Analysis of Factors Affecting Adoption of Technology in Unorganized Retail Sector

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ABSTRACT

The Indian retail sector is splintered, with local small owner-operated stores accounting for 92% of the total and the organized sector accounting for the remaining 8%. The research is significant in several ways. Firstly, technology adoption is essential for the development and prosperity of any industry, including the unorganised retail sector. This research elucidates the elements that affect the implementation of novel technologies in the unorganised retail sector. Moreover, the specific research delves into the human aspect from the perspective of the unorganised retailers vis-a-vis technology adoption. The proposed research is significant as it contributes to the technology adoption in India's loosely organised retail industry. Unstructured retail establishments have extremely low usage of technology. The expensive nature of technology and the absence of technological support systems are among the obstacles to technology adoption. No study is available showing how the UTAUT – 2 Theory is applicable in the unorganized retail sector in India. Further, no study is available regarding unorganized retailers in Kolkata city and the challenges faced by them regarding technology adoption. The design of the research procedure encompassed the stages involved in the study methodology, including literature review, data acquisition, and statistical evaluation. The researcher has used Quantified Research to obtain numerical data regarding the technology adoption patterns, preferences, and challenges among these retailers. From the perspective of research design, the researcher used conclusive process based on the results achieved by conducting statistical analysis. A paper-based questionnaire was chosen as the survey method for gathering primary data based on personal interviews with the unorganised retailers. The unstructured retail sector in the Kolkata region has absolutely no research done, and more so from the technology adoption perspective. Furthermore, no research has been done on the retail technology digital divide in different places within the geography of Kolkata. Therefore, the target respondents are the unorganized retailers across various markets in the geography of the Kolkata city. A stratified sampling method has been used, focusing on six unorganized retail categories across key markets in Kolkata. The questionnaire was meticulously crafted to uncover the multi-faceted nuances of how technology is perceived, adopted, or resisted by this crucial segment. Questionnaire Design has been structured so that the questionnaire is divided into sections based on demographics,

technology awareness, and the motivations or barriers to technology adoption. A total of 698 people from Kolkata are included in this study's sample size, with a split between unstructured retailers of different categories like Kirana, Pharmacy, Footwear, Handicrafts, Electronics and readymade garments. From the perspective of data acquisition, a structured questionnaire has been deployed covering demographics, technology awareness, adoption barriers, and interviews. Slovin's formula was applied for determining the sample size. The questionnaire used a scale made up of five Likert points as part of the methodology. As a survey method, this study also used a questionnaire to collect data for the pilot and main study. As part of the pilot project, the questionnaires were administered to the respondents in person and in printed formats. A pilot research was executed to enhance the final questionnaire, assuring clarity and efficacy in data collection, with the analysis incorporating reliability testing (Cronbach's Alpha). For the main analysis, the researcher used Descriptive Statistics, Reliability tests, multi-collinearity tests, Confirmatory Factor Analysis among various statistical tools using SPSS, PLS-SEM, t-tests and ANOVA tests. The researcher employed quantitative methods for data collection and utilised various analytical tools, including SmartPLS 4.0, SPSS, t-tests, and ANOVA tests. Key findings highlight that middle-aged, low-income male retailers in sectors like grocery and apparel are the most engaged with technology, while education and income levels are critical barriers. The SEM model reveals important relationships between constructs like effort expectancy, facilitating conditions, perceived risk, and attitudes toward technology. Confirmatory Factor Analysis The chapter also analyzes gender differences and occupation-based variances in technology perception, showing significant disparities in Performance expectancy and value. Overall, the results demonstrate that while the intention to adopt technology positively correlates with perceived benefits, substantial challenges such as perceived risk and limited facilitating conditions continue to hinder widespread technology adoption. The analysis confirms that price value, effort expectancy, facilitating factors, and performance expectancy significantly influence technology adoption, with all related hypotheses supported. Habit and behavioural intention serve as significant predictors of adoption, highlighting the essential roles of consistent usage and the intention to adapt. Demographic factors, factors, such as experience, gender as well, and their ages, significantly affect adoption rates. Interplay of Price Value, Behavioural Intention, Effort Expectancy, Facilitating Conditions, Social Influence, Hedonic Motivation, Habit, Performance expectancy, Attitude, Perceived Risk, and Benefits of Adoption highlights the complexity of technology adoption. The findings from the research significantly enrich our knowledge of the variables affecting the adoption of technology in the unorganised retail sector.

