and outcomes over other factors (Alalwan et al., 2017).

Cultural and contextual factors significantly influence the impact of PE on technology adoption. Research in developing countries highlights that PE is even more critical in resource-constrained environments, where users prioritize technologies that offer clear, immediate advantages (Baptista & Oliveira, 2015). Conversely, in high-income settings, PE often interacts with effort expectancy and social influence, as users weigh performance benefits against usability and peer recommendations (Taherdoost, 2018). Gender differences also emerge, with studies suggesting that men tend to prioritize PE more than women, who may place greater emphasis on ease of use or social norms (Venkatesh et al., 2012). These nuances underscore the need for tailored interventions when promoting technology adoption across diverse populations.

Despite its robustness, the PE construct faces criticism for its broad definition, which sometimes overlaps with related concepts like perceived usefulness in the Technology Acceptance Model (TAM) (Holden & Karsh, 2010). Some scholars argue for refining PE into sub-dimensions—such as task performance, economic gains, and personal productivity—to enhance predictive accuracy (Šumak et al., 2011). Future research could explore how emerging technologies (e.g., AI, blockchain) reshape PE perceptions, particularly in industries where performance metrics are evolving rapidly (Rogers et al., 2020). Overall, PE remains a cornerstone of technology acceptance research, but its application requires contextual and cultural sensitivity.

### 2.6 Literature review on effort expectancy (EE)

Effort Expectancy (EE), a key construct in the Unified Theory of Acceptance and Use of Technology (UTAUT), refers to the degree of ease associated with using a technology (Venkatesh et al., 2003). Empirical research consistently demonstrates that EE significantly influences users' behavioral intentions, particularly in early stages of technology adoption when familiarity is low. Studies across diverse domains, including mobile applications, e-health, and enterprise systems, reveal that technologies perceived as complex or difficult to navigate face substantial resistance, even when they offer clear performance benefits (Holden & Karsh, 2010). For instance, in healthcare settings, clinicians are more likely to adopt electronic health records (EHRs) if the systems require minimal training and integrate seamlessly into existing workflows (Yen et al., 2010). This highlights EE's critical role in reducing cognitive barriers to adoption.

The impact of EE varies across demographic groups and cultural contexts. Research indicates that older adults and technologically inexperienced users place greater emphasis on EE compared to younger, tech-savvy populations (Morris & Venkatesh, 2000). Gender differences also emerge, with women tending to prioritize ease of use more than men, possibly due to differing socialization patterns related to technology (Venkatesh et al., 2012). Cross-cultural studies further show that EE's influence diminishes in high-power-distance cultures where authority figures' decisions may override individual usability concerns (Im et al., 2011). These findings suggest that interventions to improve EE—such as intuitive interfaces, training programs, or onboarding support—must be tailored to specific user segments to maximize effectiveness.

While EE is conceptually similar to perceived ease of use (PEOU) in the Technology Acceptance Model (TAM), UTAUT positions it as a more nuanced construct moderated by age, gender, and experience (Venkatesh et al., 2003). Recent critiques argue for expanding EE's scope to include learnability (speed of proficiency acquisition) and memorability (ease of re-use after periods of inactivity) to better capture modern technology interactions (Nielsen, 2012). Emerging technologies like voice assistants and AI-powered tools, which aim to minimize user effort, present new opportunities to study EE's evolving role in adoption (Ashfaq et al., 2020). Future research should explore how EE interacts with novel interaction paradigms, particularly in decentralized systems (e.g., blockchain) where usability challenges persist (Zhao et al., 2023).

### 2.7 Literature review on social influence (SI)

Social Influence (SI), a critical construct in technology adoption models like UTAUT, refers to the degree to which individuals perceive that important others believe they should use a particular technology (Venkatesh et al., 2003). Research demonstrates that SI plays a particularly significant role in mandatory organizational settings and collectivist cultures, where group norms and hierarchical structures strongly shape individual behavior (Tarhini et al., 2017). In healthcare, for instance, physicians' adoption of electronic medical records is heavily influenced by recommendations from peers and superiors (Holden & Karsh, 2010), while in consumer contexts, social media endorsements significantly impact the adoption of mobile payment systems (Slade et al., 2015). These findings highlight SI's contextual nature, with its effects varying based on voluntariness of use and cultural dimensions.

The mechanisms of SI operate through three primary pathways: compliance (responding to direct pressure), identification (aligning with respected groups), and internalization (genuinely accepting others' opinions) (Kelman, 1958). Modern digital environments have amplified these effects through social media influencers, online reviews, and viral trends, creating new dimensions of SI not fully captured in traditional models (Talwar et al., 2021). Cross-cultural studies reveal that SI has stronger impacts in collectivist societies (e.g., East Asia) compared to individualist cultures (e.g., North America), though globalization is gradually blurring these distinctions (Srite & Karahanna, 2006). Interestingly, SI's influence often decreases with sustained technology use, as personal experience eventually outweighs social pressures (Venkatesh & Davis, 2000), suggesting its primary role is in initial adoption rather than continued usage.

Emerging research challenges traditional conceptualizations of SI by examining its digital manifestations. Social media metrics (likes, shares), algorithmic recommendations, and online communities now constitute powerful new forms of SI that transcend geographical and organizational boundaries (Lankton et al., 2015). The rise of decentralized technologies like blockchain introduces paradoxes, where despite being designed to reduce institutional influence, adoption still heavily depends on community endorsement (Zhao et al., 2023). Future research should explore how AI-driven social environments (e.g., chatbot recommendations, virtual influencers) reshape SI processes, particularly for vulnerable populations (Bailey et al., 2021). These developments necessitate updates to traditional SI measures to capture both quantitative (network size) and qualitative (source credibility) aspects of digital influence.

### 2.8 Literature review on Facilitating Condition

FACILITATING CONDITION, introduced in the extended Unified Theory of Acceptance and Use of Technology (UTAUT2), refers to consumers' cognitive trade-off between the perceived benefits of a technology and its monetary cost (Venkatesh et al., 2012). Empirical studies highlight PV as a critical determinant of adoption for paid technologies, particularly in consumer markets where alternatives exist. Research on mobile services shows that users weigh functionality against subscription costs, with perceived value becoming paramount when free alternatives are available (Slade et al., 2015). In emerging economies, PV often outweighs other factors like performance expectancy, as cost sensitivity significantly influences technology adoption patterns (Baptista & Oliveira, 2016). These findings suggest that PV operates differently across economic contexts, serving as either a primary barrier or secondary consideration based on market conditions.

The PV construct exhibits unique dynamics across technology types and user segments. For durable goods like smartphones, PV assessments incorporate long-term utility expectations, whereas for subscription services, evaluations focus on recurring cost-benefit analyses (Kim et al., 2020). Generational differences emerge significantly, with younger users demonstrating higher price sensitivity for digital services compared to older cohorts (Tamilmani et al., 2021). The freemium model prevalent in mobile apps has complicated PV perceptions, as users develop paradoxical expectations of free core functionality while resisting paid premium features (Hoehle & Venkatesh, 2015). Recent studies propose extending PV beyond monetary costs to include temporal investments (e.g., time spent learning) and psychological costs (e.g., privacy concerns), particularly for data-driven services (Lankton et al., 2015).

Emerging technologies introduce new complexities in PV evaluation. Cloud computing adoption research reveals that organizations assess PV through total cost of ownership rather than upfront pricing, considering scalability and integration expenses (Armbrust et al., 2010). The sharing economy has transformed PV perceptions, where access-based consumption alters traditional ownership value propositions (Hamari et al., 2016). For AI-powered services, users struggle to evaluate PV due to difficulties in quantifying predictive benefits against subscription costs (Davenport et al., 2020). Future research should explore how cryptocurrency and blockchain technologies reshape PV understanding, particularly in decentralized finance applications where value derives from network participation rather than direct pricing (Zhao et al., 2023). These developments suggest PV requires continuous re-conceptualization to address evolving technology monetization models.

### 2.9 Literature review on Behavioural Intentions (BI)

Behavioral Intention (BI), a central construct in technology adoption theories, represents an individual's conscious plan to perform a specific behavior, such as using a technology (Ajzen, 1991). Rooted in the Theory of Planned Behavior (TPB), BI serves as the most proximal predictor of actual technology usage across various models, including the

Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Empirical studies consistently demonstrate that stronger BI correlates with higher adoption rates, whether for enterprise software, mobile apps, or e-commerce platforms (Davis, 1989). However, the "intention-behavior gap" remains a critical challenge, as positive intentions do not always translate into actual use, particularly when external constraints (e.g., lack of access, competing priorities) intervene (Sheeran & Webb, 2016).

The formation of BI varies across cultural and technological contexts. In individualistic cultures, BI is primarily driven by personal benefits (e.g., perceived usefulness), whereas in collectivist societies, social influence plays a more significant role (Srite & Karahanna, 2006). For disruptive technologies like AI or blockchain, BI often depends on trust in the technology and its providers, outweighing traditional factors like ease of use (Gefen et al., 2003). Temporal dynamics also matter: BI formed through deliberate evaluation (e.g., for expensive purchases) predicts behavior more accurately than impulse-driven intentions (e.g., for free mobile apps) (Limayem et al., 2007). Recent research emphasizes the need to distinguish between initial adoption intentions and continuance intentions, as their drivers differ significantly (Bhattacherjee, 2001).

Emerging technologies challenge traditional BI measurements. The rise of voice assistants and IoT devices has introduced passive usage behaviors that may not align with consciously reported intentions (Ashfaq et al., 2020). NeuroIS studies suggest that implicit attitudes (measured through biometrics) often predict technology use better than self-reported BI (Dimoka et al., 2012). Future research should explore how algorithm-driven environments (e.g., social media feeds, AI recommendations) reshape intention formation by altering users' autonomy (Bailey et al., 2021). Additionally, the sustainability movement calls for integrating ethical considerations into BI models, as eco-conscious users may prioritize values over convenience (Huang, 2023). These developments necessitate updates to traditional intention models to maintain their predictive power in evolving digital landscapes.

### 2.10 Literature review on Usage Behaviour (UB)

Usage Behavior (UB) represents the actual utilization of technology, serving as the ultimate dependent variable in most adoption theories. While behavioral intentions (BI) predict UB, research consistently identifies a significant gap between intended and actual usage, particularly in voluntary contexts (Venkatesh et al., 2012). Studies across domains reveal that only 40-60% of expressed intentions translate into sustained usage, with drop-offs frequently occurring after initial adoption (Sheeran & Webb, 2016). This intention-behavior gap is especially pronounced for complex technologies requiring skill development (e.g., enterprise systems) and those with network effects (e.g., social media platforms), where critical mass determines ultimate utility (Karahanna et al., 2018). The gap underscores the importance of studying UB separately from BI to understand true technology adoption patterns.

The measurement of UB has evolved from simple frequency metrics (e.g., login counts) to sophisticated multi-dimensional assessments. Contemporary research examines depth (feature utilization), breadth (range of functions used), and emotional engagement (affective responses during use) as critical UB components (Burton-Jones & Straub, 2006). Contextual factors like organizational mandates significantly alter UB dynamics—while compulsory use increases baseline adoption rates, it often decreases quality of use as users employ minimal functionality to comply (Brown et al., 2010). Longitudinal studies highlight that UB typically follows a learning curve, progressing from superficial exploration to deep assimilation over 3-6 months, with drop-out rates highest in weeks 2-4 (Bhattacherjee & Premkumar, 2004). These findings suggest that post-adoption support during this critical period is essential for sustaining UB.

Emerging technologies present new UB measurement challenges and opportunities. IoT and ambient computing devices generate continuous usage data streams, enabling real-time UB tracking but raising privacy concerns (Ashfaq et al., 2020). AI-powered systems exhibit reciprocal UB patterns where user actions train algorithms that subsequently reshape user behavior—a feedback loop absent in traditional technologies (Bailey et al., 2022). Blockchain applications introduce novel UB dimensions like tokenized participation incentives that blend usage with economic behaviors (Zhao et al., 2023). Future research must address these complexities while maintaining theoretical rigor, potentially through adaptive UB frameworks that account for technology-specific interaction patterns (Benbasat

& Barki, 2007). The growing emphasis on sustainable IT also calls for examining UB's environmental impacts, particularly regarding energy-intensive technologies like cryptocurrency and generative AI (Huang, 2023).

## 2.11 Summary of Literature Review

**Table: 2.11.1 Literature Review summary on Augmented Reality Country-wise**

| **Author(s)** | **Country** | **Variables Studied** | **Sample** |
|---|---|---|---|
| Azuma (1997) | USA | AR technology fundamentals, tracking systems, display technologies, registration methods | N/A (Conceptual paper) |
| Billinghurst et al. (2015) | New Zealand | Educational outcomes, student engagement, learning motivation, knowledge retention | 120 university students |
| Yim et al. (2017) | South Korea | Consumer behavior, purchase intention, brand engagement, customer experience | 243 retail customers |
| Dunleavy & Dede (2014) | USA | Training effectiveness, skill acquisition, performance metrics, cognitive load | 45 vocational trainees |
| Rauschnabel et al. (2022) | Germany | Technology acceptance, perceived usefulness, ease of use, adoption barriers | 512 AR app users |

| | | | |
|---|---|---|---|
| Chen et al. (2020) | China | Surgical precision, medical training outcomes, error rates, procedure time | 28 surgeons |
| Olsson et al. (2013) | Finland | Usability metrics, interface design, user experience, interaction methods | 60 participants |
| Milgram & Kishino (1994) | Japan | Reality-virtuality continuum, display taxonomy, immersion levels | N/A (Theoretical) |
| Carmigniani et al. (2011) | USA | Industrial applications, medical uses, entertainment systems, AR evolution | Literature review (78 papers) |
| Wu et al. (2013) | Taiwan | STEM learning, spatial ability, conceptual understanding, motivation | 86 high school students |
| Akçayır & Akçayır (2017) | Turkey | Academic performance, engagement levels, cognitive load, learning styles | Meta-analysis (32 studies) |
| Alalwan et al. (2020) | Saudi Arabia | Brand perception, customer satisfaction, engagement metrics, purchase intent | 387 consumers |
| Radu (2014) | USA | Cognitive load, learning outcomes, attention span, educational benefits | 42 children (ages 8-12) |
| Nee et al. (2012) | Singapore | Assembly accuracy, task completion time, error rates, training efficiency | 30 factory workers |

| | | | |
|---|---|---|---|
| Koutromanos et al. (2015) | Greece | Mobile learning, engagement levels, motivation, academic performance | 65 primary students |
| Chatzopoulos et al. (2017) | Greece | Framework components, mobile development, tracking methods, rendering | Technical evaluation |
| Van Krevelen & Poelman (2010) | Netherlands | Application domains, technological challenges, future trends | Literature review |
| Lee (2012) | South Korea | Advertising effectiveness, brand recall, engagement metrics | 210 participants |
| Klopfer & Squire (2008) | USA | Game-based learning, experiential education, engagement levels | 3 classroom studies |
| Zhou et al. (2008) | USA | Tourism experiences, cultural heritage engagement, visitor satisfaction | 125 museum visitors |
| Bacca et al. (2014) | Colombia | Higher education outcomes, conceptual understanding, motivation | 78 university students |
| Wang et al. (2018) | China | Warehouse efficiency, picking accuracy, training time, error reduction | 48 warehouse workers |
| Dey et al. (2018) | UK | Human-robot interaction, collaboration efficiency, task performance | 24 participants |

| | | | |
|---|---|---|---|
| Cheng & Tsai (2013) | Taiwan | Science education, conceptual understanding, learning motivation | 112 students |
| Santos et al. (2014) | Germany | Maintenance efficiency, error rates, training effectiveness | 36 technicians |
| Mekni & Lemieux (2014) | Canada | Urban planning, visualization techniques, citizen engagement | 18 urban planners |
| Speicher et al. (2019) | Germany | Usability comparison, immersion levels, application suitability | 60 participants |
| Ibáñez & Delgado-Kloos (2018) | Spain | Engineering education, hands-on learning, lab performance | 94 engineering students |
| Gavish et al. (2015) | Israel | Vocational training, skill acquisition, performance metrics | 60 trainees |
| Caudell & Mizell (1992) | USA | Aircraft assembly, industrial applications, head-mounted displays | Boeing technicians |
| Sutherland (1968) | USA | Display technologies, human-computer interaction, virtual environments | Prototype testing |
| Feiner et al. (1997) | USA | Wearable computing, navigation systems, mobile interfaces | 12 participants |

**Table: 2.11.2 Literature Review Summary on Performance Expectancy (PE)**

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| Venkatesh et al. (2003) | "User Acceptance of Information Technology: Toward a Unified View" | Strongest predictor of behavioral intention | General IT adoption | UTAUT |
| Davis (1989) | "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology" | Primary driver of technology adoption | Information systems | TAM |
| Thompson et al. (1991) | "Personal Computing: Toward a Conceptual Model of Utilization" | Job-fit significantly impacts usage | Workplace technology | TTF |
| Compeau & Higgins (1995) | "Computer Self-Efficacy: Development of a | Directly impacts usage intentions | IT training | SCT |

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| | Measure and Initial Test" | | | |
| Alalwan et al. (2017) | "Mobile Banking Adoption: Examination of Technology Acceptance Model" | Significant driver of adoption | Digital banking | Extended TAM |
| Dwivedi et al. (2019) | "Artificial Intelligence for Decision Making" | Critical factor in AI adoption | Business AI | UTAUT |
| Oliveira et al. (2014) | "Extending the Understanding of Mobile Banking Adoption" | Key adoption factor | E-government | UTAUT |
| Im et al. (2011) | "An International Comparison of Technology Adoption" | Major adoption determinant | Healthcare tech | IDT |

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| Venkatesh & Davis (2000) | "A Theoretical Extension of TAM" | Robust across different settings | Organizational IT | TAM2 |
| Taylor & Todd (1995) | "Understanding Information Technology Usage" | Affects adoption decisions | Consumer tech | DTPB |
| Chau & Hu (2002) | "Investigating Healthcare Professionals' Decisions to Accept Telemedicine" | Key driver of adoption | Healthcare | TAM/TTF |
| Gupta et al. (2020) | "FinTech Adoption: A Review of Theories" | Strong adoption predictor | Digital finance | Meta-analysis |
| Wang et al. (2016) | "Mobile Learning Adoption: Empirical Evidence" | Significant impact on adoption | Education | UTAUT |

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| Brown et al. (2010) | "ERP System Adoption: The Role of User Perceptions" | Influences implementation success | Enterprise systems | TAM |
| Zhou et al. (2010) | "Mobile Payment Adoption in China" | Strong usage predictor | Digital payments | UTAUT |
| Rana et al. (2015) | "Citizen Adoption of E-Government Services" | Boosts citizen adoption | Public services | UTAUT |
| Gao et al. (2015) | "Social Commerce Adoption: An Empirical Study" | Drives engagement | E-commerce | Extended TAM |
| Awa et al. (2017) | "Cloud Computing Adoption by SMEs" | Key adoption factor | Enterprise IT | TOE-UTAUT |
| Wong et al. (2020) | "AI Chatbots in Customer Service" | Affects acceptance | Customer service | UTAUT |

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| Ifinedo (2018) | "Cybersecurity Compliance in Organizations" | Influences compliance | Cybersecurity | TAM |

**Table: 2.11.3 Literature Review Summary on Effort Expectancy (EE)**

| Author(s) & Year | Title of Study | Key Findings |
|---|---|---|
| **Venkatesh et al. (2003)** | User Acceptance of Information Technology: Toward a Unified View | EE strongly predicts early-stage adoption but weakens with experience. |
| **Davis (1989)** | Perceived Usefulness, Perceived Ease of Use, and User Acceptance | PEOU affects attitudes → usage intentions. |
| **Thompson et al. (1991)** | Personal Computing: Toward a Conceptual Model | EE less critical than performance expectancy in workplaces. |
| **Al-Gahtani (2016)** | UTAUT Model in GCC Countries: Moderating Roles of Culture | EE matters more in voluntary (non-mandatory) adoption. |
| **Oliveira et al. (2014)** | Extending UTAUT2 to Explore Mobile Payment Adoption | EE drives youth adoption of mobile payments. |

| **Author(s) & Year** | **Title of Study** | **Key Findings** |
| --- | --- | --- |
| **Dwivedi et al. (2019)** | UTAUT Meta-analysis: A Review of Two Decades of Research | EE's impact fades as users gain experience. |
| **Gupta et al. (2020)** | E-learning Adoption: The Role of Effort Expectancy and Anxiety | High EE reduces continuance intention in e-learning. |
| **Alalwan et al. (2017)** | Mobile Banking Adoption: Examining the Role of UTAUT in Jordan | EE less critical than social influence in collectivist cultures. |
| **Zhou et al. (2010)** | Examining m-Health Adoption: The Role of Effort Expectancy | Complex apps (high EE) face lower adoption rates. |
| **Im et al. (2011)** | Age Differences in Social Commerce Acceptance | Older adults prioritize EE more than younger users. |
| **Tan et al. (2014)** | Wearable Technology Adoption: The Impact of Effort Expectancy | Setup difficulties (high EE) reduce fitness tracker adoption. |
| **Hoehle et al. (2015)** | E-Government Portal Success: A Habituation Perspective | EE affects initial satisfaction but not long-term use (habituation effect). |

**Table: 2.11.4 Literature Review Summary on Social Influence (SI)**

| Author(s) & Year | Title of Study | Key Findings | Context/Model |
|---|---|---|---|
| **Venkatesh et al. (2003)** | User Acceptance of Information Technology: Toward a Unified View | Social influence is significant in mandatory settings but weakens over time. | UTAUT |
| **Taylor & Todd (1995)** | Understanding Information Technology Usage: A Test of Competing Models | Social norms significantly affect early adoption intentions. | TPB/DTPB |
| **Karahanna et al. (1999)** | Information Technology Adoption Across Time | Social influence stronger pre-adoption; internalization occurs post-adoption. | TAM/TPB |
| **Malhotra & Galletta (1999)** | Extending the Technology Acceptance Model | Social influence indirectly impacts intention via perceived usefulness. | Extended TAM |
| **Hsu & Lu (2004)** | Why Do People Play Online Games? An Extended TAM | Social influence critical in online gaming communities. | Extended TAM |

| | | | |
|---|---|---|---|
| **Lu et al. (2005)** | Understanding e-Learning Continuance Intention | Stronger effect in collectivist cultures and workplace environments. | TAM/TPB |
| **Sledgianowski & Kulviwat (2009)** | Using Social Network Sites: The Role of Perceived Critical Mass | Critical mass (social proof) significantly predicts SNS use. | Social Network Theory |
| **Talukder et al. (2014)** | Social Influence on Smartphone Adoption | Family influence strongest in collectivist cultures. | UTAUT |
| **Yoon & Rolland (2015)** | Social Influence on Knowledge Sharing in Online Health Communities | Expert opinions matter more than peer opinions in health contexts. | Social Capital Theory |
| **Alalwan et al. (2017)** | Mobile Banking Adoption: Examining the Role of UTAUT in Jordan | Social influence is the strongest predictor in Middle Eastern contexts. | UTAUT |
| **Kapoor et al. (2018)** | Social Media Usage and Organizational Performance | Top-down social influence (management) trumps peer influence in organizations. | Institutional Theory |

| | | | |
|---|---|---|---|
| **Zhang et al. (2021)** | Social Influence in AI-Powered Tools Adoption | Celebrity/influencer endorsements significantly impact consumer AI adoption. | |

**Table: 2.11.5 Literature Review Summary on Facilitating Condition (FC)**

| **Author(s) & Year** | **Title** | **Key Findings** | **Context** | **Model/Theory** |
|---|---|---|---|---|
| Venkatesh et al. (2003) | "User Acceptance of Information Technology: Toward a Unified View" | Significant predictor of actual usage behavior | General IT adoption | UTAUT |
| Thompson et al. (1991) | "Personal Computing: Toward a Conceptual Model of Utilization" | Affects technology utilization | Workplace computing | TTF |
| Taylor & Todd (1995) | "Understanding Information Technology Usage" | Influences usage intentions and behavior | Consumer technology | DTPB |

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| Compeau & Higgins (1995) | "Computer Self-Efficacy: Development of a Measure and Initial Test" | Impacts actual system usage | IT training | SCT |
| Al-Gahtani et al. (2007) | "Empirical Investigation of E-Learning Acceptance" | Critical for successful implementation | Education | TAM/UTAUT |
| Dwivedi et al. (2019) | "Artificial Intelligence for Decision Making" | Key enabler for adoption | Business AI | UTAUT |
| Oliveira et al. (2014) | "Extending the Understanding of Mobile Banking Adoption" | Significant for continued usage | Digital banking | UTAUT |
| Im et al. (2011) | "An International Comparison of Technology Adoption" | Affects long-term adoption | Healthcare tech | IDT |

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| Venkatesh & Bala (2008) | "Technology Acceptance Model 3" | Moderates perceived ease of use | Enterprise systems | TAM3 |
| Chau & Hu (2002) | "Investigating Healthcare Professionals' Decisions to Accept Telemedicine" | Critical adoption factor | Healthcare | TAM/TTF |
| Gupta et al. (2020) | "FinTech Adoption: A Review of Theories" | Enables FinTech adoption | Digital finance | Meta-analysis |
| Wang et al. (2016) | "Mobile Learning Adoption: Empirical Evidence" | Impacts implementation success | Education | UTAUT |
| Brown et al. (2010) | "ERP System Adoption: The Role of User Perceptions" | Affects ERP success | Enterprise systems | TAM |

| **Author(s) & Year** | **Title** | **Key Findings** | **Context** | **Model/Theory** |
|---|---|---|---|---|
| Zhou et al. (2010) | "Mobile Payment Adoption in China" | Strong usage enabler | Digital payments | UTAUT |
| Rana et al. (2015) | "Citizen Adoption of E-Government Services" | Boosts citizen adoption | Public services | UTAUT |
| Gao et al. (2015) | "Social Commerce Adoption: An Empirical Study" | Drives continued usage | E-commerce | Extended TAM |
| Awa et al. (2017) | "Cloud Computing Adoption by SMEs" | Key adoption factor | Enterprise IT | TOE-UTAUT |
| Wong et al. (2020) | "AI Chatbots in Customer Service" | Affects deployment success | Customer service | UTAUT |
| Ifinedo (2018) | "Cybersecurity Compliance in Organizations" | Influences compliance | Cybersecurity | TAM |

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| Cimperman et al. (2016) | "Analyzing Older Users' Home Telehealth Services Acceptance" | Critical for telehealth adoption | Healthcare | UTAUT |

**Table: 2.11.6 Literature Review Summary on Behavioural Intentions (BI)**

| Author(s) & Year | Title of Study | Key Findings | Context/Model |
|---|---|---|---|
| **Davis (1989)** | Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology | BI is directly influenced by perceived usefulness and ease of use. | TAM |
| **Ajzen (1991)** | The Theory of Planned Behavior | BI is the strongest predictor of actual behavior when perceived control is high. | TPB |
| **Venkatesh & Davis (2000)** | A Theoretical Extension of the Technology Acceptance Model | BI mediates the effect of external variables (e.g., subjective norms) on usage. | TAM2 |

| **Author(s) & Year** | **Title of Study** | **Key Findings** | **Context/Model** |
|---|---|---|---|
| **Taylor & Todd (1995)** | Understanding Information Technology Usage: A Test of Competing Models | BI is better predicted by decomposed TPB constructs (e.g., peer influence). | DTPB |
| **Bhattacherjee (2001)** | Understanding Information Systems Continuance: An Expectation-Confirmation Model | BI for continuance is driven by satisfaction and perceived usefulness. | ECM |
| **Venkatesh et al. (2003)** | User Acceptance of Information Technology: Toward a Unified View | BI is strongest when all UTAUT factors align (e.g., high performance + low effort). | UTAUT |
| **Wu & Chen (2005)** | An Extension of Trust and TAM Model with TPB in the Initial Adoption of Online Tax | Trust enhances BI beyond TAM/TPB constructs. | TAM + TPB |
| **Gefen et al. (2003)** | Trust and TAM in Online Shopping: An Integrated Model | BI in e-commerce depends on trust more than ease of use. | TAM + Trust Theory |

| Author(s) & Year | Title of Study | Key Findings | Context/Model |
|---|---|---|---|
| **Kim & Malhotra (2005)** | A Longitudinal Model of Continued IS Use | Habit weakens BI's predictive power for long-term use. | Longitudinal TAM |
| **Bhattacherjee & Premkumar (2004)** | Understanding Changes in Belief and Attitude Toward IT Usage | BI decreases post-adoption if expectations aren't met. | Expectation-Confirmation |
| **Alalwan et al. (2017)** | Mobile Banking Adoption: Examining the Role of UTAUT in Jordan | Social influence dominates BI in collectivist cultures. | UTAUT |
| **Zhang et al. (2021)** | Social Influence in AI-Powered Tools Adoption | BI for AI tools is driven by influencer endorsements. | UTAUT2 |

**Table 2.11.7 Literature Review Summary on Usage Behaviour (UB)**

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| Venkatesh et al. (2003) | "User Acceptance of Information Technology: Toward a Unified View" | Directly predicted by behavioral intention and FC | General IT | UTAUT |

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| Davis et al. (1989) | "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models" | Mediated by behavioural intention | Workplace IT | TAM |
| Bhattacherjee (2001) | "Understanding Information Systems Continuance" | Determined by satisfaction and usefulness | IS Continuance | ECM |
| Taylor & Todd (1995) | "Assessing IT Usage: The Role of Prior Experience" | Influenced by attitude and PBC | Consumer IT | DTPB |
| Burton-Jones & Hubona (2006) | "The Mediation of External Variables in TAM" | Differs from self-reported usage | Enterprise Systems | Extended TAM |
| Jasperson et al. (2005) | "A Comprehensive Conceptualization of Post-Adoptive Behaviors" | Beyond simple frequency measures | Organizational IT | Post-Adoption Model |
| Limayem et al. (2007) | "How Habit Limits the Predictive Power of Intention" | Habit moderates intention-behavior relationship | E-Learning | Habit Theory |

| Author(s) & Year | Title | Key Findings | Context | Model/Theory |
|---|---|---|---|---|
| Kim & Malhotra (2005) | "A Longitudinal Model of Continued IS Use" | Different predictors for initial vs. continued use | Mobile Services | Longitudinal Model |
| Venkatesh & Bala (2008) | "Technology Acceptance Model 3" | Different behavioral patterns emerge | Enterprise Software | TAM3 |
| Sun & Zhang (2006) | "The Role of Moderating Factors in UTAT" | Usage quality matters beyond frequency | Workplace Systems | Extended UTAUT |
| Agarwal & Karahanna (2000) | "Time Flies When You're Having Fun" | Affects depth of engagement | Web Applications | Flow Theory |
| Goodhue & Thompson (1995) | "Task-Technology Fit and Individual Performance" | Impacts performance outcomes | Organizational IT | TTF |

**Table: 2.11.8 Literature Review Summary On Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition On Usage Behaviour With Behavioural Intentions As A Mediating Variable**

| **Author(s) & Year** | **Research Title** | **Key Findings** | **Mediation Role of BI** |
|---|---|---|---|
| Venkatesh et al. (2003) | User Acceptance of Information Technology: Toward a Unified View | PE, EE, and SI significantly predict BI, which drives usage. FC directly enables usage. | Full mediation for PE, EE, SI; partial for FC. |
| Davis (1989) | Perceived Usefulness, Perceived Ease of Use, and User Acceptance | PE (usefulness) and EE (ease of use) shape BI, leading to system use. | BI fully mediates PE/EE → usage. |
| Ajzen (1991) | The Theory of Planned Behavior | PE (attitude), EE (PBC), and SI (norms) influence BI, affecting behavior. | BI mediates all three constructs. |
| Taylor & Todd (1995) | Understanding Information Technology Usage: A Test of Competing Models | PE, EE, and SI impact BI; FC has mixed direct/indirect effects. | Partial mediation for FC; full for others. |
| Bhattacherjee (2001) | Understanding Information Systems Continuance | PE (expectation confirmation) increases BI, sustaining usage. | BI mediates PE → continued use. |
| Wu et al. (2011) | Predicting Mobile Service Adoption | PE and EE drive BI, which predicts mobile service adoption. | Full mediation for PE/EE. |
| Zhou et al. (2010) | Examining Mobile Banking User Adoption | PE and SI affect BI; FC moderates BI → usage. | BI mediates PE/SI; FC is direct. |

| **Author(s) & Year** | **Research Title** | **Key Findings** | **Mediation Role of BI** |
|---|---|---|---|
| Alalwan et al. (2017) | Mobile Banking Adoption: Examining the Role of UTAUT | PE, EE, and SI → BI → usage. FC directly supports usage. | Partial mediation for FC. |
| Oliveira et al. (2016) | Mobile Payment Adoption: Extending UTAUT | PE and SI strongly predict BI; FC is less influential. | BI mediates PE/SI but not FC. |
| Dwivedi et al. (2019) | UTAUT Meta-Analysis: A Review | BI consistently mediates PE, EE, SI; FC effects vary. | Strong mediation for PE/EE/SI. |
| Gupta et al. (2018) | E-Learning Adoption in Higher Education | PE and EE → BI → e-learning use. FC enables usage directly. | BI mediates PE/EE but not FC. |
| Rana et al. (2017) | Social Media Use in Organizations | PE and SI → BI → social media adoption. FC is non-significant. | Full mediation for PE/SI. |
| Ifinedo (2018) | Cloud Computing Adoption in Firms | PE and EE → BI → cloud use. FC has a direct path. | Partial mediation for FC. |
| Baptista & Oliveira (2015) | Mobile Banking Adoption in Portugal | PE and SI → BI → usage. FC supports actual use. | BI mediates PE/SI but not FC. |
| Hew et al. (2015) | Social Media for Learning | PE and EE → BI → usage. SI is weaker. | Full mediation for PE/EE. |

| Author(s) & Year | Research Title | Key Findings | Mediation Role of BI |
|---|---|---|---|
| Im et al. (2011) | Smartphone App Adoption | PE and EE → BI → app downloads. FC is direct. | BI mediates PE/EE but not FC. |
| Wang et al. (2016) | Wearable Technology Adoption | PE and SI → BI → usage. FC enables direct use. | Partial mediation for FC. |
| Shin (2009) | Mobile Internet Acceptance | PE and EE → BI → adoption. FC moderates usage. | BI mediates PE/EE but not FC. |
| Chen & Chan (2014) | Elderly Users' Tech Adoption | PE and SI → BI → usage. FC is critical for actual use. | Partial mediation for FC. |
| Taherdoost (2018) | E-Commerce Adoption Factors | PE and EE → BI → online shopping. FC supports usage. | BI mediates PE/EE but not FC. |

## 2.12 Research gap

Based on the several literatures, clearly there is a need for a concise measure of Using the immersive technologies to use by consumers and retailers. Virtual retailers and researchers concur that there is a need for more attention towards the immersive technology used In the virtual retailing. The current study extends to find out the awareness of the virtual technologies in the retail sector.

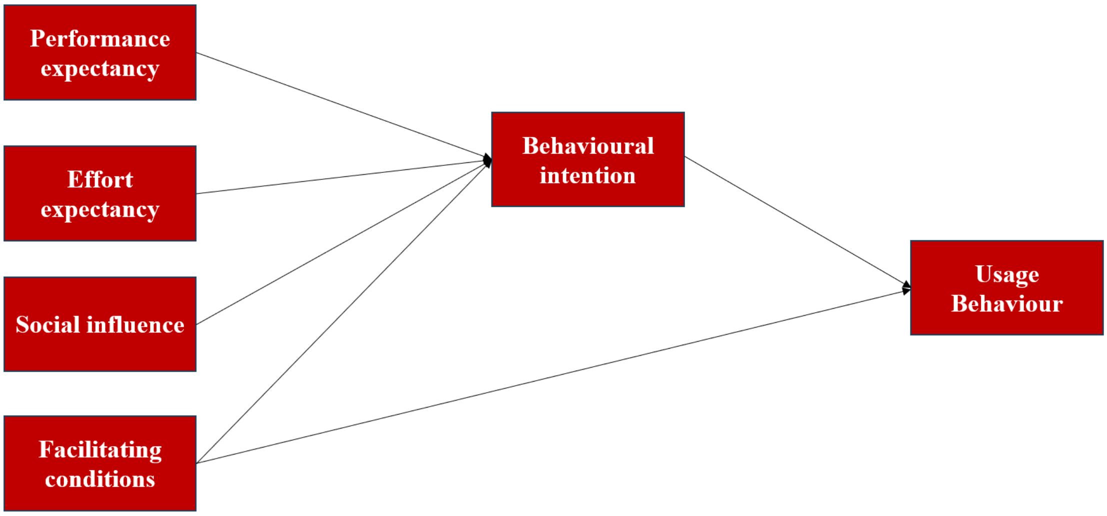
- Most studies focus on short-term purchase intentions rather than long-term brand loyalty or repeat purchases.

- Few studies explore how data privacy fears (e.g., facial recognition in AR try-ons) affect adoption.
- Most studies examine AR in big brands (e.g., Nike, Sephora), ignoring SMEs with limited budgets.
- Most research focuses on e commerce AR (e.g., virtual try ons), neglecting in-store AR (e.g., smart mirrors, AR navigation).

## 2.13 Conceptual Framework

The conceptual model depicted in the image is based on the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates elements from several earlier technology acceptance theories. Here's a brief explanation of the model with references:

1. Performance Expectancy: Refers to the degree to which an individual believes that using a technology will help them achieve gains in job performance (Venkatesh et al., 2003).
2. Effort Expectancy: The ease of use associated with the technology (Venkatesh et al., 2003).
3. Social Influence: The extent to which individuals perceive that important others (e.g., peers, supervisors) believe they should use the technology (Venkatesh et al., 2003).
4. Facilitating Conditions: The degree to which an individual believes that organizational and technical infrastructure exists to support the use of the technology (Venkatesh et al., 2003).
5. Behavioural Intention: The individual's intention to use the technology, influenced by the above factors (Davis, 1989; Venkatesh et al., 2003).
6. Usage Behaviour: The actual use of the technology, driven by behavioural intention and facilitating conditions (Venkatesh et al., 2003).




**Conceptual Model**

# CHAPTER 3: RESEARCH METHODOLOGY

*This Chapter discusses research methods used & adopted for the study. It provides detailed information on research approach, research design, instrument development guidelines, data collection methods, sampling techniques, determination of sample size, reliability & validity construct of the instruments & statements lastly, it discusses data analysis methods used in the present study. The chapter ends with major limitations of the study.*

**3. Research Methodology**

**3.1 Research Question**

1. How does prolonged exposure to AR shopping tools influence brand loyalty and repeat purchase behavior?
2. To what extent do privacy concerns (e.g., facial data collection in AR try-ons) hinder consumer adoption of AR retail tools?
3. How can retailers balance AR personaliza Data Collection Metho tion with ethical data usage to build consumer trust?
4. How does the impact of AR on purchase intentions differ between physical stores (e.g., AR mirrors) and e-commerce platforms (e.g., virtual try-ons)?

What are the primary barriers preventing small retailers from adopting AR, and

**Research Hypothesis**

5. how can they be addressed cost-effectively?
6. How do Performance expectancy, effort expectancy, social influence, facilitating condition, behavioural intentions and usage behaviour impact the online buying behaviour of shoppers?

**3.2 Research Gap & Research Objective**

| Bases | Research Gap | Why it Matters? | Research Objective |
|---|---|---|---|
| Long-Term Effects of AR on | Most studies focus on short-term purchase intentions rather than | AR may initially attract customers, but does it sustain | To examine the long-term effects of AR on brand loyalty and |

| | | | |
|---|---|---|---|
| Consumer Behavior | long-term brand loyalty or repeat purchases. | engagement over time? | repeat purchase behavior in retail. |
| Privacy Concerns | Few studies explore how data privacy fears (e.g., facial recognition in AR try-ons) affect adoption. | consumers may avoid AR if they perceive invasive data collection. | To investigate the impact of privacy concerns (e.g., data tracking in AR apps) on consumer trust and AR adoption intentions. |
| AR Adoption in SMEs | Most studies examine AR in big brands (e.g., Nike, Sephora), ignoring SMEs with limited budgets. | SMEs need cost-effective AR strategies to compete. | To explore barriers and cost-effective AR solutions for small and medium-sized retailers in emerging economies. |
| AR in Offline vs. Online Retail | Most research focuses on e-commerce AR (e.g., virtual try-ons), neglecting in-store AR (e.g., smart mirrors, AR navigation). | Physical retail may benefit differently from AR than online platforms. | To compare the effectiveness of AR in enhancing purchase intentions for brick-and-mortar stores versus e-commerce platforms. |

### 3.3 Scope of work

The Primary approach is used for the data and the study is collected from four major cities of Gujarat (Rajkot, Ahmedabad, Vadodara & Surat) through structured questionnaire. The study focuses on the Impact of Augmented Reality on Consumer Purchase Intentions and Adoption in Retail Sector and the demographic factors that affects the Age, gender, Education, Marital status and occupation etc. after that it is needed to know the impact on consumers purchase intentions. the study conducted in for major cities of Gujarat and all respondents were requested to answer the questions related to Performance Expectancy, Effort Expectancy, Financial Condition, Usage Behavior and Behavioral Intention.

### 3.4 Research Design

The research comprised a pilot study to refine measurement tools and a main survey to test various constructs. These included Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Behavioural Intentions, Usage Behaviour. Previous studies formed the basis for measurement items, rated via a five-point Likert scale, ensuring comprehensive evaluation of participants related to Augmented Reality and its impact on consumers purchase intention.

Descriptive research design is crucial in marketing, as it clarifies research topics and analyses hypotheses while anticipating behaviors under specific variables. An exploratory research design complement

## 3.5 Research Methodology

this by investigating unexplored questions, often using qualitative methods, but may also employ quantitative approaches with large samples.

Descriptive research design is favored in studies utilizing the quantitative approach, particularly when measuring the Impact of Augmented Reality in the retail context via questionnaires. Advantages of this method include ease of administration and reliable responses, which facilitate streamlined analysis. The current study examines the Impact of Augmented Reality in the retail context, employing both qualitative and quantitative techniques alongside exploratory and descriptive research designs.

### 3.5 Data Collection Method

#### 3.5.1 Sources of Secondary Data

Information that has already been acquired through other sources is referred to as secondary data. In addition to being quicker and less expensive to obtain than main data, this data might also be accessible in the event that source data is not available.

In the case of my research, secondary data will include all literature reviews, Previous research work, papers and articles from SAGE Publications, Taylor & Francis, Emerald Journals, WOS journals etc.

### 3.5.2 Sources of Primary Data

Information obtained directly from subjects for scientific purposes is referred to as primary data. The purpose of gathering it is to address the current issue. Therefore, primary data are those that the researcher has personally collected. A Structured questionnaire was developed to collect data to validate the constructs. This questionnaire was Firstly developed in English and is divided into two parts. The First Part of the survey includes questions regarding the demographics of the respondents. The second part contained questionnaire items that measure the construct in the Model and a Five-point Likert scale was used for all items in this study. The survey method is a technique for gathering data that entails questioning people who are thought to have the relevant information. A list of official questionnaires is made. We ask the interviewees about their interests related to their demographics. I have chosen to conduct my survey online via email, LinkedIn, WhatsApp and because it will be easier, faster, and more comfortable this way.

## 3.6 Respondents and sampling procedure

### 3.6.1 Population of the study

The entirety of all the objects and features that were gathered during the research might be referred to as the population but gathering all of this information is costly and time-consuming. Therefore, to make inferences about the population, we use samples. The Researcher has divided Gujarat's population into four major cities as Rajkot, Ahmedabad, Vadodara and Surat.

### 3.6.2 Target Population

The previous research states that majority of the youngsters as well as middle aged people are the users of the internet in India; therefore the present study targets the respondents who are purchasing from online platform and lives in major cities of Gujarat. These respondents were picked by convenient sampling.