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1.1 BACKGROUND OF THE STUDY

Retail as a capacity is fundamental in any economy. It consolidates the assorted necessities of shoppers with proficient proposals from makers. These retail capacities are grouping creation, production network of materials, monetary exchanges among retailers and clients, data predominance and additional offices. Ordinarily, retailers of blocks and mortar have performed most of these capacities. There are other forms of retail, such as mail order and door-to-door form, but physical fixed retail is the main (Gauri et al., 2021). Retail as a function is part of the retail value chain. The most relevant forms of this value chain include the (brand) manufacturer, the institutional retailer, and the consumer, while the institutional retailer is the sole or highest-grossing agent for the performance of retail activities. Fixed retail has the most significant role in institutional retail (The discussion solely centers on the impact of e-commerce on conventional brick-and-mortar retail, encompassing various modes of e-commerce such as mail order or door-to-door mail (e.g. offline stores, home sales) (Hansen, 2021). With the increasing percentage of retail shops in the retail fee chain, the superiority of fixed retail is structurally challenged because of its actions throughout online formats, along with natural gaming, online operations of manufacturers, and systems. Whilst present save labels is participating in this transition thru a multi-channel method, a sizeable component of their sales is pushed by using new gamers, mainly Amazon (Beck & Rygl, 2015). In 2017, Amazon in the U.S. accounted for about 4% of all retail sales (Ukeni, 2015). “The store existed just because the Internet was not invented,” According to the statement made by Oliver Samwer, the Chief Executive Officer of

Rocket Internet. The trend of customers opting for the ease of digital shopping and mail-order delivery has decreased store visits for numerous physical retailers (Mróz, 2021).

In India, retail is generally unorganized, with most stores being small, independent, and family-owned. In India, a significant percentage of citizens are dependent on retail trade to make a decent living. The emergence of shopping mall culture in India has notably impacted traditional grocery stores. Traditional grocery stores endeavor to compete and increase revenue by better-displaying products, offering finance, offering free home delivery, and building long-term customer relationships. By contacting customers in their immediate area and improving the quality of their services, unorganised retailers aim to compete with organised retailers. (Sangvikar et al., 2019). Digital transformation, or digitization, refers to a business strategy predicated on modifications to the way digital technology is applied in every facet of human society (Hermsen et al., 2016). This is usually achieved through digitization. In other words, "the ability to digitalize an existing product or service to provide an advantage over tangible products" (Dambrauskaitė, 2023). Consequently, they take marketing alternatives based totally on the viability of previous customers but do not consider their potential profitability. The consumer-centric approach includes an individual interpretation of the clients, assessment of their ability profitability and edition of marketing and verbal exchange techniques. To transition switching to an approach centred around customers from a product-centric one, retailers must commit themselves to developing analytical capabilities. Linked customers depart behind digital footprints through social media and virtual stories, allowing entrepreneurs to gain insights into the associated analysis. Analytics permit entrepreneurs to develop expertise in how their clients eat their items and services in the new statistics-rich global, tune their internal income sports and the delivery chain, control their workforce and predict capacity threats across the whole value chain (Jones & Comfort, 2019). While growth in the retail sector has shown that the related analytics and performative metrics have been used, this trend in emerging markets is not as apparent (Wiefel, 2015). While emerging market retailers know about the advantages of analytics, the failure of monetary, technological and human capital constitutes a crucial impediment to implementing and deploying applicable analytics and performance measures (Wiefel, 2015). Adopting consumer focus and success measures across the retail supply chain remains difficult. A good deal of this field's research is abstract, with very little consideration paid to the literature on newly developed markets (Jones & Comfort, 2019).

1.2 ROLE OF DISRUPTIVE TECHNOLOGIES WITHIN THE FIELD OF RETAILING

In India, the commerce of retail is separated, with the organized sector making up 8% of the total and local small owner-operated establishments making up 92%. Increasing disposable income, urbanization, the financial capacity of the younger generation, nuclear family structures, and advancements in technology, especially in information and communication technology, all foster India's retail success (Ramanan & Ramanakumar, 2014). The history of retail is also a history of society’s relationship with technology. When looking at the evolution of retailing, it’s clear that technology has been a critical enabler of progress. The consumer’s expectations rise in unison with the advancement of technology. The power has passed from the store to the consumer in this age of fast meals and rapid lives. This transformation is made possible by the confluence of a few innovative tools. (Pantano, Eleonora, 2014). In the current corporate environment, it is critical to research digital payment systems and their benefits. Small traders' transactions are minimal, and their turnover is very low regarding money's worth. However, their livelihood and economic activity allow them to earn money. The challenge of tendering correct changes and returning changes for larger denominations is always present in these lesser-value transactions. For minor traders, it means a loss of business or sales. Furthermore, due to transactional concerns, buyers avoid shopping with petty traders. Following the demonetization policy, their business was significantly boosted due to the implementation of a digital e-wallet payment. It makes their life good with cashless transactions (Sivasubramanian et al , 2020). In small businesses, innovation in the business model positively impacts the firm's performance (Kamboj, 2018). Utilizing technology facilitates a machine to consistently execute tasks capable of being replicated with a predetermined set of directives without experiencing exhaustion, thereby enabling the human intellect to engage in and concentrate on more crucial responsibilities. The application of technology in the retail industry helps teams delight their customers by allowing the team members to focus on the customers' needs. And more business means happier customers. With an unprecedented speed of ground-breaking advancements, technology has significantly improved customers' lives during the previous few decades. Most were unexpected, changing customers' behavior and motivating them to seek high-quality goods and services (Gungor, 2018). The critical point is that companies that do not understand the uniqueness of innovative technology are not successful in their market (Dhillon et al., 2001). Managerial emphasis on innovation enables new markets to be created and the tools used to effectively transform creative ideas (Niu et al., 2013). Where retailers can reinvent consistently is one of the essential things to compete effectively. Past studies have highlighted that innovation capacity can vary in number, and the type of innovation amongst companies operating in the same field may also differ (Cao, 2014). In the same market, innovators could thrive, depending on their internal capital and strategic direction (Kerin et al., 1992). For example, retailers adopted various innovation strategies, such as the introduction of self-service technology innovation to transfer tasks traditionally executed by employees to an automatic machine that introduces additional technological innovations capable of entertaining and including more consumers through the provision of exciting shopping experiences or the development of new integration systems (Evan, 2011). Furthermore, the bulk of stores do not have any innovative products (Demirkan et al., 2014). As a result, the new competitive landscape has witnessed a wide heterogeneity of innovative advancements and strategies (Hristov et al., 2015). The retail industry is not just the most diverse but also a nuanced, demanding and challenging sector – with tremendous opportunities – that can help companies maintain their competitive lead based on customer tastes through a consistent plan and positioning (Renko et al., 2014). A critical approach is designing and implementing store technology, but if retailers understand the advantages of technology, the technology implementation could be more successful (Verhoef et al., 2009; Grewal et al., 2018). The primary goals of retailers are decreasing expenses and effectiveness in operations (Grewal et al., 2018). When evaluating the introduction of cutting-edge technology, shopkeepers take into consideration the IRR, payback duration, NPV and the return on investment. They are typically adopted without a full grasp of how shopping experiences impact shopping, and frequently without utilising innovations to meet the needs of customers. In addition, retailers could be better off by differentiating between technology that improves operating performance and innovations that maximize consumer service (Grewal et al., 2018).