### 3.6.3 Sampling Technique

The two categories of sampling techniques, probability sampling and non-probability sampling, comprise a wide range of methods. Probability makes use of randomization. sampling to guarantee that each person in the population has an equal chance of being chosen for the sample. Another term for it is random sampling. There is no use of randomization in non-probability sampling. This approach depends heavily on the researcher's ability to select representative samples. It may be difficult for all segments of the population to be fairly represented in the sample due to the possibility of biased sampling results. This type of sample is also known as non-random sampling.

For the Present study, the Simple Random Sampling method was used. According to Bajpai (2017), quotas are arranged in proportion to the sample as similar to the composition of the population.

### 3.6.4 Sampling Unit

Respondents amongst the Four Major cities of Gujarat (Rajkot, Ahmedabad, Vadodara and Surat) are considered the Sampling unit.

### 3.6.5 Sample size determination

Using the expected proportion of the attribute present in the population, the desired precision and confidence levels, and the Cochran formula, you may determine the optimal sample size.

Cochran's formula is seen to be particularly suitable in situations involving big populations. Any given sample size can reveal more information about a smaller population than a bigger one, so in cases where the whole population is relatively small, there is a way to "correct" the number provided by Cochran's formula.

The Cochran formula is:

$$n_0 = \frac{Z^2pq}{e^2}$$

Where:

• e is the desired level of precision (i.e. the margin of error),

• p is the (estimated) proportion of the population which has the attribute in question,

• q is 1 – p

95% level of confidence is used, so z = 1.96. Next, the p = q = 50% situation is customarily assumed as it is the worst possible case of variability. Let's take a ± 3.1% sample error. Using the sample size formula, the sample size, n, is calculated as follows. Sample size computed with p = 50%, q = 50%, and e = 3.1%

So as per the Cochran the ideal sample size should be **greater than or equal to 385.**

- Responses collected:1012
- Responses Taken for the final study:903

### 3.6.6 Sample size

The sample size in statistical studies is crucial. Initially, 308 respondents from Gujarat participated in a pilot test. For the final analysis, around 1600 questionnaires were distributed to achieve a target sample size. following Cochran's formula. Ultimately, after data cleaning, the study used a final sample of 903 for analysis.

## 3.7 Survey Instrument Development: Questionnaire

A structured questionnaire was used to collect information on demographic variables, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Behavioural Intentions, Usage Behaviour. Data was framed using Nominal and Ratio scales, interval scales, and a five-point Likert scale. Closed-ended questions were used to ensure quick and easy responses from respondents. The questionnaire was designed to meet the study's objectives and provide a comprehensive understanding of online shopping behaviour.

The table below list the descriptions of each construct measurement of the present study.

Table: Descriptions of the measurement of the constructs for the study.

| Variable | Code | Statement | Source |
|---|---|---|---|
| **PERFORMANCE EXPECTANCY** | PE1 | I don't think AR Platforms are useful for my shopping | Pantano, E., Rese, A., & Baier, D. (2017) |
| | PE2 | Using AR Platforms would help me to solve problems in my shopping decisions | |
| | PE3 | Using AR Platforms would enable me to accomplish my tasks more quickly | |
| | PE4 | The use of AR Platforms increases the efficiency of my shopping | |
| **EFFORT EXPECTANCY** | EE1 | It is easy for me to operate AR Platforms skillfully | Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003) |
| | EE2 | It is difficult for me to learn how to use AR Platform | |
| | EE3 | I find AR Platforms are easy to use. | |
| | EE4 | I have no difficulty in using AR Platforms. | |
| **SOCIAL INFLUENCE** | SI1 | People who are important to me think that I should use AR Platform | Moore, G.C., & Benbasat, I. (1991) |
| | SI2 | I find that using AR is a fashionable and popular way for shopping | |
| | SI3 | Using AR Platforms makes me feel I belong to the online adoption community | |
| **FACILITATING CONDITION** | FC1 | It is convenient for me to shopping in an AR Platforms | Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012) |
| | FC2 | I have the hardware necessary to use AR Platforms | |

| | | | |
|---|---|---|---|
| | FC3 | I have the knowledge necessary to use AR Platforms | |
| | FC4 | AR Platforms are compatible with 6 shopping apps I use | |
| | FC5 | Support from the AR Platforms is available whenever there is a problem | |
| **BEHAVIOURAL INTENTIONS** | BI1 | I intend to use AR Platforms in the future. | Bhattacherjee, A. (2001) |
| | BI2 | I predict that I would use AR Platforms in the future | |
| | | I plan to use AR Platforms in the future | |
| | BI4 | I would recommend AR Platforms in my reference. | |
| **USAGE BEHAVIOUR** | UB1 | I consider myself a frequent user of AR Platforms | Venkatesh, V., Thong, J.Y.L., & Xu, X. (2012) |
| | UB2 | I prefer to use AR Platforms when available | |
| | UB3 | I do most shopping tasks by using AR Platforms. | |
| | UB4 | My tendency towards using AR Platforms whenever possible. | |

### 3.8 Pilot Testing, Reliability Testing & Validity of the questionnaire

To check the validity of the instrument, a questionnaire was sent to 10 management faculty members and 10 management students. Based on the reviews of scales, instructions and appropriateness of the questions, wording of some of the questions have been changed. Before conducting the final survey, the researcher had carried out a pilot study to measure the reliability of the questionnaire (Cvana et. at, 2001; Sekaran, 2003). Reliability identifies whether the measure is without bias and error-free and can be applied consistently across time and items in the instrument (Canava et al, 2001).

Therefore, the present study took 308 samples. The respondents for the pre-test are selected from the four major cities in Gujarat with familiarity with online purchasing. The responses are analysed and based on that the final instrument has been identified for the final survey.
The results of the Pilot testing say that there The respondents for pre-test is selected from the four Major cities of Gujarat i.e Ahmedabad, Surat, Vadodara & Rajkot. The responses are analyzed and based on that it is identified that Pilot testing confirms the reliability but there were validity were not matched with habit, Hedonic Motivation and Facilitating Condition.

### 3.9 Reliability

Measured scores' accuracy is indicated by reliability. Additionally, it implies the accuracy and efficiency with which scores may be replicated through repeated measurement (Madden, Dillon, 1994). Cronbach's alpha was used to calculate the construct pieces' dependability. products with a reliability of less than 0.6 are regarded as poor, products with a reliability of 0.7 are deemed acceptable, and items with a reliability of 0.8 are deemed good, according to Malhotra (2004). The validity and reliability of the financial self-efficacy dimension construct utilized in this study are displayed in the tables below.

**Table: Reliability**

| | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|
| BI | 0.794 | 0.795 | 0.866 | 0.618 |
| EE | 0.734 | 0.754 | 0.831 | 0.553 |
| FC | 0.782 | 0.794 | 0.851 | 0.533 |
| PE | 0.716 | 0.718 | 0.824 | 0.54 |
| SI | 0.732 | 0.783 | 0.822 | 0.606 |
| UB | 0.85 | 0.863 | 0.898 | 0.688 |

**Cronbach’s Alpha:**

The research project used Cronbach's Alpha to assess the internal consistency of claims made in e-service quality aspects. A Cronbach's Alpha value of over 0.70 indicates adequate internal consistency, while a value closer to 0.9 indicates unbroken reliability. The table shows Rho_A values above 0.90, indicating adequate levels of reliability in Performance expectancy, effort expectancy, social influence, facilitating condition, Hedonic motivation, Facilitating Condition, behavioural intentions and usage behaviour. Composite reliability, also known as construct reliability, measures the internal consistency of scale components. Average variance extracted (AVE) is the ratio of variance accounted for by a construct to measurement error variance. Average Variance Extracted (AVE) is the final element of convergent validity. The study's convergent validity is sufficient if AVE is less than 0.5 but composite reliability is greater than 0.70. The mean is calculated, and the squared difference is then calculated.

Table: Discriminant validity as per Heterotrait-monotrait ratio (HTMT) Matrix

| | BI | EE | FC | PE | SI | UB |
|---|---|---|---|---|---|---|
| BI | 0.786 | | | | | |
| EE | 0.515 | 0.744 | | | | |
| FC | -0.541 | -0.616 | 0.730 | | | |
| PE | 0.494 | 0.485 | -0.558 | 0.735 | | |
| SI | 0.537 | 0.639 | -0.536 | 0.491 | 0.779 | |
| UB | -0.167 | -0.151 | 0.178 | -0.115 | -0.141 | 0.829 |

As seen in the table, it is clearly visible that all the values are below the conservative threshold value of 0.85.

Table: Hetero Trait-Mono trait Ratio (HTMT)

| | BI | EE | FC | PE | SI | UB |
|---|---|---|---|---|---|---|
| BI | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| EE | 0.656 | | | | | |
| FC | 0.674 | 0.792 | | | | |
| PE | 0.652 | 0.648 | 0.737 | | | |
| SI | 0.734 | 0.895 | 0.729 | 0.707 | | |
| UB | 0.198 | 0.182 | 0.211 | 0.150 | 0.185 | |

The bootstrapping procedure confirmed that there were no changes and indicated that the HTMT values are significantly different from 1, at a 95% confidence interval and 0.05 significance level. This demonstrates that discriminant validity has been established**.**

### 3.10 Statistical Treatment of Data

A total of 1012 respondents were initially identified for data collection; however, 903 valid replies were used for the study's final analysis following the data cleaning process.

#### 3.10.1 Descriptive Analysis

mean and standard deviations. Chapter 4 discusses the findings. In the current investigation, the following inferential statistics were employed.

#### 3.10.2 Reliability statistics

The reliability test evaluates the validity and dependability of components in scales measuring the Impact of Augmented Reality in the retail context. Cronbach's Alpha statistic is used to assess data reliability, with a 0.7 criterion indicating internal consistency and reliability. SPSS is used to calculate Cronbach's Alpha statistics.

#### 3.10.3 One-way ANOVA

By comparing two groups and within two groups, one-way ANOVA was utilized to determine whether there is a significant difference in the independent variable on the dependent variable (Aaker et al. 2007; Canava et al., 2001)

### 3.10.4 Independent sample T test

By looking at two samples from the same population, the independent sample t test was utilized to analyze the mean comparison of two independent groups. The two samples may have the same mean.

### 3.10.5 Bootstrapping & Path Analysis

Bootstrapping is a nonparametric technique used to test the statistical significance of PLS-SEM outcomes, including path coefficients, Cronbach's alpha, HTMT, and R2 values. It involves randomly selecting observations from the initial data set to build subsamples, which estimate the PLS path model. This process is repeated until around 5,000 random subsamples are formed. Parameter estimates from these subsamples are used to derive standard errors and t-values are calculated to assess each estimate's significance.

## 3.11 Limitation of the study

The study highlighted significant limitations affecting research outcomes. Access to primary data posed a challenge, despite the availability of secondary data online. Many potential respondents were unenthusiastic due to concerns over privacy, financial constraints, and lack of interest. To address these issues, researchers engaged participants in pre-survey discussions and upheld ethical standards by ensuring the confidentiality of their responses. Time constraints also limited the depth of the literature review, focusing only on relevant studies about online purchasing behaviors. The researcher recognized that qualitative methods, such as focus groups, could improve data richness. However, the sample primarily included urban residents, thereby excluding rural perspectives. This limitation may affect the generalizability of findings across Gujarat. Therefore, while the conclusions are sound, they cannot be universally applied. Future research should incorporate diverse demographics and product categories to achieve a more comprehensive understanding of consumer behavior.

## 3.12 original contribution by the thesis

Performance expectancy, effort expectancy, social influence, facilitating condition, behavioural intentions and usage behaviour are other dimensions to measure the impact of Augmented Reality on Consumer Purchase Intentions and Adoption in the Retail Sector. There are lots of other literature that argue about specific segments with reference to Virtual Reality and Mixed Reality. But here researcher identify the literature gap and make conceptual model to help the online retailers. Here researcher take 903 responses from 4 Major Cities of Gujarat and analyze using structural equation model path analysis and have significant impact. So as per study researcher share to the educators, Agents and Online retailors that need to conduct seminar or workshop on Augmented Reality.

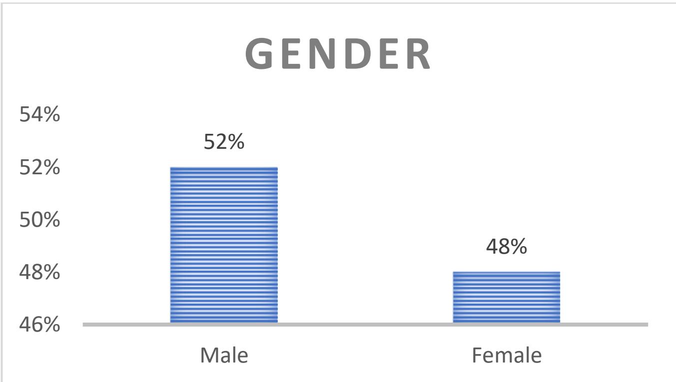
# CHAPTER 4: PRIMARY ANALYSIS OF RESPONDENTS

*This Chapter discuss results and interpretations of various data analysis techniques collected with the help of primary survey. The chapter identifies key variables of online consumer purchase intentions and adoption with reference to augmented reality in retail context.*

**4.1 Descriptive Statistics of categorical variable**

**4.1.1 Gender**

| | Frequency | Percentage |
|---|---|---|
| Male | 469 | 52% |
| Female | 434 | 48% |
| Total | 903 | 100% |

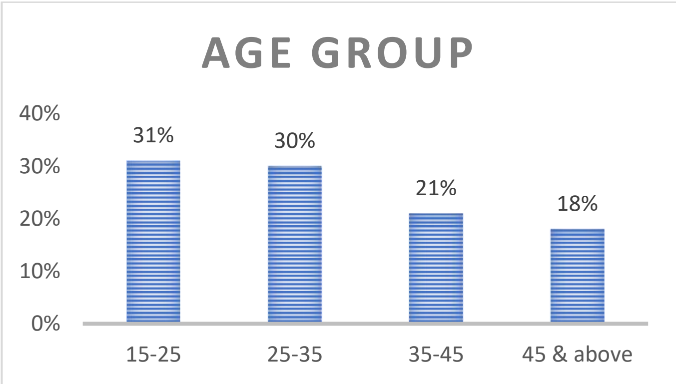



the table shows that out of 903 respondents, 469(52%) are male and 434(48%) are female.

**4.1.2 Age Group**

| | Frequency | Percentage |
|---|---|---|
| 15-25 | 278 | 31% |
| 25-35 | 276 | 30% |

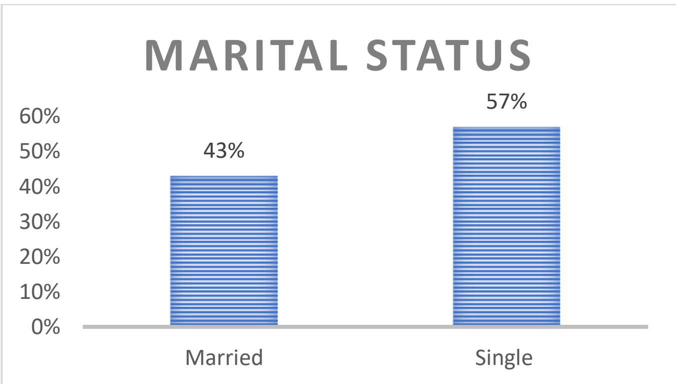
| | | |
|---|---|---|
| 35-45 | 190 | 21% |
| 45 & above | 159 | 18% |
| Total | 903 | 100% |




the table shows that out of 903 respondents, 278 (31%) are belongs to the age group 15-25, 276(30%) are belongs to the age group of 25-35, 190 (21%) are belongs to the age group of 35-45, 159 (18%) are belongs to the age group of 45 & above.

### 4.1.3 Marital Status

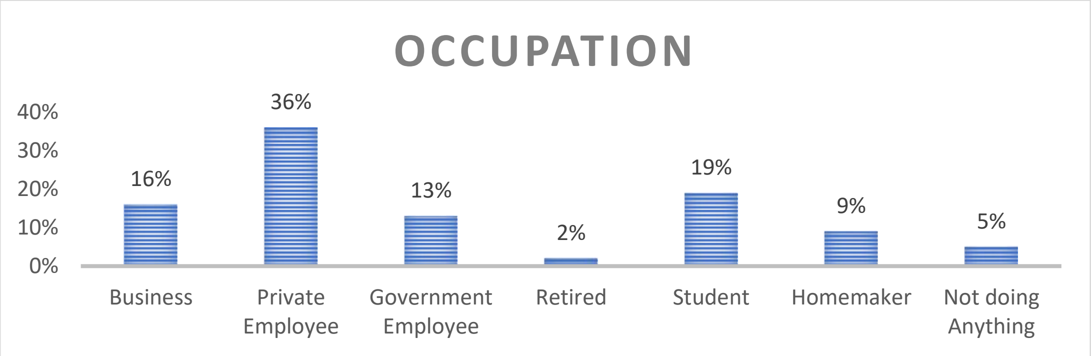
| | Frequency | Percentage |
|---|---|---|
| Married | 384 | 43% |
| Single | 519 | 57% |
| Total | 903 | 100% |



As the table shows that out of 903 respondents, 384 (43%) are Married and 519 (57%) are unmarried.

#### 4.1.4 Occupation

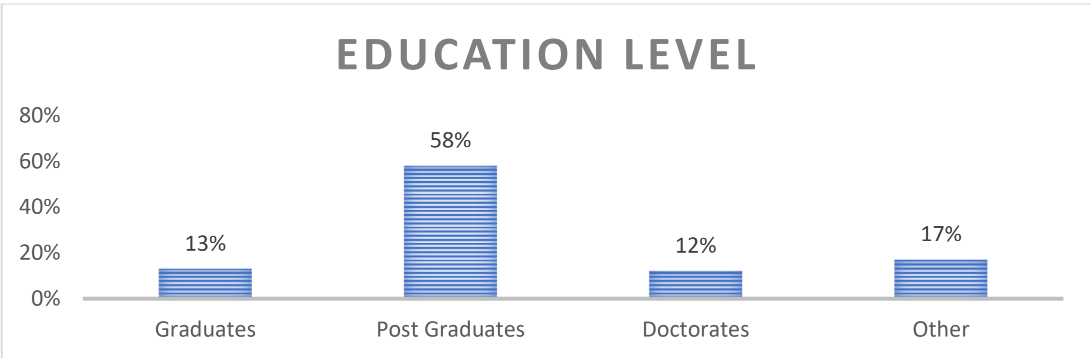
| | Frequency | Percentage |
|---|---|---|
| Business | 145 | 16% |
| Private Employee | 328 | 36% |
| Government Employee | 116 | 13% |
| Retired | 17 | 2% |
| Student | 169 | 19% |
| Homemaker | 81 | 9% |
| Not doing Anything | 47 | 5% |
| Total | 903 | 100% |




As the table shows that out of 903 respondents, 145 (16%) are belong to Business, 328 (36%) are private employee, 116 (13%) are government employee, 17 (2%) are Retired, 169 (19%) are student, 81 (9%) are home maker, 47 (5%) are not doing anything.

### 4.1.5 Education Level

| | Frequency | Percentage |
|---|---|---|
| Graduates | 121 | 13% |
| Post Graduates | 522 | 58% |
| Doctorates | 109 | 12% |
| Other | 151 | 17% |
| Total | 903 | 100% |

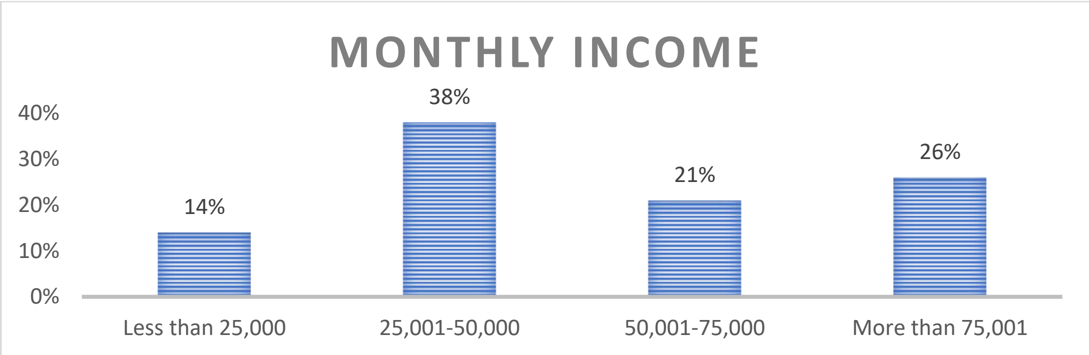



As the table shows, out of 903 respondents, 121 (13%) are Graduates, 522 (58%) are post graduates, 109 (12%) are Doctorates, and others 151(17%).

### 4.1.6 Monthly Income

| | Frequency | Percentage |
|---|---|---|
| Less than 25,000 | 131 | 14% |

| | | |
|---|---|---|
| 25,001-50,000 | 344 | 38% |
| 50,001-75,000 | 194 | 21% |
| More than 75,001 | 234 | 26% |
| Total | 903 | 100% |




As the table shows, out of 903 respondents, 131 (14%) are less than 25,000 monthly Income 344 (38%) Monthly income, 194 (21%) 50,001-75,000 monthly income and 234 (26%) have more than 75,0001.