Apart from its dedication to fulfilling market requirements for novel and high-quality commodities and amenities, information technology is progressively perceived as enhancing a company's competitiveness (Chen & Tsou, 2012). Extensive research into cutting-edge technology and the subsequent creation of new systems for merchants have caused a disruptive innovation process in the retail sector (Gunday et al, 2008). This has made a wide range of new information systems accessible to traditional organizations. Furthermore, the novelty of these inventions impacts customer and vendor familiarity and experience, which has implications for their future successful use (Pantano & Viassone, 2014). The significance of information systems requires the creation of novel metrics and assessment techniques, as posited by (Grant et al, 2013). Service innovation is often characterized by a focus on non-technological progress and a modest allocation of resources towards Research and Development (R&D), as was noted by (Trigo, 2013). The R&D efforts of the retail industry are primarily concentrated on developing novel products rather than exploring innovative approaches to enhance service delivery. Consequently, retailers frequently adopt technological advancements produced by external manufacturers at an early stage. Due to their limited creative capacity, retailers outsource all research and development endeavors. Notwithstanding the prevailing circumstances, innovative technologies for vending commodities and amenities are rapidly changing (Fiorito et al., 2010). To help the retailers obtain timely and accurate information about market trends and the vending process, a variety of interactive and cutting-edge systems are available (Walter et al., 2012). Retail establishments have shown great success using augmented reality, and this trend is predicted to continue (Bennett & Savani, 2011). Adopting augmented reality has emerged as a noteworthy trend that has recently garnered considerable attention and acceptance across diverse sectors. Implementing computer-generated innovation in retail establishments holds promise for revolutionizing the customer experience, particularly within the fashion retail sector. Consumers in fashion retail stores might be motivated to buy and try on more things thanks to technology, ensuring sustainable profitability in the retail outlets (Menon et al., 2020). Since its inception, augmented reality has shown that it may increase the activity, productivity, and effect of processes in various nations. Its cutting-edge technology, which offers smooth and genuine experiences while allowing users to interact with virtual and real-time applications, is the cause of this. The use of augmented reality technology could greatly increase a brand's perceived value and image among consumers and improve their level of engagement (Menon et al., 2020). Virtual changing rooms and smart/digital mirrors have had a big impact. Without requiring the customer to try on the dress, intelligent mirrors can produce a representation of how they would appear in a different style. The Smart Fitting Room system is intended to recognise the clothing items that a customer brings into the fitting room and then show the colours, models, and sizes that are available online or in the local store. Effective visual aids may make it easier for customers to locate the business or item they're looking for. The data gathered from an augmented reality app can help retailers understand their consumers' preferences and learn more about their buying habits (Menon et al., 2020). Additionally, many businesses with a retail concentration have created e-commerce platforms (Pantano & Viassone, 2014). As a result, various retailers' innovative tactics are consistently heterogeneous. Even though technology-based developments are only in their early stages of adoption in the unorganized retail sector, other sectors have now implemented more mature and complex systems. The gaming industry prioritizes the development of advanced haptic technology and implementations, enriched virtual and augmented reality scenarios, multimodal connectivity, immersive visual storytelling systems, and personalized interfaces to enhance user engagement and enjoyment (Hamam et al., 2013). Retailers are finding it difficult to provide value to their customers. Customers seek “value” not only in terms of pricing, atmosphere and appearance, quality, service, and information but also in terms of choices, convenience, service, and entertainment. Retailers benefit from information technology (I.T.) because it allows them to control expenses and provide better customer value. Technology improves the customer’s buying experience by delivering convenience, faster service, and more value (Ramesh Babu et al., 2012). Retail customers exhibit a willingness to adopt technological interventions that address their primary concerns, including but not limited to extended wait times at checkout counters, inadequate product information within stores, challenges in locating products, and instances of stock unavailability. The utilisation of technology is increasingly seen as a useful tool for building and maintaining relationships. A company's competitiveness may be impacted by information technology since it can help adjust the supply chain to satisfy consumer demands. The store must consistently make long-term investments and make adjustments in the majority of sectors in order to obtain a competitive edge from IT (Ramesh Babu et al., 2012). Basic tasks including selling goods, getting item-by-item sales data, stock control, purchasing, management reporting, customer information, and accounting are all done by retailers using IT. Businesses today need to come up with fresh ways to serve their clients and set themselves apart from the services offered by their rivals. Technology use facilitates the gathering and sharing of information (Ramesh Babu et al., 2012). Retail data can assist in the implementation of a variety of marketing decisions: -

- The utilization of retail data can aid in evaluating the potential success of novel product lines and quantifying their influence on the sales of various goods.

- Electronic point of sale, or EPOS, is another tool that retailers may use to quickly and accurately report on how customers are responding to promotions that are held at their establishments.
- Electronic point of sale (EPOS) systems can produce comprehensive, up-to-date, and precise sales data, which has emerged as a crucial marketing resource for retailers and supplier marketing divisions. Retailers who have a lot of frequent sales, stock-keeping units, and clients are the main users of electronic point of sale (EPOS), a computer-based billing system. Increasing efficiency and streamlining billing processes are two of the main objectives of point-of-sale automation. A simple EPOS, which is frequently a standard PC with all of its add-ons (weighing scales, barcode scanner), can process payments quickly, update inventory, and produce real-time sales and inventory information (Ramesh Babu et al., 2012).

Mobile payments are commonly defined as payment services conducted through a mobile device and are subject to financial regulations. They are also popularly known as mobile money transfer or mobile wallet. Numerous establishments have already obtained applications for money transfer companies and are taking a proactive approach. Some of India's most notable mobile wallets which include PhonePe, Google Pay, Paytm etc. (Saravanakumar et al. , 2020).