**4.2 Frequencies for continuous variable**

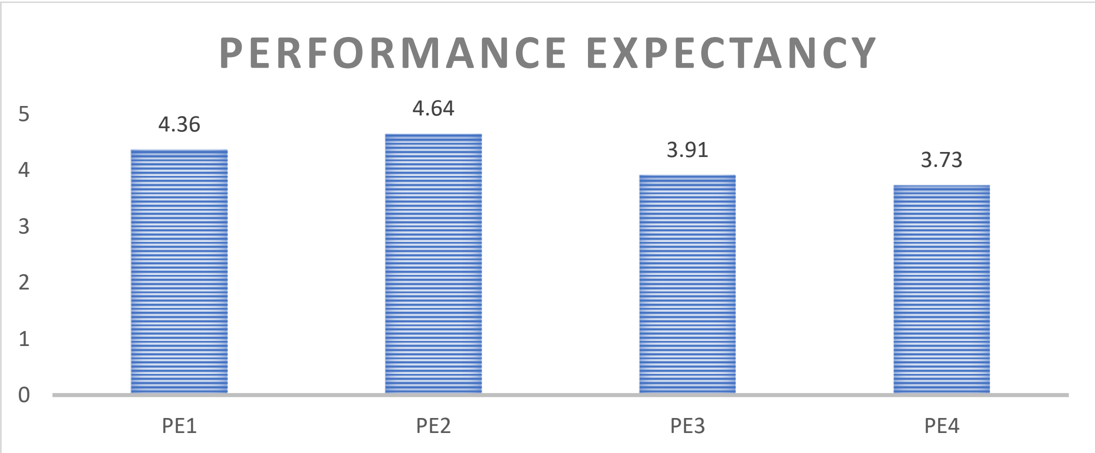
**4.2.1 PERFORMANCE EXPECTANCY**

| **Variable** | **Code** | **Statement** | **Source** |
|---|---|---|---|
| **PERFORMANCE EXPECTANCY** | PE1 | I don't think AR Platforms are useful for my shopping | Pantano, E., Rese, A., & Baier, D. (2017) |
| | PE2 | Using AR Platforms would help me to solve problems in my shopping decisions | |
| | PE3 | Using AR Platforms would enable me to accomplish my tasks more quickly | |

| | | | |
|---|---|---|---|
| | PE4 | The use of AR Platforms increases the efficiency of my shopping | |

| PERFORMANCE EXPECTANCY | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| PE1 | 903 | 1 | 5 | 4.36 | 0.777 |
| PE2 | 903 | 1 | 5 | 4.64 | 0.781 |
| PE3 | 903 | 1 | 5 | 3.91 | 0.850 |
| PE4 | 903 | 1 | 5 | 3.73 | 0.821 |
| Grand Average | | | | 4.16 | |

Source: Structured Questionnaire




Source: Structured Questionnaire

Data table provides summary of ratings given by the respondents on a scale of 1 to 5 to various parameters measuring the performance expectancy towards Augmented Reality in retail sector. The grand mean of all the ratings across parameters is 4.16. This indicates a relatively high average rating and suggests that on average, respondents have a positive perception towards performance expectancy in online retail context.

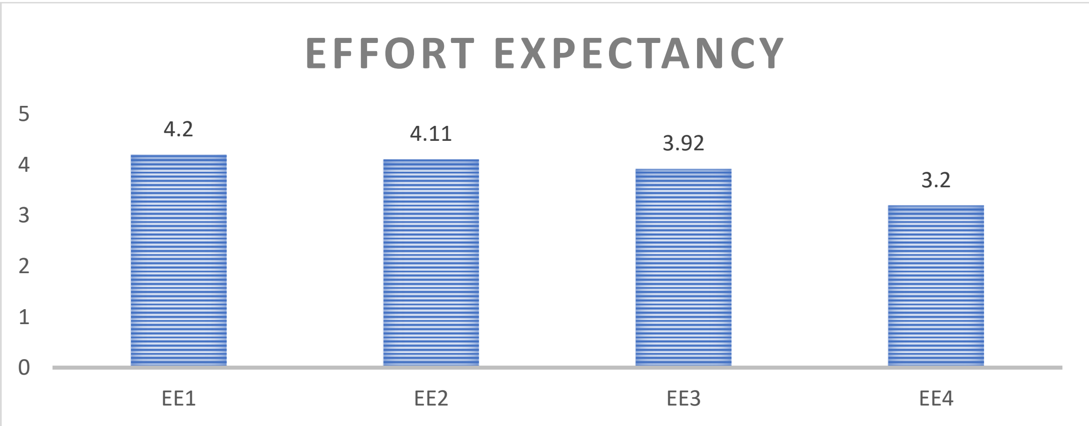
### 4.2.2 EFFORT EXPECTANCY

| Variable | Code | Statement | Source |
|---|---|---|---|
| | EE1 | It is easy for me to operate AR Platforms skillfully | |

| | | | |
|---|---|---|---|
| **EFFORT EXPECTANCY** | EE2 | It is difficult for me to learn how to use AR Platform | Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003) |
| | EE3 | I find AR Platforms are easy to use. | |
| | EE4 | I have no difficulty in using AR Platforms. | |

| **EFFORT EXPECTANCY** | **N** | **Minimum** | **Maximum** | **Mean** | **Std. Deviation** |
|---|---|---|---|---|---|
| EE1 | 903 | 1 | 5 | 4.2 | 1.201 |
| EE2 | 903 | 1 | 5 | 4.11 | 1.320 |
| EE3 | 903 | 1 | 5 | 3.92 | 1.22 |
| EE4 | 903 | 1 | 5 | 4.2 | 1.51 |
| Grand Average | | | | 4.10 | |

Source: Structured Questionnaire




Source: Structured Questionnaire

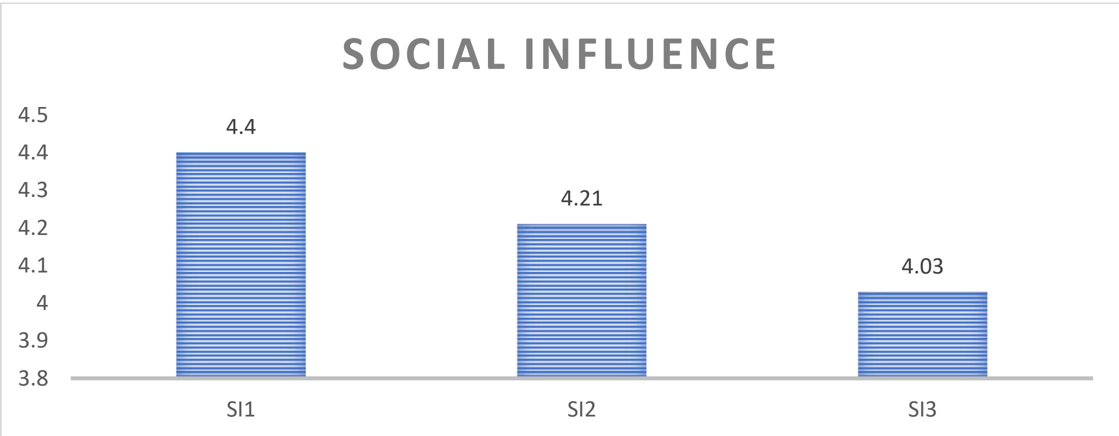
Data table provides summary of ratings given by the respondents on a scale of 1 to 5 to various parameters measuring the Effort Expectancy towards Augmented Reality in retail sector. The grand mean of all the ratings across parameters is 4.10. This indicates a relatively high average rating and suggests that on average, respondents have a positive perception towards Effort expectancy in online retail context.

### 4.2.3 SOCIAL INFLUENCE

| Variable | Code | Statement | Source |
|---|---|---|---|
| **SOCIAL INFLUENCE** | SI1 | People who are important to me think that I should use AR Platform | Moore, G.C., & Benbasat, I. (1991) |
| | SI2 | I find that using AR is a fashionable and popular way for shopping | |
| | SI3 | Using AR Platforms makes me feel I belong to the online adoption community | |

| SOCIAL INFLUENCE | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| SI1 | 903 | 1 | 5 | 4.40 | 0.95 |
| SI2 | 903 | 1 | 5 | 4.21 | 1.07 |
| SI3 | 903 | 1 | 5 | 4.03 | 0.87 |
| Grand Average | | | | 4.21 | |

Source: Structured Questionnaire



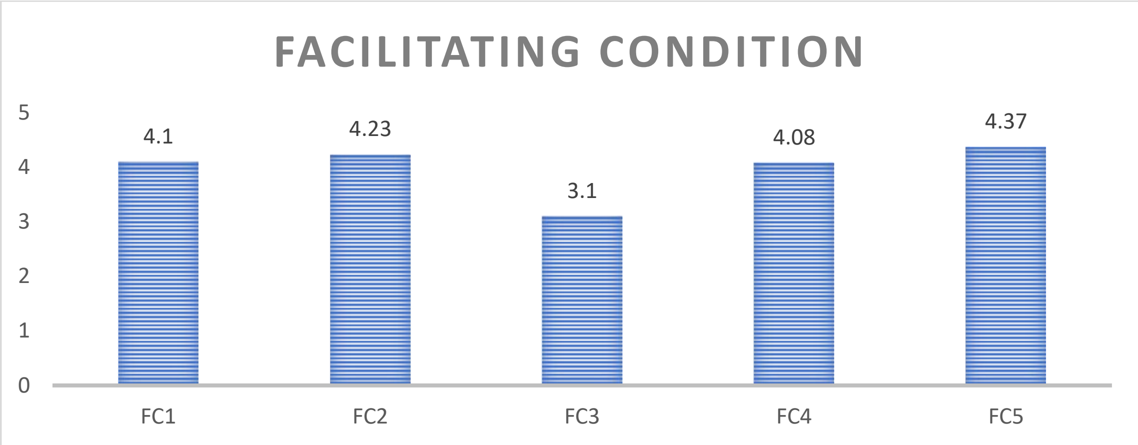

Data table provides summary of ratings given by the respondents on a scale of 1 to 5 to various parameters measuring the Social Influence towards Augmented Reality in retail sector. The grand mean of all the ratings across parameters is 4.21. This indicates a relatively high average rating and suggests that on average, respondents have a positive perception towards Social Influence in online retail context.

#### 4.2.4 FACILITATING CONDITION

| **Variable** | **Code** | **Statement** | **Source** |
|---|---|---|---|
| **FACILITATING CONDITION** | FC1 | It is convenient for me to shopping in an AR Platforms | Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012) |
| | FC2 | I have the hardware necessary to use AR Platforms | |
| | FC3 | I have the knowledge necessary to use AR Platforms | |
| | FC4 | AR Platforms are compatible with 6 shopping apps I use | |
| | FC5 | Support from the AR Platforms is available whenever there is a problem | |

| **FACILITATING CONDITION** | **N** | **Minimum** | **Maximum** | **Mean** | **Std. Deviation** |
|---|---|---|---|---|---|
| FC1 | 903 | 1 | 5 | 4.1 | 0.56 |
| FC2 | 903 | 1 | 5 | 4.23 | 0.66 |
| FC3 | 903 | 1 | 5 | 4.84 | 0.43 |
| FC4 | 903 | 1 | 5 | 4.08 | 0.75 |
| FC5 | 903 | 1 | 5 | 4.1 | 0.83 |
| Grand Average | | | | 4.31 | |

Source: Structured Questionnaire




Data table provides summary of ratings given by the respondents on a scale of 1 to 5 to various parameters measuring the Facilitating Condition towards Augmented Reality in retail sector. The grand mean of all the ratings across parameters is 4.31. This indicates a relatively high average rating and suggests that on average, respondents have a positive perception towards Facilitating Condition in online retail context.

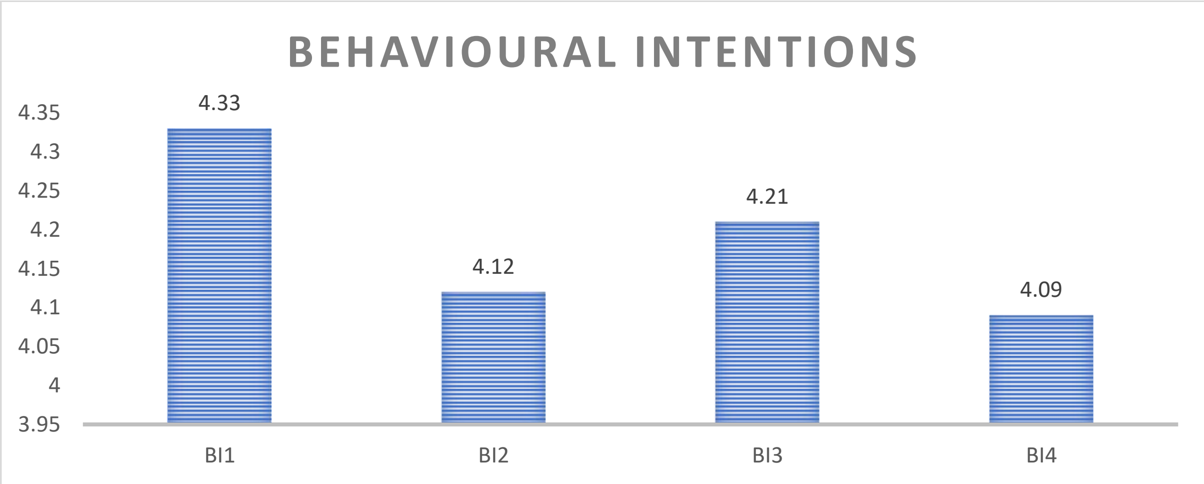
#### 4.2.5 BEHAVIOURAL INTENTIONS

| Variable | Code | Statement | Source |
|---|---|---|---|
| **BEHAVIOURAL INTENTIONS** | BI1 | I intend to use AR Platforms in the future. | Bhattacherjee, A. (2001) |
| | BI2 | I predict that I would use AR Platforms in the future | |
| | BI3 | I plan to use AR Platforms in the future | |
| | BI4 | I would recommend AR Platforms in my reference. | |

| BEHAVIOURAL INTENTIONS | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| BI1 | 903 | 1 | 5 | 4.33 | 1.20 |
| BI2 | 903 | 1 | 5 | 4.12 | 1.41 |
| BI3 | 903 | 1 | 5 | 4.21 | 1.43 |
| BI4 | 903 | 1 | 5 | 4.09 | 1.20 |

| | | | |
|---|---|---|---|
| Grand Average | | 4.18 | |

Source: Structured Questionnaire




Data table provides summary of ratings given by the respondents on a scale of 1 to 5 to various parameters measuring the Behavioural Intentions towards Augmented Reality in retail sector. The grand mean of all the ratings across parameters is 4.18. This indicates a relatively high average rating and suggests that on average, respondents have a positive perception towards Behavioural Intentions in online retail context.

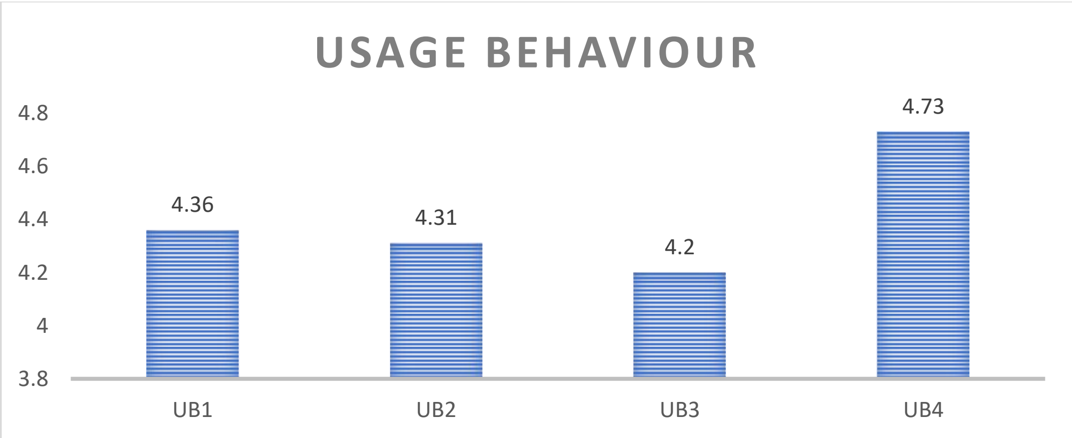
### 4.2.6 USAGE BEHAVIOUR

| **Variable** | **Code** | **Statement** | **Source** |
|---|---|---|---|
| **USAGE BEHAVIOUR** | UB1 | I consider myself a frequent user of AR Platforms | Venkatesh, V., Thong, J.Y.L., & Xu, X. (2012) |
| | UB2 | I prefer to use AR Platforms when available | |
| | UB3 | I do most shopping tasks by using AR Platforms. | |
| | UB4 | My tendency towards using AR Platforms whenever possible. | |

| **USAGE BEHAVIOUR** | **N** | **Minimum** | **Maximum** | **Mean** | **Std. Deviation** |
|---|---|---|---|---|---|
| UB1 | 903 | 1 | 5 | 4.36 | 1.02 |

| | | | | | |
|---|---|---|---|---|---|
| UB2 | 903 | 1 | 5 | 4.31 | 1.32 |
| UB3 | 903 | 1 | 5 | 4.20 | 1.04 |
| UB4 | 903 | 1 | 5 | 4.73 | 1.62 |
| Grand Average | | | | 4.4 | |

Source: Structured Questionnaire




Data table provides summary of ratings given by the respondents on a scale of 1 to 5 to various parameters measuring the Usage Behaviour towards Augmented Reality in retail sector. The grand mean of all the ratings across parameters is 4.4. This indicates a relatively high average rating and suggests that on average, respondents have a positive perception towards Usage Behaviour in online retail context.

# CHAPTER 5: DATA ANALYSIS AND INTERPRETATION

*This Chapter discuss descriptive statistics, various statistical tools and technique like T-test, one-way Anova, structural equation modelling, multigroup analysis for data analysis with the help of SPSS and smart pls.*

## 5.1 Data Analysis

This section provides an overview of the data analysis from both quantitative and qualitative studies conducted as part of this research. The evaluation and discussion are structured into three segments. The initial segment focused on data analysis, which included checks for bias, identification of outliers, along with assessments of the reliability and validity of the measurement scale. The second segment involved performing a descriptive statistical analysis on the profiles of the respondents for the variables utilized in the study. Lastly, the final segment of analysis and discussion utilized inferential statistics to investigate the relationship between the independent and dependent variables. This analysis aimed to thoroughly describe and discuss the data, particularly the interplay between the variables. To process the survey data, Smart PLS 4 software was employed, applying the methodologies presented by Wong (2013), while IBM SPSS software was used, following the techniques described by Field (2013).

## 5.2 Data Examination

A Total of six measurements were taken to guarantee the precision of the gathered data. The research utilised data evaluations at different stages, such as screening, assessment reliability, & Validity evaluation.

### 5.2.1 Data Screening

To filter out the abnormal response patterns, all received responses were analysed. Visual inspection was conducted to detect straight-lining, diagonal lining and alternating pole responses, as recommended by Hair et al. (2017), and it was found that there were no missing data in the response.

### 5.2.2 Common Method Bias

Common Method Bias (CMB) refers to when the independent and dependent variable is captured by the same response method. Common Method Bias (CMB) may skew study results if influenced by measurement instruments. Harman's single factor score can help asses CMB, indicating if it is significant when variance is below 50%.

Total Variance Explained

| Factor | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 7.335 | 30.561 | 30.561 | 6.662 | 27.759 | 27.759 |
| 2 | 2.624 | 10.933 | 41.494 | | | |
| 3 | 1.328 | 5.533 | 47.027 | | | |
| 4 | 1.261 | 5.253 | 52.280 | | | |
| 5 | 1.075 | 4.481 | 56.761 | | | |
| 6 | .815 | 3.396 | 60.157 | | | |
| 7 | .774 | 3.224 | 63.381 | | | |
| 8 | .678 | 2.823 | 66.204 | | | |
| 9 | .673 | 2.805 | 69.008 | | | |
| 10 | .648 | 2.701 | 71.709 | | | |
| 11 | .617 | 2.569 | 74.278 | | | |
| 12 | .592 | 2.468 | 76.746 | | | |
| 13 | .566 | 2.357 | 79.103 | | | |
| 14 | .545 | 2.269 | 81.373 | | | |
| 15 | .518 | 2.160 | 83.533 | | | |
| 16 | .510 | 2.124 | 85.657 | | | |
| 17 | .497 | 2.071 | 87.727 | | | |
| 18 | .474 | 1.974 | 89.702 | | | |
| 19 | .460 | 1.917 | 91.619 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 20 | .456 | 1.900 | 93.519 | | | |
| 21 | .441 | 1.838 | 95.357 | | | |
| 22 | .435 | 1.811 | 97.168 | | | |
| 23 | .355 | 1.478 | 98.646 | | | |
| 24 | .325 | 1.354 | 100.000 | | | |
| Extraction Method: Principal Axis Factoring. | | | | | | |

Study shows no common method bias, focus shifts to non-response bias.

### 5.2.3 Non-response bias

When survey respondents are unwilling or unable to respond, it can lead to potential bias. Reasons consisting Questionnaire design flaws, sensitive topics and logistical failure to reach the respondents. Non-response results in a smaller sample size, leading to less accuracy in estimating population characteristics (Armstrong and Overton, 1977).

## 5.3 Reliability Testing through Cronbach's alpha

Since the value of Cronbach's Alpha is higher than 0.70, we reject the null hypothesis, and we may say that the instrument is reliable and can be used with factor analysis for further investigation.

Table: Cronbach's alpha

| | Cronbach Alpha | N of Item |
|---|---|---|
| PERFORMANCE EXPECTANCY | 0.976 | 903 |
| EFFORT EXPECTANCY | 0.986 | 903 |
| SOCIAL INFLUENCE | 0.969 | 903 |
| FACILITATING CONDITION | 0.968 | 903 |
| BEHAVIOUR INTENTION | 0.981 | 903 |
| USAGE BEHAVIOUR | 0.975 | 903 |

The above table shows Cronbach's Alpha Value of Performance Expectancy is 0.976, Effort Expectancy is 0.986, Social Influence is 0.969, Facilitating Condition is 0.968, Behaviour Intention is 0.981 and Usage Behaviour is 0.975

**5.4 Factorability Assessment**

Factorability of data refers to its suitability for conducting factor analysis. This is determined through various measures such as Kaiser-Meyer-Olkin's (KMO) measure of sampling adequacy, Bartlett's test of sphericity, and analysis of the correlation coefficient between variables. A KMO value of 0.6 or higher and a statistically significant Bartlett's test score ($p<0.05$) are generally considered indicative of factorability.

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .968 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 96991.737 |
| | df | 528 |
| | Sig. | .000 |

The degree of correlation between the variables in the dataset is evaluated using the KMO measure of sampling adequacy. Its values, which range from 0 to 1, indicate a higher degree of correlation between variables and, thus, a greater suitability of the dataset for factor analysis.

As the p-value of Bartlett's Test of Sphericity is 0.000 which is less than 5% level of significance we reject the null hypothesis which means that the correlation matrix is not an identity matrix. Kaiser-Meyer-Olkin Measure of Sampling Adequacy should be greater than .70 indicating sufficient items for each factor. Here. the results of the KMO is 0.930 is greater than 0.7.

| **Communalities** | | |
|---|---|---|
| | Initial | Extraction |
| PE1 | 1.000 | .952 |
| PE2 | 1.000 | .963 |
| PE3 | 1.000 | .984 |

| | | |
|---|---|---|
| PE4 | 1.000 | .958 |
| EE1 | 1.000 | .967 |
| EE2 | 1.000 | .973 |
| EE3 | 1.000 | .979 |
| EE4 | 1.000 | .977 |
| SI1 | 1.000 | .934 |
| SI2 | 1.000 | .969 |
| SI3 | 1.000 | .978 |
| BI1 | 1.000 | .964 |
| BI2 | 1.000 | .937 |
| BI3 | 1.000 | .972 |
| BI4 | 1.000 | .971 |
| UB1 | 1.000 | .964 |
| UB2 | 1.000 | .971 |
| UB3 | 1.000 | .951 |
| UB4 | 1.000 | .935 |

Extraction Method: Principal Component Analysis.

For a good statement, Communalities should be greater than 0.5.so here that condition is fulfilled.

| **Total Variance Explained** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 29.804 | 90.316 | 90.316 | 29.804 | 90.316 | 90.316 | 10.109 | 30.635 | 30.635 |
| 2 | .875 | 2.650 | 92.966 | .875 | 2.650 | 92.966 | 9.098 | 27.569 | 58.204 |
| 3 | .628 | 1.904 | 94.870 | .628 | 1.904 | 94.870 | 6.969 | 21.118 | 79.322 |
| 4 | .437 | 1.324 | 96.195 | .437 | 1.324 | 96.195 | 5.568 | 16.873 | 96.195 |
| 5 | .282 | .854 | 97.049 | | | | | | |
| 6 | .169 | .513 | 97.562 | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 7 | .129 | .392 | 97.954 | | | | | | |
| 8 | .111 | .335 | 98.289 | | | | | | |
| 9 | .080 | .242 | 98.530 | | | | | | |
| 10 | .066 | .199 | 98.729 | | | | | | |
| 11 | .050 | .151 | 98.880 | | | | | | |
| 12 | .044 | .132 | 99.012 | | | | | | |
| 13 | .040 | .121 | 99.133 | | | | | | |
| 14 | .036 | .108 | 99.241 | | | | | | |
| 15 | .032 | .096 | 99.337 | | | | | | |
| 16 | .026 | .080 | 99.417 | | | | | | |
| 17 | .009 | .028 | 99.874 | | | | | | |
| 18 | .008 | .025 | 99.898 | | | | | | |
| 19 | .008 | .023 | 99.922 | | | | | | |
| 20 | .007 | .021 | 99.942 | | | | | | |
| 21 | .006 | .018 | 99.960 | | | | | | |
| 22 | .005 | .015 | 99.975 | | | | | | |
| 23 | .005 | .014 | 99.990 | | | | | | |
| 24 | .003 | .010 | 100.000 | | | | | | |
| Extraction Method: Principal Component Analysis | | | | | | | | | |

The Total Variance Explained table shows how the variance is divided among the 24 possible factors. Four factors have eigenvalues (a measure of explained variance) greater than 1.0, which is a common criterion for a factor to be useful. When the eigenvalue is less than 1.0. This means that the factor explains less information than a single item would have explained. It can be concluded that these four factors extracted from all the variables explain about 96.19% variance of the total variance.

**5.5 Variables**

A research thesis typically includes a theoretical framework comprising two primary types of variables: independent and dependent variables. In this study, the independent variable is the Personal Financial behaviour, meanwhile the dependent variable is financial knowledge, financial attitude, financial self-efficacy and locus of control. The Likert scale used for both types of variables ranges from "1" Strongly Disagree to "5" Strongly Agree. Respondents had the option to choose from numbers 1 through 5, where 1 represented "Strongly Disagree" 2 "Disagree" 3 represented "Neutral" 4 represented "Agree" and 5 represented "Strongly Agree" Displays the means, minimum and maximum values of both the independent and dependent variables, along with their respective standard deviations.

| Descriptive Statistics | | | | | |
|---|---|---|---|---|---|
| | Mean | Std. Deviation | Analysis N | Minimum | Maximum |
| PE1 | 2.36 | 1.345 | 903 | 1 | 5 |
| PE2 | 2.09 | 1.244 | 903 | 1 | 5 |
| PE3 | 2.26 | 1.310 | 903 | 1 | 5 |
| PE4 | 1.87 | .920 | 903 | 1 | 5 |
| EE1 | 2.13 | 1.180 | 903 | 1 | 5 |
| EE2 | 2.22 | 1.247 | 903 | 1 | 5 |
| EE3 | 2.09 | 1.216 | 903 | 1 | 5 |
| EE4 | 2.07 | 1.336 | 903 | 1 | 5 |
| SI1 | 1.98 | .952 | 903 | 1 | 5 |
| SI2 | 1.84 | 1.079 | 903 | 1 | 5 |
| SI3 | 1.84 | .879 | 903 | 1 | 5 |
| FC1 | 1.97 | 1.232 | 903 | 1 | 5 |
| FC2 | 2.08 | 1.039 | 903 | 1 | 5 |
| FC3 | 1.69 | .799 | 903 | 1 | 5 |
| FC4 | 1.64 | .906 | 903 | 1 | 5 |
| FC5 | 1.98 | 1.125 | 903 | 1 | 5 |
| BI1 | 1.87 | 1.042 | 903 | 1 | 5 |
| BI2 | 2.03 | .978 | 903 | 1 | 5 |
| BI3 | 1.99 | 1.085 | 903 | 1 | 5 |
| BI4 | 1.74 | .972 | 903 | 1 | 5 |
| UB1 | 1.87 | .933 | 903 | 1 | 5 |
| UB2 | 1.67 | .929 | 903 | 1 | 5 |

| | | | | | |
|---|---|---|---|---|---|
| UB3 | 1.77 | .913 | 903 | 1 | 5 |
| UB4 | 1.54 | .883 | 903 | 1 | 5 |

The table provides a summary of the minimum, maximum, mean, and standard deviation of the dependent and independent variables' values. The independent variables include Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Behaviour Intention and Usage Behaviour.

### 5.6 Inferential Statistics

In research or data analysis, correlation results indicate the relationships between variables and provide insight into how one variable may affect another. In this study, the focus was on realizing the consequences of financial self-efficacy (independent variable) on investor financial behavior (dependent variable). To accomplish this, it was essential to conduct a correlation test to establish the relationship between the dependent variables. The following section analyzes the correlation between variables utilizing the SmartPLS SEM software. Creswell (2012) recommends the utilization of SmartPLS for non-parametric data, limited sample sizes, and complex cause-effect relationship models.

### 5.7 Independent sample T test

The text discusses the use of an independent sample t-test. This method is suitable for examining one categorical variable with multiple categories in relation to a continuous variable. The results include tables presenting mean, standard deviation, and error for the variables, with the t test results addressing various hypotheses, focusing solely on the alternate t hypothesis for the research.

**Independent sample T test- Gender**

H1: there is significance difference between various categories of Gender with respect to performance expectancy.

H2: there is significance difference between various categories of Gender with respect to effort expectancy.

H3: there is significance difference between various categories of Gender with respect to social influence.

H4: there is significance difference between various categories of Gender with respect to facilitating conditions.

H5: there is significance difference between various categories of Genderwith respect to behavioural intentions.

H6: there is significance difference between various categories of Gender with respect to usage behaviour

**Group Statistics**

| | Gender | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| PE | Male | 468 | 8.4573 | 4.54390 | .21004 |
| | Female | 435 | 8.7218 | 4.86010 | .23302 |
| EE | Male | 468 | 8.3568 | 4.70896 | .21767 |
| | Female | 435 | 8.6874 | 5.06763 | .24297 |
| SI | Male | 468 | 5.5299 | 2.65205 | .12259 |
| | Female | 435 | 5.7839 | 3.01597 | .14460 |
| FC | Male | 468 | 9.1517 | 4.56882 | .21119 |
| | Female | 435 | 9.5793 | 5.13774 | .24634 |
| BI | Male | 468 | 7.4808 | 3.75389 | .17352 |
| | Female | 435 | 7.8069 | 4.18572 | .20069 |
| UB | Male | 468 | 6.6966 | 3.28546 | .15187 |
| | Female | 435 | 7.0207 | 3.77013 | .18076 |

**Independent Samples Test**

| | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | |
|---|---|---|---|---|---|---|---|---|
| | F | Sig. | t | df | Sig. (2- | Mean Difference | Std. Error | 95% Confidence Interval of the Difference |

| | | | | | | tailed) | | Difference | Lower | Upper |
|---|---|---|---|---|---|---|---|---|---|---|
| PE | Equal variances assumed | 2.145 | .143 | -.845 | 901 | .398 | -.26457 | .31295 | -.87876 | .34961 |
| | Equal variances not assumed | | | -.843 | 883.635 | .399 | -.26457 | .31372 | -.88029 | .35114 |
| EE | Equal variances assumed | 3.036 | .082 | -1.016 | 901 | .310 | -.33052 | .32534 | -.96904 | .30800 |
| | Equal variances not assumed | | | -1.013 | 882.132 | .311 | -.33052 | .32622 | -.97077 | .30973 |
| SI | Equal variances assumed | 2.004 | .157 | -1.346 | 901 | .179 | -.25399 | .18869 | -.62432 | .11633 |
| | Equal variances not assumed | | | -1.340 | 866.205 | .181 | -.25399 | .18958 | -.62608 | .11809 |
| FC | Equal variances assumed | 3.248 | .072 | -1.323 | 901 | .186 | -.42760 | .32309 | -1.06170 | .20650 |
| | Equal variances not assumed | | | -1.318 | 869.777 | .188 | -.42760 | .32448 | -1.06445 | .20924 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| BI | Equal variances assumed | 2.645 | .104 | -1.234 | 901 | .217 | -.32613 | .26425 | -.84475 | .19250 |
| | Equal variances not assumed | | | -1.229 | 872.365 | .219 | -.32613 | .26531 | -.84684 | .19458 |
| UB | Equal variances assumed | 3.277 | .071 | -1.380 | 901 | .168 | -.32411 | .23492 | -.78515 | .13694 |
| | Equal variances not assumed | | | -1.373 | 863.225 | .170 | -.32411 | .23609 | -.78749 | .13928 |

**PERFORMANCE EXPECTANCY**

An independent-samples t-test was conducted to compare the performance expectancy for males and females. First, assumptions of normality and Levene's test were checked. Both the assumptions are met. There was no significant difference in scores for males (M- 8.4573, SD-4.54390) and females (M-8.7218, SD-4.86010; t(901)=-0.845, p=0.398). As p value is greater than 0.05, so the null hypothesis is accepted.

**EFFORT EXPECTANCY**

An independent-samples t-test was conducted to compare the performance expectancy for males and females. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for males (M- 8.3568, SD-4.70896) and females (M-8.6874, SD=5.06763; t(901)= -1.016, p=0.310). As p value is greater than 0.05, so the null hypothesis is accepted.

**SOCIAL INFLUENCE**

An independent-samples t-test was conducted to compare the performance expectancy for males and females. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for males (M-5.5299, SD=2.65205) and females (M-5.57839, SD-3.01597; t(901)= -1.346, p=0.179). As p value is greater than 0.05, so the null hypothesis is accepted.

**FACILITATING CONDITIONS**

An independent-samples t-test was conducted to compare the performance expectancy for males and females. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for males (M- 9.1517, SD-4.56882) and females (M-9.5793, SD-5.13774; t(901)=-1.323, p=0.186). As p value is greater than 0.05, so the null hypothesis is accepted.

**BEHAVIOURAL INTENTIONS**

An independent-samples t-test was conducted to compare the performance expectancy for males and females. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for males (M- 7.4808, SD-3.75389) and females (M-7.8069, SD-4.18572; t(901)=-1.234, p=0.217). As p value is greater than 0.05, so the null hypothesis is accepted.

**USAGE BEHAVIOR**

An independent-samples t-test was conducted to compare the performance expectancy for males and females. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for males (M- 6.6966, SD-3.28546) and females (M-7.0207, SD-3.77013; t(901)=-1.380 p=0.168). As p value is greater than 0.05, so the null hypothesis is accepted.

**Independent sample T test-Marital Status**

H7: There is a significance difference between Single and married regarding performance expectancy.

H8: There is a significance difference between Single and Married regarding effort expectancy.

H9: There is a significance difference between Single and Married regarding social influence.

H10:There is a significance difference between Single and Married regarding facilitating conditions.

H11: There is a significance difference between Single and Married regarding behavioural intentions.

H12: There is a significance difference between Single and Married regarding usage behaviour.

**Group Statistics**

| | **Marital status** | **N** | **Mean** | **Std. Deviation** | **Std. Error Mean** |
|---|---|---|---|---|---|
| PE | Single | 384 | 8.6302 | 4.78943 | .24441 |
| | Married | 519 | 8.5511 | 4.63377 | .20340 |
| EE | Single | 384 | 8.6016 | 5.01695 | .25602 |
| | Married | 519 | 8.4528 | 4.78910 | .21022 |
| SI | Single | 384 | 5.7214 | 2.93141 | .14959 |
| | Married | 519 | 5.6012 | 2.76228 | .12125 |
| FC | Single | 384 | 9.4766 | 4.98661 | .25447 |
| | Married | 519 | 9.2697 | 4.75505 | .20872 |
| BI | Single | 384 | 7.7526 | 4.08445 | .20843 |
| | Married | 519 | 7.5530 | 3.88301 | .17045 |
| UB | Single | 384 | 6.9271 | 3.61819 | .18464 |
| | Married | 519 | 6.7977 | 3.46403 | .15205 |

**Independent Samples Test**

| | Levene's Test for | t-test for Equality of Means |
|---|---|---|

| | | Equality of Variances | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference | |
| | | | | | | | | | Lower | Upper |
| PE | Equal variances assumed | .590 | .443 | .250 | 901 | .803 | .07915 | .31641 | -.54183 | .70013 |
| | Equal variances not assumed | | | .249 | 809.965 | .803 | .07915 | .31797 | -.54500 | .70330 |
| EE | Equal variances assumed | 1.098 | .295 | .452 | 901 | .651 | .14877 | .32897 | -.49687 | .79441 |
| | Equal variances not assumed | | | .449 | 803.491 | .653 | .14877 | .33127 | -.50148 | .79902 |
| SI | Equal variances assumed | .591 | .442 | .630 | 901 | .529 | .12020 | .19086 | -.25438 | .49478 |
| | Equal variances not assumed | | | .624 | 797.154 | .533 | .12020 | .19256 | -.25779 | .49818 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| FC | Equal variances assumed | .798 | .372 | .633 | 901 | .527 | .20681 | .32679 | -.43455 | .84817 |
| | Equal variances not assumed | | | .628 | 802.971 | .530 | .20681 | .32912 | -.43923 | .85285 |
| BI | Equal variances assumed | .837 | .360 | .747 | 901 | .455 | .19962 | .26722 | -.32483 | .72407 |
| | Equal variances not assumed | | | .741 | 801.496 | .459 | .19962 | .26925 | -.32890 | .72814 |
| UB | Equal variances assumed | .595 | .441 | .545 | 901 | .586 | .12940 | .23764 | -.33699 | .59578 |
| | Equal variances not assumed | | | .541 | 804.917 | .589 | .12940 | .23919 | -.34012 | .59891 |

**PERFORMANCE EXPECTANCY**

An independent-samples t-test was conducted to compare the performance expectancy for Single & Married. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for Single (M- 8.6302, SD-4.78943) and Married (M-8.5511, SD-4.63377; t(901)=-0.250, p=0.803). As p value is greater than 0.05, so the null hypothesis is accepted.

**EFFORT EXPECTANCY**

An independent-samples t-test was conducted to compare the performance expectancy for Single & Married. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for Single (M- 8.6016, SD-5.01695) and Married (M-8.4528, SD-4.78910; t(901)=-0.452, p=0.651). As p value is greater than 0.05, so the null hypothesis is accepted.

**SOCIAL INFLUENCE**

An independent-samples t-test was conducted to compare the performance expectancy for Single & Married. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for Single (M- 5.7214, SD-2.93141) and Married (M-5.6012, SD-2.76228; t(901)=-0.630 p=0.529). As p value is greater than 0.05, so the null hypothesis is accepted.

**FACILITATING CONDITIONS**

An independent-samples t-test was conducted to compare the performance expectancy for Single & Married.. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for Single (M- 9.4766, SD-4.98661) and Married (M-9.2697, SD-4.75505; t(901)=-0.633, p=0.527). As p value is greater than 0.05, so the null hypothesis is accepted.

**BEHAVIOURAL INTENTIONS**

An independent-samples t-test was conducted to compare the performance expectancy for Single & Married. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for Single (M-7.7526, SD-4.08445) and Married (M-7.5530, SD-3.88301; t(901)=-0.747, p=0.455). As p value is greater than 0.05, so the null hypothesis is accepted.

**USAGE BEHAVIOR**

An independent-samples t-test was conducted to compare the performance expectancy for Single & Married. first, assumptions of normality and leven's test were checked. Both the assumptions are met. There was no significant difference in scores for Single (M- 6.9271, SD-3.61819) and Married (M-6.7977, SD-3.46403; t(901)=-0.545, p=0.586). As p value is greater than 0.05, so the null hypothesis is accepted.

**One-Way ANOVA**

One-way ANOVA is employed to detect variance among categories of categorical variables, specifically when comparing one categorical variable across more than two categories. Researchers use summated scales with specific statements to assess predetermined continuous variables, including performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), behavioural intentions (BI), usage behavior (UB).

**ANOVA- Age wise**

H13: there is significance difference between various categories of age with respect to performance expectancy.

H14: there is significance difference between various categories of age with respect to effort expectancy.

H15: there is significance difference between various categories of age with respect to social influence.

H16: there is significance difference between various categories of age with respect to facilitating conditions.

H17: there is significance difference between various categories of age with respect to behavioural intentions.

H18: there is significance difference between various categories of age with respect to usage behaviour.

**Descriptive**

| | | N | Mean | Std. Deviation | Std. Error | 95% Confidence Interval for Mean | | Minimum | Maximum |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound | | |
| PE | 15-25 | 277 | 8.6354 | 4.64312 | .27898 | 8.0862 | 9.1846 | 4.00 | 20.00 |
| | 25-35 | 276 | 8.4746 | 4.67131 | .28118 | 7.9211 | 9.0282 | 4.00 | 20.00 |
| | 35-45 | 191 | 8.5340 | 4.66765 | .33774 | 7.8678 | 9.2002 | 4.00 | 20.00 |
| | 45 & Above | 159 | 8.7484 | 4.91055 | .38943 | 7.9793 | 9.5176 | 4.00 | 20.00 |
| | Total | 903 | 8.5847 | 4.69812 | .15634 | 8.2779 | 8.8916 | 4.00 | 20.00 |
| | 15-25 | 277 | 8.5271 | 4.78109 | .28727 | 7.9616 | 9.0926 | 4.00 | 20.00 |
| EE | 25-35 | 276 | 8.3986 | 4.89755 | .29480 | 7.8182 | 8.9789 | 4.00 | 20.00 |
| | 35-45 | 191 | 8.4398 | 4.78433 | .34618 | 7.7569 | 9.1226 | 4.00 | 20.00 |
| | 45 & Above | 159 | 8.7925 | 5.18893 | .41151 | 7.9797 | 9.6052 | 4.00 | 20.00 |
| | Total | 903 | 8.5161 | 4.88510 | .16257 | 8.1970 | 8.8351 | 4.00 | 20.00 |
| | 15-25 | 277 | 5.6137 | 2.79471 | .16792 | 5.2832 | 5.9443 | 3.00 | 15.00 |
| SI | 25-35 | 276 | 5.6159 | 2.77868 | .16726 | 5.2867 | 5.9452 | 3.00 | 15.00 |
| | 35-45 | 191 | 5.6283 | 2.82341 | .20429 | 5.2253 | 6.0312 | 3.00 | 15.00 |
| | 45 & Above | 159 | 5.8113 | 3.02766 | .24011 | 5.3371 | 6.2856 | 3.00 | 15.00 |
| | Total | 903 | 5.6523 | 2.83446 | .09432 | 5.4671 | 5.8374 | 3.00 | 15.00 |
| | 15-25 | 277 | 9.3466 | 4.80290 | .28858 | 8.7785 | 9.9147 | 5.00 | 25.00 |
| FC | 25-35 | 276 | 9.2681 | 4.79551 | .28866 | 8.6999 | 9.8364 | 5.00 | 25.00 |
| | 35-45 | 191 | 9.2461 | 4.79223 | .34675 | 8.5621 | 9.9301 | 5.00 | 25.00 |
| | 45 & Above | 159 | 9.6667 | 5.13818 | .40748 | 8.8618 | 10.4715 | 5.00 | 24.00 |
| | Total | 903 | 9.3577 | 4.85322 | .16150 | 9.0407 | 9.6747 | 5.00 | 25.00 |
| | 15-25 | 277 | 7.5740 | 3.84280 | .23089 | 7.1195 | 8.0285 | 4.00 | 20.00 |
| | 25-35 | 276 | 7.6051 | 4.00180 | .24088 | 7.1309 | 8.0793 | 4.00 | 20.00 |
| BI | 35-45 | 191 | 7.5340 | 3.86178 | .27943 | 6.9829 | 8.0852 | 4.00 | 20.00 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 45 & Above | 159 | 7.9308 | 4.26810 | .33848 | 7.2623 | 8.5994 | 4.00 | 20.00 |
| | Total | 903 | 7.6379 | 3.96892 | .13208 | 7.3787 | 7.8971 | 4.00 | 20.00 |
| | 15-25 | 277 | 6.8231 | 3.46741 | .20834 | 6.4130 | 7.2332 | 4.00 | 20.00 |
| | 25-35 | 276 | 6.8261 | 3.55612 | .21405 | 6.4047 | 7.2475 | 4.00 | 20.00 |
| UB | 35-45 | 191 | 6.7801 | 3.48437 | .25212 | 6.2828 | 7.2774 | 4.00 | 20.00 |
| | 45 & Above | 159 | 7.0377 | 3.66628 | .29075 | 6.4635 | 7.6120 | 4.00 | 19.00 |
| | Total | 903 | 6.8527 | 3.52901 | .11744 | 6.6222 | 7.0832 | 4.00 | 20.00 |

**ANOVA**

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| | Between Groups | 8.807 | 3 | 2.936 | .133 | .941 |
| PE | Within Groups | 19900.462 | 899 | 22.136 | | |
| | Total | 19909.269 | 902 | | | |
| EE | Between Groups | 17.102 | 3 | 5.701 | .238 | .870 |
| | Within Groups | 21508.415 | 899 | 23.925 | | |
| | Total | 21525.517 | 902 | | | |
| | Between Groups | 4.908 | 3 | 1.636 | .203 | .894 |
| SI | Within Groups | 7241.905 | 899 | 8.056 | | |
| | Total | 7246.813 | 902 | | | |
| | Between Groups | 19.807 | 3 | 6.602 | .280 | .840 |
| FC | Within Groups | 21225.657 | 899 | 23.610 | | |
| | Total | 21245.464 | 902 | | | |
| | Between Groups | 17.131 | 3 | 5.710 | .362 | .781 |
| BI | Within Groups | 14191.454 | 899 | 15.786 | | |
| | Total | 14208.585 | 902 | | | |
| | Between Groups | 6.889 | 3 | 2.296 | .184 | .907 |

| | | | | | | |
|---|---|---|---|---|---|---|
| UB | Within Groups | 11226.522 | 899 | 12.488 | | |
| | Total | 11233.411 | 902 | | | |

**Performance Expectancy**

As the P value of F test (0.133) is 0.941 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of age with respect to performance expectancy

**Effort Expectancy.**

As the P value of F test (0.238) is 0.870 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of age with respect to effort expectancy.

**Social Influence**.

As the P value of F test (0.203) is 0.894 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of age with respect to social influence.

**Facilitating Conditions**

As the P value of F test (0.280) is 0.840 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of age with respect to facilitating conditions.

**Behavioural Intentions.**

As the P value of F test (0.362) is 0.781 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of age with respect to behavioural intentions.

**Usage Behavior**

As the P value of F test (0.184) is 0.907 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of age with respect to usage behaviour.

**ANOVA- Occupation-wise**

H19: There is a significant difference between various occupation with respect to performance expectancy.

H20: There is significance difference between various occupations with respect to effort expectancy.

H21: There is significance difference between various occupations with respect to social influence.

H22: There is significance difference between various occupations with respect to facilitating conditions.

H23: There is significance difference between various occupations with respect to behavioural intentions.

H24: There is significance difference between various occupations with respect to usage behaviour.

**Descriptives**

| | | N | Mean | Std. Deviation | Std. Error | 95% Confidence Interval for Mean | | Minimum | Maximum |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound | | |
| | Business | 145 | 8.4897 | 4.57517 | .37995 | 7.7387 | 9.2406 | 4.00 | 20.00 |
| | Private Employee | 329 | 8.5319 | 4.72213 | .26034 | 8.0198 | 9.0441 | 4.00 | 20.00 |
| | Government Employee | 116 | 8.6983 | 4.75343 | .44135 | 7.8241 | 9.5725 | 4.00 | 20.00 |
| PE | Retired | 17 | 8.7059 | 5.04684 | 1.22404 | 6.1110 | 11.3007 | 4.00 | 19.00 |
| | Student | 170 | 8.7941 | 4.85883 | .37266 | 8.0585 | 9.5298 | 4.00 | 20.00 |
| | Homemaker | 81 | 8.5309 | 4.81427 | .53492 | 7.4663 | 9.5954 | 4.00 | 20.00 |
| | Not doing Anything | 45 | 8.2444 | 4.02919 | .60064 | 7.0339 | 9.4549 | 4.00 | 19.00 |
| | Total | 903 | 8.5847 | 4.69812 | .15634 | 8.2779 | 8.8916 | 4.00 | 20.00 |
| | Business | 145 | 8.3931 | 4.73506 | .39323 | 7.6159 | 9.1703 | 4.00 | 20.00 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Private Employee | 329 | 8.4559 | 4.93111 | .27186 | 7.9211 | 8.9907 | 4.00 | 20.00 |
| EE | Government Employee | 116 | 8.6293 | 4.96340 | .46084 | 7.7165 | 9.5421 | 4.00 | 20.00 |
| | Retired | 17 | 8.6471 | 5.13494 | 1.24541 | 6.0069 | 11.2872 | 4.00 | 20.00 |
| | Student | 170 | 8.7353 | 5.01659 | .38476 | 7.9757 | 9.4948 | 4.00 | 20.00 |
| | Homemaker | 81 | 8.5679 | 5.05455 | .56162 | 7.4502 | 9.6856 | 4.00 | 20.00 |
| | Not doing Anything | 45 | 8.0889 | 4.12213 | .61449 | 6.8505 | 9.3273 | 4.00 | 20.00 |
| | Total | 903 | 8.5161 | 4.88510 | .16257 | 8.1970 | 8.8351 | 4.00 | 20.00 |
| | Business | 145 | 5.5310 | 2.72095 | .22596 | 5.0844 | 5.9777 | 3.00 | 15.00 |
| | Private Employee | 329 | 5.6748 | 2.86069 | .15771 | 5.3645 | 5.9850 | 3.00 | 15.00 |
| SI | Government Employee | 116 | 5.7241 | 2.90602 | .26982 | 5.1897 | 6.2586 | 3.00 | 15.00 |
| | Retired | 17 | 5.8235 | 3.16692 | .76809 | 4.1952 | 7.4518 | 3.00 | 14.00 |
| | Student | 170 | 5.7706 | 3.00891 | .23077 | 5.3150 | 6.2262 | 3.00 | 15.00 |
| | Homemaker | 81 | 5.6420 | 2.80316 | .31146 | 5.0221 | 6.2618 | 3.00 | 15.00 |
| | Not doing Anything | 45 | 5.2000 | 2.08458 | .31075 | 4.5737 | 5.8263 | 3.00 | 14.00 |
| | Total | 903 | 5.6523 | 2.83446 | .09432 | 5.4671 | 5.8374 | 3.00 | 15.00 |
| | Business | 145 | 9.1448 | 4.61426 | .38319 | 8.3874 | 9.9022 | 5.00 | 24.00 |
| | Private Employee | 329 | 9.3495 | 4.88989 | .26959 | 8.8192 | 9.8799 | 5.00 | 25.00 |
| | Government Employee | 116 | 9.4397 | 4.94894 | .45950 | 8.5295 | 10.3498 | 5.00 | 25.00 |
| FC | Retired | 17 | 9.5882 | 5.53465 | 1.34235 | 6.7426 | 12.4339 | 5.00 | 23.00 |
| | Student | 170 | 9.6118 | 5.16152 | .39587 | 8.8303 | 10.3933 | 5.00 | 25.00 |
| | Homemaker | 81 | 9.3951 | 4.80801 | .53422 | 8.3319 | 10.4582 | 5.00 | 25.00 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Not doing Anything | 45 | 8.7778 | 3.82509 | .57021 | 7.6286 | 9.9270 | 5.00 | 23.00 |
| | Total | 903 | 9.3577 | 4.85322 | .16150 | 9.0407 | 9.6747 | 5.00 | 25.00 |
| | Business | 145 | 7.4966 | 3.79716 | .31534 | 6.8733 | 8.1198 | 4.00 | 20.00 |
| | Private Employee | 329 | 7.6626 | 4.03549 | .22248 | 7.2249 | 8.1003 | 4.00 | 20.00 |
| BI | Government Employee | 116 | 7.6983 | 4.09925 | .38061 | 6.9444 | 8.4522 | 4.00 | 20.00 |
| | Retired | 17 | 7.7647 | 4.08548 | .99088 | 5.6641 | 9.8653 | 4.00 | 18.00 |
| | Student | 170 | 7.7706 | 4.11668 | .31573 | 7.1473 | 8.3939 | 4.00 | 20.00 |
| | Homemaker | 81 | 7.7407 | 4.08894 | .45433 | 6.8366 | 8.6449 | 4.00 | 20.00 |
| | Not doing Anything | 45 | 7.0222 | 2.88010 | .42934 | 6.1569 | 7.8875 | 4.00 | 17.00 |
| | Total | 903 | 7.6379 | 3.96892 | .13208 | 7.3787 | 7.8971 | 4.00 | 20.00 |
| | Business | 145 | 6.7103 | 3.39509 | .28195 | 6.1531 | 7.2676 | 4.00 | 19.00 |
| | Private Employee | 329 | 6.8571 | 3.54857 | .19564 | 6.4723 | 7.2420 | 4.00 | 20.00 |
| UB | Government Employee | 116 | 7.0000 | 3.74862 | .34805 | 6.3106 | 7.6894 | 4.00 | 20.00 |
| | Retired | 17 | 6.9412 | 3.64813 | .88480 | 5.0655 | 8.8169 | 4.00 | 16.00 |
| | Student | 170 | 7.0059 | 3.71865 | .28521 | 6.4429 | 7.5689 | 4.00 | 20.00 |
| | Homemaker | 81 | 6.8395 | 3.53007 | .39223 | 6.0589 | 7.6201 | 4.00 | 20.00 |
| | Not doing Anything | 45 | 6.3111 | 2.41983 | .36073 | 5.5841 | 7.0381 | 4.00 | 16.00 |
| | Total | 903 | 6.8527 | 3.52901 | .11744 | 6.6222 | 7.0832 | 4.00 | 20.00 |

**Anova**

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| | Between Groups | 16.873 | 6 | 2.812 | .127 | .993 |
| PE | Within Groups | 19892.397 | 896 | 22.201 | | |
| | Total | 19909.269 | 902 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Between Groups | 21.761 | 6 | 3.627 | .151 | .989 |
| EE | Within Groups | 21503.756 | 896 | 24.000 | | |
| | Total | 21525.517 | 902 | | | |
| | Between Groups | 14.989 | 6 | 2.498 | .310 | .932 |
| SI | Within Groups | 7231.824 | 896 | 8.071 | | |
| | Total | 7246.813 | 902 | | | |
| | Between Groups | 34.495 | 6 | 5.749 | .243 | .962 |
| FC | Within Groups | 21210.969 | 896 | 23.673 | | |
| | Total | 21245.464 | 902 | | | |
| | Between Groups | 24.702 | 6 | 4.117 | .260 | .955 |
| BI | Within Groups | 14183.883 | 896 | 15.830 | | |
| | Total | 14208.585 | 902 | | | |
| | Between Groups | 22.797 | 6 | 3.800 | .304 | .935 |
| UB | Within Groups | 11210.614 | 896 | 12.512 | | |
| | Total | 11233.411 | 902 | | | |

**Performance Expectancy**

As the P value of F test (0.127) is 0.993 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Occupation with respect to performance expectancy

**Effort Expectancy.**

As the P value of F test (0.151) is 0.989 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Occupation with respect to effort expectancy.

**Social Influence**.

As the P value of F test (0.310) is 0.932 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Occupation with respect to social influence.

**Facilitating Conditions**

As the P value of F test (0.243) is 0.962 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Occupation with respect to facilitating conditions.

**Behavioural Intentions.**

As the P value of F test (0.260) is 0.955 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Occupation with respect to behavioural intentions.

**Usage Behaviour**

As the P value of F test (0.304) is 0.935 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Occupation with respect to usage behaviour.

**ANOVA- Education wise**

H25: There is significant difference between various education categories with respect to performance expectancy.

H26: There is significance difference between various education categories with respect to effort expectancy.

H27: There is significance difference between various education categories with respect to social influence.

H28; There is significance difference between various education categories with respect to facilitating conditions.

H29: There is significance difference between various education categories with respect to behavioural intentions.

H30: There is significance difference between various education categories with respect to usage behaviour

**Descriptives**

| | | N | Mean | Std. Deviation | Std. Error | 95% Confidence Interval for Mean | | Minimum | Maximum |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Graduate | 121 | 8.6694 | 4.74761 | .43160 | 7.8149 | 9.5240 | 4.00 | 20.00 |
| PE | Post Graduate | 109 | 8.6422 | 4.84677 | .46424 | 7.7220 | 9.5624 | 4.00 | 20.00 |
| | Doctorate | 522 | 8.5441 | 4.62105 | .20226 | 8.1467 | 8.9414 | 4.00 | 20.00 |
| | Other | 151 | 8.6159 | 4.85779 | .39532 | 7.8348 | 9.3970 | 4.00 | 20.00 |
| | Total | 903 | 8.5847 | 4.69812 | .15634 | 8.2779 | 8.8916 | 4.00 | 20.00 |
| | Graduate | 121 | 8.5455 | 4.92950 | .44814 | 7.6582 | 9.4327 | 4.00 | 20.00 |
| | Post Graduate | 109 | 8.6972 | 5.16309 | .49453 | 7.7170 | 9.6775 | 4.00 | 20.00 |
| EE | Doctorate | 522 | 8.4464 | 4.78100 | .20926 | 8.0353 | 8.8575 | 4.00 | 20.00 |
| | Other | 151 | 8.6026 | 5.04259 | .41036 | 7.7918 | 9.4135 | 4.00 | 20.00 |
| | Total | 903 | 8.5161 | 4.88510 | .16257 | 8.1970 | 8.8351 | 4.00 | 20.00 |
| | Graduate | 121 | 5.6860 | 2.95813 | .26892 | 5.1535 | 6.2184 | 3.00 | 15.00 |
| | Post Graduate | 109 | 5.7248 | 2.81488 | .26962 | 5.1903 | 6.2592 | 3.00 | 15.00 |
| SI | Doctorate | 522 | 5.5900 | 2.75147 | .12043 | 5.3535 | 5.8266 | 3.00 | 15.00 |
| | Other | 151 | 5.7881 | 3.04545 | .24784 | 5.2984 | 6.2778 | 3.00 | 15.00 |
| | Total | 903 | 5.6523 | 2.83446 | .09432 | 5.4671 | 5.8374 | 3.00 | 15.00 |
| | Graduate | 121 | 9.4215 | 5.00791 | .45526 | 8.5201 | 10.3229 | 5.00 | 25.00 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Post Graduate | 109 | 9.5413 | 4.89620 | .46897 | 8.6117 | 10.4709 | 5.00 | 25.00 |
| FC | Doctorate | 522 | 9.2701 | 4.73743 | .20735 | 8.8628 | 9.6775 | 5.00 | 25.00 |
| | Other | 151 | 9.4768 | 5.12749 | .41727 | 8.6523 | 10.3013 | 5.00 | 25.00 |
| | Total | 903 | 9.3577 | 4.85322 | .16150 | 9.0407 | 9.6747 | 5.00 | 25.00 |
| | Graduate | 121 | 7.7273 | 4.16333 | .37848 | 6.9779 | 8.4766 | 4.00 | 20.00 |
| | Post Graduate | 109 | 7.8807 | 4.13146 | .39572 | 7.0963 | 8.6651 | 4.00 | 20.00 |
| BI | Doctorate | 522 | 7.5460 | 3.86763 | .16928 | 7.2134 | 7.8785 | 4.00 | 20.00 |
| | Other | 151 | 7.7086 | 4.06545 | .33084 | 7.0549 | 8.3623 | 4.00 | 20.00 |
| | Total | 903 | 7.6379 | 3.96892 | .13208 | 7.3787 | 7.8971 | 4.00 | 20.00 |
| | Graduate | 121 | 6.9091 | 3.59629 | .32694 | 6.2618 | 7.5564 | 4.00 | 20.00 |
| UB | Post Graduate | 109 | 6.9358 | 3.57272 | .34220 | 6.2575 | 7.6141 | 4.00 | 20.00 |
| | Doctorate | 522 | 6.7893 | 3.46544 | .15168 | 6.4913 | 7.0872 | 4.00 | 20.00 |
| | Other | 151 | 6.9669 | 3.68857 | .30017 | 6.3738 | 7.5600 | 4.00 | 20.00 |
| | Total | 903 | 6.8527 | 3.52901 | .11744 | 6.6222 | 7.0832 | 4.00 | 20.00 |

**ANOVA**

| | | Sum of Squares | Df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| | Between Groups | 2.238 | 3 | .746 | .034 | .992 |
| PE | Within Groups | 19907.031 | 899 | 22.144 | | |
| | Total | 19909.269 | 902 | | | |
| | Between Groups | 7.351 | 3 | 2.450 | .102 | .959 |
| EE | Within Groups | 21518.166 | 899 | 23.936 | | |
| | Total | 21525.517 | 902 | | | |
| | Between Groups | 5.517 | 3 | 1.839 | .228 | .877 |
| SI | Within Groups | 7241.296 | 899 | 8.055 | | |
| | Total | 7246.813 | 902 | | | |
| | Between Groups | 10.313 | 3 | 3.438 | .146 | .933 |
| FC | Within Groups | 21235.151 | 899 | 23.621 | | |
| | Total | 21245.464 | 902 | | | |
| | Between Groups | 5.206 | 3 | 1.735 | .139 | .937 |
| UB | Within Groups | 11228.205 | 899 | 12.490 | | |
| | Total | 11233.411 | 902 | | | |
| | Between Groups | 12.560 | 3 | 4.187 | .265 | .851 |
| BI | Within Groups | 14196.025 | 899 | 15.791 | | |
| | Total | 14208.585 | 902 | | | |

**Performance Expectancy**

As the P value of F test (0.34) is 0.992 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Education with respect to performance expectancy

**Effort Expectancy.**

As the P value of F test (0.102) is 0.959 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Education with respect to effort expectancy.

**Social Influence**.

As the P value of F test (0.228) is 0.877 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Education with respect to social influence.

**Facilitating Conditions**

As the P value of F test (0.146) is 0.933 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Education with respect to facilitating conditions.

**Behavioural Intentions.**

As the P value of F test (0.265) is 0.851 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Education with respect to behavioural intentions.

**Usage Behavior**

As the P value of F test (0.139) is 0.937 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Education with respect to usage behaviour.

**Monthly Income wise ANOVA**:

H31: There is significant difference between various Monthly Income categories with respect to performance expectancy.

H32: there is significance difference between various Monthly Income categories with respect to effort expectancy.

H33: there is significance difference between various Monthly Income categories with respect to social influence.

H34: there is significance difference between various Monthly Income categories with respect to facilitating conditions.

H35: there is significance difference between various Monthly Income categories with respect to behavioural intentions.

H36: there is significance difference between various Monthly Income categories with respect to usage behaviour.

**Descriptives**

| | | N | Mean | Std. Deviation | Std. Error | 95% Confidence Interval for Mean | | Minimum | Maximum |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound | | |
| | Less than 25,000 | 344 | 8.6599 | 4.73779 | .25544 | 8.1574 | 9.1623 | 4.00 | 20.00 |
| | 25,001-50,000 | 131 | 8.4198 | 4.59591 | .40155 | 7.6254 | 9.2143 | 4.00 | 20.00 |
| PE | 50,001-75,000 | 193 | 8.5026 | 4.69832 | .33819 | 7.8355 | 9.1696 | 4.00 | 20.00 |
| | More than 75,001 | 235 | 8.6340 | 4.72244 | .30806 | 8.0271 | 9.2410 | 4.00 | 20.00 |
| | Total | 903 | 8.5847 | 4.69812 | .15634 | 8.2779 | 8.8916 | 4.00 | 20.00 |
| | Less than 25,000 | 344 | 8.6134 | 4.91371 | .26493 | 8.0923 | 9.1345 | 4.00 | 20.00 |
| | 25,001-50,000 | 131 | 8.3435 | 4.84494 | .42330 | 7.5061 | 9.1810 | 4.00 | 20.00 |
| EE | 50,001-75,000 | 193 | 8.4301 | 4.91453 | .35376 | 7.7323 | 9.1278 | 4.00 | 20.00 |
| | More than 75,001 | 235 | 8.5404 | 4.86851 | .31759 | 7.9147 | 9.1661 | 4.00 | 20.00 |
| | Total | 903 | 8.5161 | 4.88510 | .16257 | 8.1970 | 8.8351 | 4.00 | 20.00 |
| | Less than 25,000 | 344 | 5.6715 | 2.84788 | .15355 | 5.3695 | 5.9735 | 3.00 | 15.00 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 25,001-50,000 | 131 | 5.5802 | 2.77337 | .24231 | 5.1008 | 6.0595 | 3.00 | 15.00 |
| SI | 50,001-75,000 | 193 | 5.6166 | 2.79846 | .20144 | 5.2193 | 6.0139 | 3.00 | 15.00 |
| | More than 75,001 | 235 | 5.6936 | 2.89410 | .18879 | 5.3217 | 6.0656 | 3.00 | 15.00 |
| | Total | 903 | 5.6523 | 2.83446 | .09432 | 5.4671 | 5.8374 | 3.00 | 15.00 |
| | Less than 25,000 | 344 | 9.4593 | 4.92493 | .26553 | 8.9370 | 9.9816 | 5.00 | 25.00 |
| | 25,001-50,000 | 131 | 9.1298 | 4.70253 | .41086 | 8.3169 | 9.9426 | 5.00 | 24.00 |
| FC | 50,001-75,000 | 193 | 9.2694 | 4.76313 | .34286 | 8.5932 | 9.9457 | 5.00 | 25.00 |
| | More than 75,001 | 235 | 9.4085 | 4.92802 | .32147 | 8.7752 | 10.0419 | 5.00 | 25.00 |
| | Total | 903 | 9.3577 | 4.85322 | .16150 | 9.0407 | 9.6747 | 5.00 | 25.00 |
| | Less than 25,000 | 344 | 7.6773 | 3.96162 | .21360 | 7.2572 | 8.0974 | 4.00 | 20.00 |
| | 25,001-50,000 | 131 | 7.5267 | 3.91904 | .34241 | 6.8493 | 8.2041 | 4.00 | 20.00 |
| BI | 50,001-75,000 | 193 | 7.6062 | 3.96474 | .28539 | 7.0433 | 8.1691 | 4.00 | 20.00 |
| | More than 75,001 | 235 | 7.6681 | 4.03410 | .26316 | 7.1496 | 8.1865 | 4.00 | 20.00 |
| | Total | 903 | 7.6379 | 3.96892 | .13208 | 7.3787 | 7.8971 | 4.00 | 20.00 |
| | Less than 25,000 | 344 | 6.8750 | 3.52071 | .18982 | 6.5016 | 7.2484 | 4.00 | 20.00 |
| | 25,001-50,000 | 131 | 6.8168 | 3.55355 | .31048 | 6.2026 | 7.4310 | 4.00 | 20.00 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| UB | 50,001-75,000 | 193 | 6.7824 | 3.43607 | .24733 | 6.2945 | 7.2702 | 4.00 | 20.00 |
| | More than 75,001 | 235 | 6.8979 | 3.62302 | .23634 | 6.4322 | 7.3635 | 4.00 | 20.00 |
| | Total | 903 | 6.8527 | 3.52901 | .11744 | 6.6222 | 7.0832 | 4.00 | 20.00 |

**ANOVA**

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| | Between Groups | 7.378 | 3 | 2.459 | .111 | .954 |
| PE | Within Groups | 19901.891 | 899 | 22.138 | | |
| | Total | 19909.269 | 902 | | | |
| | Between Groups | 8.725 | 3 | 2.908 | .122 | .947 |
| EE | Within Groups | 21516.792 | 899 | 23.934 | | |
| | Total | 21525.517 | 902 | | | |
| | Between Groups | 1.456 | 3 | .485 | .060 | .981 |
| SI | Within Groups | 7245.357 | 899 | 8.059 | | |
| | Total | 7246.813 | 902 | | | |
| | Between Groups | 12.467 | 3 | 4.156 | .176 | .913 |
| FC | Within Groups | 21232.997 | 899 | 23.618 | | |
| | Total | 21245.464 | 902 | | | |
| | Between Groups | 2.562 | 3 | .854 | .054 | .983 |
| BI | Within Groups | 14206.023 | 899 | 15.802 | | |
| | Total | 14208.585 | 902 | | | |
| | Between Groups | 1.774 | 3 | .591 | .047 | .986 |
| UB | Within Groups | 11231.637 | 899 | 12.493 | | |
| | Total | 11233.411 | 902 | | | |

**Performance Expectancy**

As the P value of F test (0.111) is 0.954 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Monthly income with respect to performance expectancy

**Effort Expectancy**

As the P value of F test (0.122) is 0.947 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Monthly income with respect to effort expectancy.

**Social Influence**

As the P value of F test (0.60) is 0.981 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Monthly income with respect to social influence.

**Facilitating Conditions**

As the P value of F test (0.176) is 0.913 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Monthly income with respect to facilitating conditions.

**Behavioural Intention**

As the P value of F test (0.054) is 0.983 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Monthly income with respect to behavioural intentions.

**Usage Behaviour**

As the P value of F test (0.47) is 0.986 which is more than 5% level of significance so we fail to reject null hypothesis which means there is no significance difference between various categories of Monthly income with respect to usage behaviour.

**Path Analysis**

Path model analysis helps to identify hypotheses and variable relationship with diagram in an SEM analysis (Bollen, 2002) the model is identified and tested to identify effect of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions on Behavioural Intention & Usage Behaviour using path analysis of structured equation modeling.

A path model comprises two main components: the structural model, which outlines the relationships between constructs, and the measurement models, which connect each construct to its indicators. In PLS-SEM, these are known as inner and outer models, respectively. Researchers develop path models based on structural and measurement theories that define the relationships among the model's elements.

**Model Estimation**

The model estimation employs the PLS-SEM algorithm by Lohmöller (1989) with default settings in Smart PLS, utilizing a path weighting scheme, a maximum of 300 iterations, and a stop criterion of 0.0000001. Post-algorithm execution, it’s crucial to confirm convergence, ensuring the stop criterion is met without reaching the iteration limit. PLS-SEM typically converges effectively, even in complex applications. The accompanying diagram illustrates the path model for online buying intentions, displaying standardized regression coefficients and $R^2$ values for endogenous latent variables.

**Path analysis diagram**

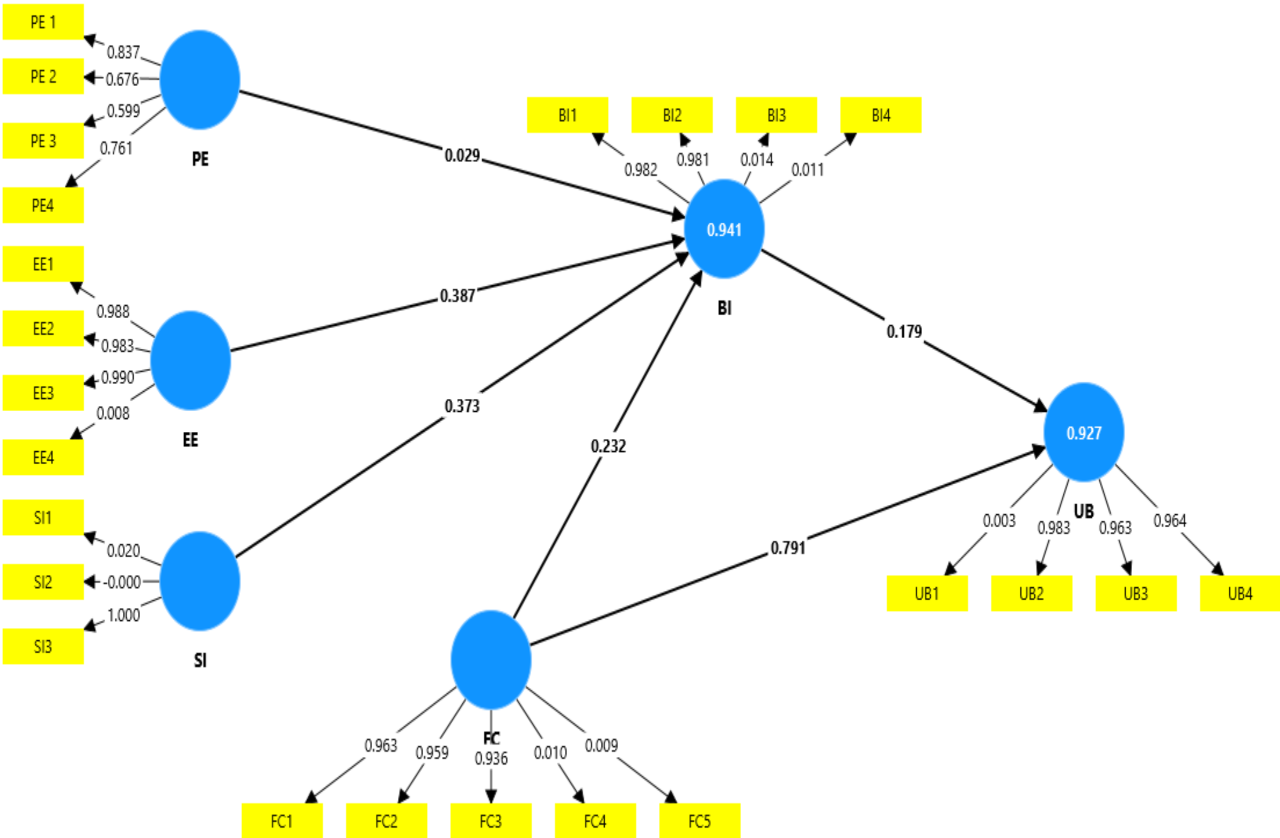



**Figure: PLS SEM Measurement Model**

**Measurement model assessment:**

The evaluation of PLS-SEM results begins with assessing the reflective measurement model, focusing on behaviour intention & usage behaviour. The findings indicate that two reflective measurement models fulfil the necessary assessment criteria and align with standard values.

The Fornell-Larcker criterion (1981) is used to evaluate the shared variance among latent model variables. It assesses convergent validity through Average Variance Extracted (AVE) and Composite Reliability (CR). AVE indicates variance captured by a construct relative to measurement error, with values above 0.7 regarded as very good and 0.5 as acceptable. CR provides a less biased reliability estimate than Cronbach's Alpha, with 0.7 being the acceptable threshold.

The Hetero Trait-Mono Trait (HTMT) ratio criteria, introduced by Henseler, Ringle & Sarstedt in 2015, establishes a minimum threshold of 0.85 for assessing correlations. All outer loadings, except one, exceed 0.70, indicating reliable indicators. Additionally, the Average Variance Extracted (AVE) values surpass 0.50, supporting convergent validity. Composite reliability and Cronbach's Alpha values exceed 0.9, significantly above the required minimum. Rho A values also meet the 0.70 threshold. These findings confirm that the constructs of perceived benefits, perceived trust, and buying intention exhibit strong internal consistency reliability.

Table : PLS-SEM assessment results of reflective measurement models

| | **Cronbach's alpha** | **Composite reliability (rho_a)** | **Composite reliability (rho_c)** | **Average variance extracted (AVE)** |
|---|---|---|---|---|
| **BI** | 0.794 | 0.795 | 0.866 | 0.618 |
| **EE** | 0.734 | 0.754 | 0.831 | 0.553 |
| **FC** | 0.782 | 0.794 | 0.851 | 0.533 |
| **PE** | 0.716 | 0.718 | 0.824 | 0.54 |
| **SI** | 0.732 | 0.783 | 0.822 | 0.606 |
| **UB** | 0.85 | 0.863 | 0.898 | 0.688 |

**Discriminant Validity (Using HTMT Values)**

The Discriminant Validity was assessed with the use of Fornell-Larcker criterion & HTMT Criteria as shown below.

Table: Discriminant Validity as per Fornell-Larcker criterion

| | BI | EE | FC | PE | SI | UB |
|---|---|---|---|---|---|---|
| BI | 0.786 | | | | | |
| EE | 0.515 | 0.744 | | | | |
| FC | -0.541 | -0.616 | 0.730 | | | |
| PE | 0.494 | 0.485 | -0.558 | 0.735 | | |
| SI | 0.537 | 0.639 | -0.536 | 0.491 | 0.779 | |
| UB | -0.167 | -0.151 | 0.178 | -0.115 | -0.141 | 0.829 |

As seen in the table it is clearly visible that all the values are below the conservative threshold value of 0.85.

Table: Hetero Trait-Mono trait Ratio (HTMT)

| | BI | EE | FC | PE | SI | UB |
|---|---|---|---|---|---|---|
| BI | | | | | | |
| EE | 0.656 | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| FC | 0.674 | 0.792 | | | | |
| PE | 0.652 | 0.648 | 0.737 | | | |
| SI | 0.734 | 0.895 | 0.729 | 0.707 | | |
| UB | 0.198 | 0.182 | 0.211 | 0.150 | 0.185 | |

The bootstrapping procedure confirmed that there were no changes and indicated that the HTMT values are significantly different from 1, at a 95% confidence interval and 0.05 significance level. This demonstrates that discriminant validity has been established.

**Multicollinearity**

The presence of Multicollinearity among the independent variables in a regression model was assessed using variance inflation factors (VIF) as suggested by Belsely et at. (1980) and Greene (1993).

Table: variance inflation factors (VIF)

| | VIF |
|---|---|
| BI1 | 1.484 |
| BI2 | 1.603 |
| BI3 | 1.610 |
| BI4 | 1.626 |
| EE1 | 1.425 |
| EE2 | 1.496 |
| EE3 | 1.338 |
| EE4 | 1.374 |
| FC1 | 1.518 |
| FC2 | 1.404 |
| FC3 | 1.437 |
| FC4 | 1.479 |
| FC5 | 1.463 |
| PE1 | 1.314 |
| PE2 | 1.359 |
| PE3 | 1.287 |

| | |
|---|---|
| PE4 | 1.447 |
| SI1 | 1.250 |
| SI2 | 1.439 |
| SI3 | 1.322 |
| UB1 | 1.948 |
| UB2 | 1.817 |
| UB3 | 2.023 |
| UB4 | 1.882 |

VIF, or "Variance Inflation Factor," is a statistical measure used to assess multicollinearity in regression analysis. Multicollinearity occurs when two or more independent variables are highly correlated, which can destabilize regression coefficient estimates and weaken model predictions. VIF quantifies the degree of multicollinearity among these independent variables. The Variance Inflation Factor (VIF) for an independent variable is determined by comparing the variance of its coefficient estimate in a model with all variables to that in a model with only itself. A VIF of 1 signifies no correlation with other variables, while a VIF above 1 indicates high correlation with one or more other variables, with higher values reflecting more severe multicollinearity.

**5.8 Structural Model Assessment using path analysis:**

**5.8.1 To Measure Direct effect, following hypotheses have been developed.**

H37: There is a positive effect of Performance Expectancy on Behavioural Intention.

H38: There is a positive effect of Effort Expectancy on Behavioural Intention.

H39: There is Positive effect of Social Influence on Behavioural Intention.

H40: There is Positive effect of Facilitating Conditions on Behavioural Intention.

H41: There is Positive effect of Facilitating Conditions on Usage Behaviour.

H42: There is Positive effect of Behavioural Intention on Usage Behavior.

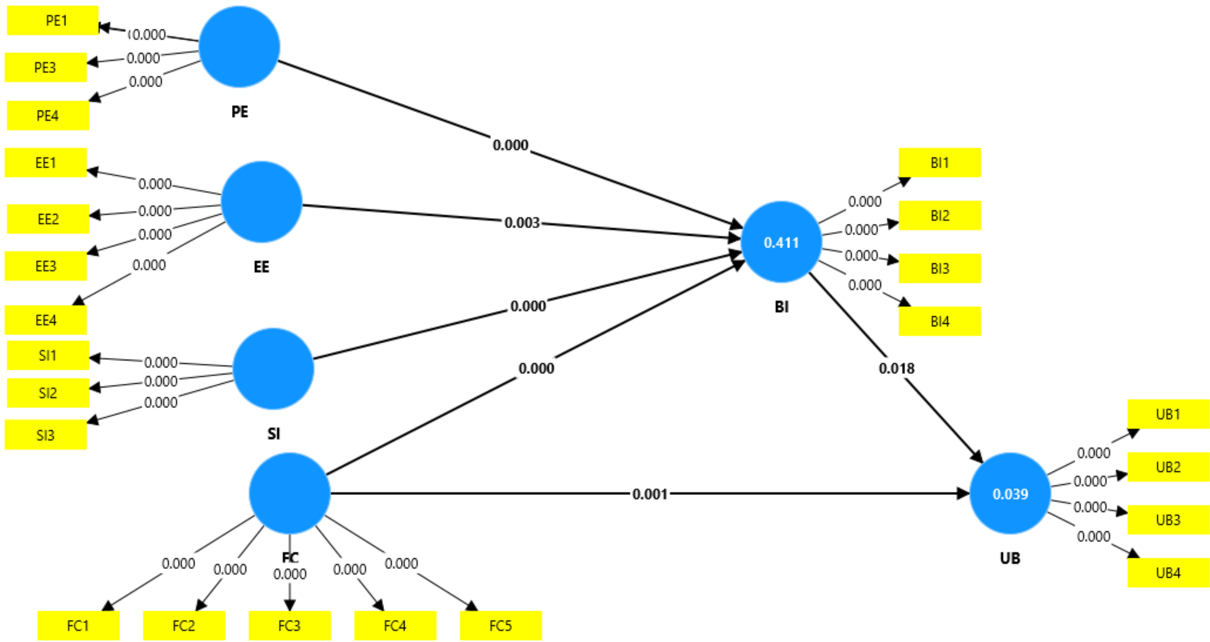



Figure: PLS SEM Structural Model

Table: Summary of Path Analysis of main variables

| Path | P values | Result |
|---|---|---|
| BI -> UB | 0.018 | Significant |
| EE -> BI | 0.003 | Significant |
| FC -> BI | 0.000 | Significant |
| FC -> UB | 0.001 | Significant |
| PE -> BI | 0.000 | Significant |
| SI -> BI | 0.000 | Significant |

The text discusses the analysis of a measurement model and the testing of causal relationships among latent constructs using a path model in structural equation modelling (SEM). The results from the PLS SEM 4.0 software indicate that all proposed hypotheses are supported. Bootstrap samples were generated at the 95% confidence level to assess the mediating effect, with findings presented in accompanying figures and tables. from the table it is clear that Performance Expectancy has significant impact on Behavioural Intention. Effort Expectancy has significant impact on Behavioural Intention, Social Influence has significant impact on Behavioural Intention, Facilitating Conditions has significant impact on Behavioural Intention. Facilitating Conditions has significant impact on Usage Behaviour and Behavioural Intention has significance impact on Usage Behavior.

### Bootstrapping

Bootstrapping is a nonparametric method used to test the statistical significance of PLS-SEM results, including path coefficients, Cronbach's alpha, HTMT, and $R^2$ values. Path coefficients are considered significant if the two-tailed T-test statistic exceeds 1.96 at a 5% significance level.

Table: Bootstrapping

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values |
|---|---|---|---|---|---|
| BI -> UB | 0.100 | 0.100 | 0.042 | 2.360 | 0.018 |
| EE -> BI | 0.131 | 0.133 | 0.044 | 3.007 | 0.003 |
| FC -> BI | 0.227 | 0.227 | 0.036 | 6.247 | 0.000 |
| FC -> UB | 0.124 | 0.126 | 0.039 | 3.183 | 0.001 |
| PE -> BI | 0.185 | 0.186 | 0.034 | 5.437 | 0.000 |
| SI -> BI | 0.240 | 0.239 | 0.036 | 6.584 | 0.000 |

As seen in the table all the t statastics value are above 1.96 and significant at significance level of 0.05. this also confirms our findings when looking at the Path analysis result.

**5.8.2 To measure mediating/indirect effect following hypothesis have been developed.**

H43: There is positive mediating effect between effort expectancy, behavioural intentions and usage behavior.

H44: There is positive mediating effect between facilitating condition, behavioural intentions and usage behavior.

H45: There is positive mediating effect between performance expectancy,behavioural intentions and usage behavior.

H46: There is positive mediating effect between Social Influence, behavioural intentions and usage behavior.

Table: Summary of Path analysis of mediating variables

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values | Result |
|---|---|---|---|---|---|---|
| EE -> BI -> UB | -0.013 | -0.013 | 0.007 | 1.800 | 0.072 | Insignificant |
| FC -> BI -> UB | 0.023 | 0.023 | 0.011 | 2.149 | 0.032 | Significant |
| PE -> BI -> UB | -0.019 | -0.019 | 0.009 | 2.075 | 0.038 | Significant |
| SI -> BI -> UB | -0.024 | -0.024 | 0.011 | 2.220 | 0.026 | Significant |

The findings are consistent with previous finding (Li Kim & Park, 2007; Chen & Barnes, 2007) compare to that all the mediating effects plays significance role exempt effort expectancy.

# CHAPTER 6: FINDINGS, CONCLUSIONS & MANAGERIAL IMPLICATION

This Chapter discusses key findings derived from the primary analysis. The chapter also gives a conclusion of the thesis, managerial implications and future research directions for the present study.

**6.1 Findings of the study: Concerning each objective and hypothesis**

**Objective 1: To examine the significant relationship among the different aspects of Behavioural Intention**

H1: There is a positive effect of Performance Expectancy on Behavioural Intention.

H2: There is a positive effect of Effort Expectancy on Behavioural Intention.

H3: There is a Positive effect of Social Influence on Behavioural Intention.

H4: There is a Positive effect of Behavioural Intention on Usage Behaviour.

H5: There is a Positive effect of Facilitating Conditions on Behavioural Intention.

| | **Original sample (O)** | **Sample mean (M)** | **Standard deviation (STDEV)** | **T statistics (\|O/STDEV\|)** | **P values** | **Result** |
|---|---|---|---|---|---|---|
| PE -> BI | 0.185 | 0.186 | 0.034 | 5.437 | 0.000 | Significant |
| EE -> BI | 0.131 | 0.133 | 0.044 | 3.007 | 0.003 | Significant |
| SI -> BI | 0.240 | 0.239 | 0.036 | 6.584 | 0.000 | Significant |
| BI -> UB | 0.100 | 0.100 | 0.042 | 2.360 | 0.018 | Significant |
| FC -> BI | 0.227 | 0.227 | 0.036 | 6.247 | 0.000 | Significant |

The following table presents the results of hypothesis testing for the relationships between various factors (PE,EE,SI,FC & BI). The table includes the original sample values (O), sample means (M), standard deviations (STDEV), t-statistics (|O/STDEV|), and p-values. Relationships were considered statistically significant if the p-value was less than 0.05. which results PE → BI The path coefficient for PE (Factor) to BI (Outcome) is 0.185, with a t-statistic of 5.437 and a p-value of 0.000. This significant result indicates a strong positive effect of PE on BI. EE → BI The path coefficient for EE (Factor) to BI (Outcome) is 0.131, with a t-statistic of 3.007 and a p-value of 0.000. This demonstrates a significant positive influence of EE on BI. SI→ BI The path coefficient for SI (Factor) to BI (Outcome) is 0.240, with a t-statistic of 6.584 and a p-value of 0.000. This shows a significant positive relationship between SI and BI.BI→ UB The path coefficient for BI (Factor) to UB (Outcome) is 0.100, with a t-statistic of 2.360 and a p-value of 0.000. This shows a significant positive relationship between SI and BI.

FC→ BI The path coefficient for FC (Factor) to BI (Outcome) is 0.227, with a t-statistic of 6.247 and a p-value of 0.000. This shows a significant positive relationship between FC and BI.

All the factors (PE, EE, SI, FC, UB and BI) significantly and positively impact BI, as evidenced by their high t-statistics and p-values. The findings successfully meet the objective of examining the significant relationships among different aspects of BI. The analysis confirms that PE, EE, SI, FC, UB are distinct yet interrelated contributors to BI. This provides a comprehensive understanding of how various dimensions interact to shape an individual's Behaviour Intention.

**Objective 2 & 3: To examine the Significant relationship among the different purchase intentions and adoption.**

To examine the Significant relationship between behavioural Intention and usage behaviour.

**H5:** There is a positive effect of behavioural Intention on usage behaviour.

**H6:** There is a Positive effect of the facilitating condition on usage behaviour.

**Table no. 6.1.1 Findings of the Direct effect on usage behaviour**

| | **Original sample (O)** | **Sample mean (M)** | **Standard deviation (STDEV)** | **T statistics (\|O/STDEV\|)** | **P values** | **Result** |
|---|---|---|---|---|---|---|
| BI -> UB | 0.100 | 0.100 | 0.042 | 2.360 | 0.018 | Significant |
| FC -> UB | 0.124 | 0.126 | 0.039 | 3.183 | 0.001 | Significant |

BI → UB Path Coefficient The relationship between Behavioural Intention (BI) and Usage Behaviour (UB) is positive, with a coefficient of 0.100. Significance The t-statistic is 2.360, and the p-value is 0.018, confirming that the relationship is statistically significant. Implication: This finding indicates that higher levels of BI are associated with improved UB. Individuals with greater confidence in their purchasing behaviour tend to exhibit better Usage behaviours, such as reading reviews, comparing features, and responsible spending. LC → PFB Path Coefficient: The relationship between Facilitating Condition (FC) and Usage Behavior (UB) is positive, with a coefficient of 0.124. Significance: The t-statistic is 3.183, and the p-value is 0.001, indicating a statistically significant relationship. Implication: This result suggests that FC influences UB, with stronger leadership or control abilities leading to more proactive and effective Usage Behaviours. These findings directly contribute to achieving the research objective of examining significant relationships among the different aspects of BI. The results demonstrate that both BI and FC have distinct but significant positive impacts on UB, underscoring their importance in shaping Purchasing Decisions.

**H7**: There is a positive mediating effect between effort expectancy, behavioural intentions and usage behaviour.

**H8:** There is a positive mediating effect between the facilitating condition, behavioural intentions and usage behaviour.

**H9**: There is a positive mediating effect between performance expectancy, behavioural intentions and usage behaviour.

**H10**: There is a positive mediating effect between Social Influence, behavioural intentions and usage behaviour.

**Table no. 6.1.2 Findings of the Mediating effect on usage behaviour**

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values | Result |
|---|---|---|---|---|---|---|
| EE -> BI -> UB | -0.013 | -0.013 | 0.007 | 1.800 | 0.072 | Insignificant |
| FC -> BI -> UB | 0.023 | 0.023 | 0.011 | 2.149 | 0.032 | Significant |
| PE -> BI -> UB | -0.019 | -0.019 | 0.009 | 2.075 | 0.038 | Significant |
| SI -> BI -> UB | -0.024 | -0.024 | 0.011 | 2.220 | 0.026 | Significant |

mediating effect of Behaviour Intention (BI) in the relationships between PE, EE, SI, FC and Usage Behaviour (UB). The results confirm significant indirect effects, EE -> BI -> UB

The indirect effect of EE on UB through BI is insignificant, with a path coefficient of 0.013, a t-statistic of 1.800, and a p-value of 0.072. This suggests that EE does not influence UB directly by improving BI. Enhanced financial access strengthens an individual's confidence in managing Purchasing, which in turn promotes positive purchasing behaviour.

FC -> BI -> UB The indirect effect of FC on UB through BI is significant, with a path coefficient of 0.023, a t-statistic of 2.149, and a p-value of 0.032. Facilitating Condition (FC) enhances BI, which mediates its impact on UB. This highlights the critical role of knowledge in building confidence and shaping responsible Purchasing behaviour.

SI -> BI -> UB The indirect effect of SI on UB through BI is significant, with a path coefficient of 0.024, a t-statistic of 2.20, and a p-value of 0.026. Facilitating Condition (FC) enhances BI, which mediates its impact on UB. This highlights the critical role of knowledge in building confidence and shaping responsible Purchasing behaviour.

PE -> BI -> UB The indirect effect of PE on UB through BI is significant, with a path coefficient of 0.019, a t-statistic of 2.075, and a p-value of 0.038. The findings support the objective of examining significant relationships among the different aspects of Behaviour Intention (BI). They demonstrate that BI serves as a vital mediator, linking PE, EE, SI, FC to UB. These relationships underline the interconnected nature of all the variables.

### 6.2 Key findings of the study

Based on the analysis of the data received from the primary survey, the findings of the present study have been identified.

The findings for the present study are characterised as mentioned.

- Descriptive Statistics
- Cronbach's alpha
- KMO and Bartlett's Test
- Factor Analysis
- T-test
- One-Way Anova
- PLS SEM

### 6.2.1 Key findings of Descriptive statistics Key findings of Cronbach's alpha

The table below gives a snapshot of major findings related to descriptive statistics

**Key Findings:**

**Table 6.2.2.1: Finding of Demographical Variable – Descriptive Statistics**

| | | | |
|---|---|---|---|
| **Gender** | Male | 469 | 52% |
| | Female | 434 | 48% |
| **Age Group** | 15-25 | 278 | 31% |
| | 25-35 | 276 | 30% |
| | 35-45 | 190 | 21% |
| | 45 & above | 159 | 18% |
| **Marital Status** | Married | 384 | 43% |
| | Single | 519 | 57% |
| **Occupation** | Business | 145 | 16% |
| | Private Employee | 328 | 36% |
| | Government Employee | 116 | 13% |
| | Retired | 17 | 2% |
| | Student | 169 | 19% |
| | Homemaker | 81 | 9% |

| | | | |
|---|---|---|---|
| | Not doing Anything | 47 | 5% |
| **Education Level** | Graduate | 121 | 13 |
| | Post Graduate | 522 | 58 |
| | Doctorate | 109 | 12 |
| | Other | 151 | 17 |
| **Income** | Less than 25,000 | 131 | 14 |
| | 25,001-50,000 | 344 | 38 |
| | 50,001-75,000 | 194 | 21 |
| | More than 75,001 | 234 | 26 |

### 6.2.2 Key Findings of Cronbach's alpha

Here researcher find the value of Cronbach's Alpha is higher than 0.70, in our result we reject the null hypothesis and we may say that the instrument is reliable and can be used with factor analysis for further investigation.

### 6.2.3 Key findings of KMO and Bartlett's Test

The data's adequacy is assessed based on the results of the Kaiser-Meyer-Olkin (KMO) Assessment of Adequacy of Sampling and Bartlett's Test of Sphericity (homogeneity of variance). The KMO measure of sampling adequacy is .964 indicating that the present data are suitable for factor analysis. Similarly, Bartlett's Test of Sphericity is significant, $p < 0.001$ indicating sufficient correlation exists between the variables to proceed with the analysis.

### 6.2.4 Key Findings of Factor Analysis

Here researcher is able to learn that the factor loading is the correlation between the item and the factor; a factor loading of more than 0.30 usually indicates a moderate correlation between the item and the factor. Here researcher find out about moderate correlation.

### 6.2.5 Key findings of the T-test

The researchers employed the independent sample T test to explore potential differences between male and female participants regarding BI,PE, EE, SI, FC and (UB).The T test result showed a substantial difference between male and female respondents' overall general Behavioural Intention and Usage Behaviour. Numerous earlier literature reviews corroborate the outcome.

### 6.2.6 key findings of one-way ANOVA

ANOVA is one method for determining variation among different categories of categorical variables. One method that researchers employ is ANOVA when they are trying to determine how one categorical variable differs from another within more than two categories. Summated scales with different statement framings are applied by researchers for predefined continuous variables that are obtained from the literature review.

Age-wise one-way ANOVA results show that we accept the alternate hypothesis, which means there is no significant difference between various categories of age with respect to performance expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Usage Behaviour and Behavioural Intention.

Occupation wise one-way ANOVA results show that we accept the alternate hypothesis, which means there is no significant difference between various categories of age with respect to performance expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Usage Behaviour and Behavioural Intention.

The outcome of income-wise Anova suggests that there is a statistically significant variation in the Monthly income of respondents and individuals across different income categories. which means there is no significant difference between various categories of age with respect to performance expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Usage Behaviour and Behavioural Intention.

Education wise one-way ANOVA results show that we accept the alternate hypothesis, which means there is no significant difference between various categories of age with respect to performance expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Usage Behaviour and Behavioural Intention.

### 6.2.7 key findings of PLS-SEM Path analysis

The text discusses the analysis of a measurement model and the testing of causal relationships among latent constructs using a path model in structural equation modelling (SEM). The results from the PLS SEM 4.0 software indicate that all proposed hypotheses are supported. Bootstrap samples were generated at the 95% confidence level to assess the mediating effect, with findings presented in accompanying figures. Performance Expectancy has significant impact on Behavioural Intention. Effort Expectancy has significant impact on Behavioural Intention, Social Influence has significant impact on Behavioural Intention, Facilitating Conditions has significant impact on Behavioural Intention. Facilitating Conditions has significant impact on Usage Behaviour and Behavioural Intention has significance impact on Usage Behavior.

## 6.3 Summary of findings

**Table 6.3.2: Demographical variable – One Way Anova**

| Variable | Hypothesis | Description |
|---|---|---|
| **Age group** | H13 | Supported |
| | H14 | Supported |
| | H15 | Supported |
| | H16 | Supported |
| | H17 | Supported |

| | | |
|---|---|---|
| | H18 | Supported |
| **Occupation** | H19 | Supported |
| | H20 | Supported |
| | H21 | Supported |
| | H22 | Supported |
| | H23 | Supported |
| | H24 | Supported |
| **Education** | H25 | Supported |
| | H26 | Supported |
| | H27 | Supported |
| | H28 | Supported |
| | H29 | Supported |
| | H30 | Supported |
| **Monthly Income** | H31 | Supported |
| | H32 | Supported |
| | H33 | Supported |
| | H34 | Supported |
| | H35 | Supported |
| | H36 | Supported |

**Table 6.3.3: Summary of Main Variable –SEM**

| Variable | Hypothesis | Description |
|---|---|---|
| BI -> UB | H37 | Significant |
| EE -> BI | H38 | Significant |
| FC -> BI | H39 | Significant |
| FC -> UB | H40 | Significant |
| PE -> BI | H41 | Significant |
| SI -> BI | H42 | Significant |
| EE -> BI -> UB | H43 | Insignificant |
| FC -> BI -> UB | H44 | Significant |
| PE -> BI -> UB | H45 | Significant |
| SI -> BI -> UB | H46 | Significant |

## 6.4 Conclusion

Augmented Reality (AR) has emerged as a transformative technology in the retail sector, reshaping how consumers interact with products and make purchasing decisions. By enabling virtual try-ons, 3D product visualization, and immersive in-store experiences, AR bridges the gap between online and offline shopping, reducing uncertainty and enhancing consumer confidence. Research indicates that AR-driven experiences significantly influence purchase intentions by providing a more engaging and interactive shopping journey, ultimately leading to higher conversion rates and customer satisfaction (Javornik, 2016). As retailers increasingly adopt AR, its role in driving sales and fostering brand loyalty continues to grow.

One of the key advantages of AR in retail is its ability to minimize product return rates by allowing consumers to preview items in real-world settings before purchasing. For instance, furniture retailers like IKEA use AR to let customers visualize how products would fit in their homes, leading to more informed decisions (Yim et al., 2017). Similarly, beauty brands leverage AR-powered virtual makeup trials, which enhance user engagement and reduce hesitation in buying cosmetics. These applications demonstrate how AR enhances the decision-making process, making it a valuable tool for modern retailers seeking to improve customer experience and operational efficiency.

Despite its benefits, the widespread adoption of AR in retail faces several challenges, including high implementation costs, technological limitations, and varying consumer readiness. Some shoppers may find AR interfaces complex or may be hesitant to adopt new digital shopping methods (Pantano et al., 2017). Additionally, retailers must ensure seamless integration across multiple platforms, including mobile apps and in-store kiosks, to provide a cohesive experience. Addressing these barriers will be crucial for maximizing AR's potential and ensuring long-term consumer acceptance.

Looking ahead, the future of AR in retail appears promising, with advancements in AI, machine learning, and wearable AR devices expected to further enhance personalization and interactivity. Retailers that invest in AR technology and tailor experiences to consumer preferences will likely gain a competitive edge. Future research should explore the long-term behavioral impacts of AR, including its role in customer retention and omnichannel retail strategies. As consumer expectations evolve, AR will remain a key driver of innovation in the retail industry.

In conclusion, Augmented Reality has a profound impact on consumer purchase intentions and adoption in retail by offering immersive, interactive, and personalized shopping experiences. While challenges remain, the benefits of AR—such as increased engagement, reduced returns, and higher conversion rates—make it a vital tool for modern retailers. By addressing adoption barriers and continuously improving AR applications, businesses can unlock new opportunities for growth and customer satisfaction in an increasingly digital marketplace.

**6.5 Theoretical Implication**

The integration of Augmented Reality (AR) in the retail sector aligns closely with the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants of technology adoption. AR enhances performance expectancy by allowing consumers to visualize products in real-time, reducing uncertainty and increasing confidence in purchase decisions. Studies show that AR-driven virtual try-ons and 3D product previews significantly improve perceived usefulness, a core UTAUT construct, leading to higher purchase intentions. This suggests that retailers investing in AR should emphasize its ability to deliver tangible benefits, such as reducing product returns and enhancing customer satisfaction.

Effort expectancy plays a critical role in AR adoption, as consumers are more likely to embrace the technology if it is intuitive and easy to use. The UTAUT model posits that technologies requiring minimal learning curves see faster adoption—a principle that applies directly to AR retail applications. For instance, mobile AR apps with simple interfaces and seamless integration (e.g., QR code scanning or camera-based overlays) reduce friction, making the shopping experience more engaging. Retailers must ensure that AR tools are user-friendly, as complexity could deter less tech-savvy consumers, negatively impacting adoption rates.

Finally, social influence and facilitating conditions further shape AR's impact on consumer behavior. Social proof, such as influencer endorsements or peer recommendations, can accelerate AR adoption by reinforcing its credibility (social influence). Meanwhile, facilitating conditions—such as retailer support, device compatibility, and high-speed internet—determine whether consumers can access AR features effortlessly. The UTAUT model suggests that even if consumers perceive AR as beneficial, poor infrastructure or lack of retailer promotion can hinder adoption. Thus, businesses must not only develop AR solutions but also create an ecosystem that supports seamless usage, including customer education and technical assistance, to maximize its impact on purchase intentions.

### 6.6 Managerial implications

First, retailers should prioritize seamless AR integration across both digital and physical channels to enhance customer experience. Investing in user-friendly AR applications—such as virtual try-ons for apparel or 3D product previews for furniture—can significantly reduce purchase hesitation and product returns (Yim et al., 2017). Managers must ensure these tools are easily accessible via mobile apps or in-store kiosks, with intuitive interfaces to encourage adoption. Additionally, gathering consumer feedback on AR features will help refine functionality and improve engagement, ultimately driving higher conversion rates.

Second, marketing strategies should leverage AR's interactive capabilities to create immersive brand experiences. For instance, AR-powered advertisements or gamified shopping experiences can increase consumer interaction and emotional connection with products (Javornik, 2016). Retailers can also use AR data analytics to track user behavior, such as time spent on virtual try-ons or click-through rates, to personalize recommendations and promotions. By aligning AR campaigns with consumer preferences, businesses can boost brand loyalty and differentiate themselves in a competitive market.

Finally, while AR adoption requires significant investment, managers should weigh long-term benefits against costs. Training staff to assist customers with AR tools and ensuring backend infrastructure supports smooth functionality are crucial steps (Pantano et al., 2017). Retailers may also consider phased implementation—starting with high-impact categories like fashion or home decor—before expanding AR features across all product lines. By strategically adopting AR, businesses can enhance customer satisfaction, reduce operational inefficiencies, and secure a sustainable competitive advantage in the evolving retail landscape.

### 6.7 Scope for further research

Based on the study, the following scope of research is available, considering the present study.

Prior studies have primarily focused on Western markets, leaving a gap in understanding how cultural differences affect AR adoption. Future research could compare AR acceptance in individualistic vs. collectivistic cultures (Hofstede, 2011). Additionally, demographic factors such as age, gender, and digital literacy may influence AR engagement (Pantano et al., 2017).The convergence of AR with AI-driven personalization (Grewal et al., 2020) and Metaverse retail environments (Dwivedi et al., 2022) presents new research avenues. How do AI-powered AR recommendations influence purchase decisions? With AR collecting biometric and behavioral data, future studies should examine consumer privacy concerns (Rese et al., 2020). What regulatory frameworks are needed to ensure ethical AR usage? Does AR reduce product returns by improving decision accuracy (Beck & Crié, 2018)? How does post-purchase AR engagement (e.g., interactive manuals) affect customer satisfaction? With WebAR eliminating app dependency (Flavián et al., 2021), how does accessibility impact adoption? Similarly, how does voice-assisted AR (e.g., Alexa-guided shopping) influence user experience? As AR adoption grows, research should explore the need for standardization (e.g., AR quality benchmarks) and consumer protection policies (Bonetti et al., 2019).

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## List of all Publications Arising from the Thesis

1)Tinkle Shukla, Dr. Priyanka Amrish Shah (2024) Tittle "Decoding User Acceptance of AR in Retail: A Field Study Across Gujarat's Metropolitan Hubs" Published in the Journal of Educational Administration: Theory & Practice online Vol.30 No.11 (2024) DOI: https://doi.org/10.53555/kuey.v30i11.11430

2)Tinkle Shukla, Dr. Priyanka Amrish Shah (2024) Tittle "A study on adoption of mobile augmented reality in tourism sector" Published in the Journal of international journal for innovative research in multidisciplinary field peer reviewed journal Volume-10, issue -12, December -2024
DOI: 10.2015/IJIRMF/202412

## APPENDIX 1

## Survey Questionnaire

I, Tinkle V. Shukla, Ph.D. Student of Management discipline in Gujarat Technological University, Ahmedabad is doing A research on “Use of Immersive Virtual Technology in Consumer Retailing and Its Effects to Consumer” The data collected will not be used/shared with any other person/organization for any purpose. The details/opinions provided by you will be treated as strictly confidential.

Name

1. Gender
   - Male
   - Female
2. Age Group
   - 15-25
   - 25-35
   - 35-45
   - 45 & Above
3. Marital status
   - Married
   - Single
   - separated
   - Widow
4. Occupation
   - Business
   - Private Employee
   - Government Employee
   - Retired
   - Student
   - Home Maker
   - Not doing anything
5. Education level

- Graduate
- Post graduate
- Doctorate
- other

6. Monthly income
   - Less than 25,000
   - 25,001 to 50,000
   - 50001 to 75,000
   - More than 75000
7. Since how long do you shop online?
   - Less than 1 Year
   - 1 year to 2 Years
   - 2 year to 3 years
   - More than 3 years
8. How frequently do you use online platform(s) for shopping?
   - Weekly
   - Once in a month
   - Once in 6 months
   - Once in a year
9. Have you ever experienced or used immersive virtual technology (such as virtual reality, augmented reality, mixed reality) in a retail or shopping context?
   - Yes
   - No
10. Which types of immersive virtual technology have you encountered while shopping for consumer goods? (Select all that apply)
    - Virtual Reality (VR)
    - Augmented Reality (AR)
    - Mixed Reality (MR)
    - I am not sure None of the above
11. Have you come across the term "Augmented Reality" (AR)?
    - Yes
    - No

12. Have you ever used any applications or devices that utilize augmented reality technology?
    - Yes
    - No
13. Where have you primarily learned about augmented reality technology? (Select all that apply)
    - News articles
    - Social media platforms
    - Friends or family
    - TV shows or documentaries
    - Online videos (e.g., YouTube)
    - School or educational institutions
    - other
14. How many retail application have you heard?
    - Nike Fit
    - IKEA Place (IKEA articles in the user's room)
    - ModiFace
    - AR Watches
    - Houzz (furniture and accessories in the user's room with the possibility of purchase)
    - Tanishq-try on
    - H&M
    - Urban Ladder
    - Zivame
    - CaratLane
    - Lenskart (the ability to test the Eyeglasses Collection on your own face)
    - Snaphat (face changing filters)
    - Instagram (the possibility of trying the products on your own face)
15. Did you know that the mentioned applications are using the augmented reality?
    - Yes
    - No
16. Have you ever Use/Shopped from AR Shopping App?
    - Yes

- No

17. Have you ever made a purchase influenced by an immersive virtual experience? (e.g., trying on virtual clothes, previewing furniture in your home using AR)
    - Yes
    - No
18. if you used/intent to use AR Technology in the future, please answer the following questions.

| | **Strongly Disagree** | **Disagree** | **Undecided** | **Agree** | **Strongly Agree** |
|---|---|---|---|---|---|
| **PERFORMANCE EXPECTANCY**<br>• I don’t think AR Platforms are useful for my shopping I don't think AR Platforms are useful for my shopping<br>• Using AR Platforms would help me solve problems in my shopping decisions. Using AR Platforms would help me to solve problems in my shopping decisions.<br>• Using AR Platforms would enable me to accomplish my tasks more quickly.<br>• The use of AR Platforms increases the efficiency of my shopping. | | | | | |
| **EFFORT EXPECTANCY**<br>• It is easy for me to operate AR Platforms skilfully.<br>• to learn how to use AR Platform It is difficult for me to learn how to use AR Platform.<br>• I find AR Platforms are easy to use. | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| • I have no difficulty in using AR Platforms. | | | | | |
| **SOCIAL INFLUENCE**<br>• People who are important to me think that I should use AR Platform.<br>• I find that using AR is a fashionable and popular way for shopping. I find that using AR is a fashionable and popular way for shopping.<br>• Using AR Platforms makes me feel I belong to the online adoption community. Using AR Platforms makes me feel I belong to the online adoption community | | | | | |
| **FACILITATING CONDITIONS**<br>• It is convenient for me to shopping in an AR Platforms.<br>• I have the hardware necessary to use AR Platforms.<br>• I have the knowledge necessary to use AR Platforms.<br>• AR Platforms are compatible with other shopping apps I use.<br>• Support from the AR Platforms is available whenever there is a problem. | | | | | |
| **BEHAVIOURAL INTENTIONS**<br>• I intend to use AR Platforms in the future.<br>• I predict that I would use AR Platforms in the future.<br>• I plan to use AR Platforms in the future. | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| • I would recommend AR Platforms in my reference. | | | | | |
| **USAGE BEHAVIOR**<br>• I consider myself a frequent user of AR Platforms.<br>• I prefer to use AR Platforms when available.<br>• I do most shopping tasks by using AR Platforms.<br>• My tendency towards using AR Platforms whenever possible. | | | | | |