1.3 TECHNOLOGY ADOPTION BY RETAIL INDUSTRY

Retailers adopted novel technology by making assumptions about the extent to which customers would utilize it and the accuracy with which managers would gather data to forecast future demand patterns. Consequently, a crucial area of inquiry has shifted towards the willingness of customers to embrace contemporary technology rather than the successful implementation or adoption of such technology by merchants and the labour force. The original purpose of the TAM was to forecast Internet users' behaviour using four basic constructs—performance expectancy, mood, behavioural intention, and perceived usefulness; which were meticulously assessed by Dr Davis (Davis et al., Technology acceptance model, 1989). The term "performance expectancy" describes how much someone thinks that using a particular system would not require a great deal of effort. On the other hand, perceived usefulness refers to the extent to which an individual believes that utilising a specific technique would enhance their performance. These constructs have a major impact on the mindset that reflects an individual's evaluation of the system and the subsequent behaviour (Pantano & Di Pietro, 2012). TRA serves as the foundation for the TAM (Fishbein and Ajzen, 1975). TRA states that an individual's perspective on certain behaviours and subjective norms have an impact on their behavioural intention. The latter speaks about the expectations of others about how a particular behaviour should be carried out, thus illustrating the degree to which other people's views impact a person's behaviour (Lee, Fairhurst, & Lee, 2009; Lin & Chang, 2011; Lee & Yang, 2013; Schuster et al., 2013). Academic studies have focused on the identification of radio frequency also known as RFID (Kowatesh & Maass, 2010; Cao & Li, 2018). Because of this, previous research has used the traditional Technology Acceptance Model approach, which entails building augmented models that include extra variables to more thoroughly explain the factors influencing technology adoption across the various technologies under investigation. This research separated the diverse range of characteristics into four primary categories: social pressure, technological safety and cost (Pantano and DiPietro, 2012; Lee, 2014). Despite retailers acknowledging the significance of customers in the process, the comprehension of their position in the market remains limited (Andreu et al, 2010). The most effective techniques to encourage customers to actively participate in the process of collaborative creation and to use the knowledge they gain from these experiences to create new goods and services while utilising social media and other modern internet-based technologies are the subject of numerous recent research (Greer & Lei, 2012; Kohler et al., 2011; Sawhney et al., 2005; Tao and Xu, 2018). UTAUT2 was investigated in order to gain a greater grasp of behavioural intention (BI), which encompasses attitudes towards technology as a mediator and the digital payment option as an innovative component of online buying. The present research adds to our insight of how BI while purchasing products online is impacted by attitudes towards technology and digital payment options. It recommends that to make shopping online more pleasurable, administration and governance should implement the digital payment technique as an assistance mechanism (Gupta, et al., 2024).

1.4 TECHNOLOGY ADOPTION BY UNSTRUCTURED RETAILERS

For retailers, adopting technology has become more and more important. According to a recent study, there are eight major elements that drive technology adoption. The desire for payment apps and the ease and financial savings of procurement applications are, by far, the most important aspect (Greer & Lei, 2012; Kohler et al., 2011; Sawhney et al., 2005; Tao and Xu, 2018). Since 2017, the use of technology in retail has more than doubled, and one of the most popular technologies is artificial intelligence (Tao and Xu, 2018). The COVID-19 contagion has sped up the adoption of technology in the retail industry; among these technologies is the Internet of Things. Adoption of technology is essential for unstructured merchants to maintain efficiency and competitiveness. Data monetisation is one important adoption area that enables merchants to better understand their customers and develop more focused marketing strategies. Supply chain management is another field where implementing technology might be advantageous. Retailers may reduce costs and improve inventory management by using technology like blockchain and RFID tagging to track their goods more precisely and effectively. However, in unstructured retail settings, technology adoption may also encounter difficulties. The absence of technological infrastructure, which makes introducing new technologies challenging, is one possible obstacle to adoption. One potential barrier to adoption is the lack of technological infrastructure, making implementing new technologies difficult. The expense of technology, which can require a large investment from shops, is another difficulty. Additionally, implementing new technology may necessitate major adjustments to personnel training and business procedures, which could be difficult for smaller stores with fewer resources. Unstructured retailers need to adopt technology if they want to be successful and competitive in the current market. Adopting new technologies, such supply chain management and data monetisation, can result in significant cost savings and better customer experiences, even while there are obstacles to technology adoption, such as the absence of technological infrastructure and the expense of technology. Retailers should think about what influences the adoption of technology and create plans to get beyond any obstacles. The incorporation of technological advancements and many customer convenience considerations is causing significant changes in the business model of the retail industry. Harikrishnan et al., (2024) studied and focused on the shift of customers from unorganized retailers to organized retailers. The aggregated diverse factors and focused on major variables like procurement convenience and innovative technologies. Harikrishnan et al., (2024) identified several technological impacts on unorganized retailers and concluded that innovative technologies act as catalysts in shifting consumers from unorganized retailers to organized retailers.

1.5 TYPE OF UNSTRUCTURED RETAILERS

India's retail industry is one that is growing quickly and contributes significantly to the GDP of the country. Organised and unorganised retail are the two divisions of the Indian retail market. The unorganised retail industry is dominated by small, mostly unstructured retailers, most of which are family-run businesses. Based on the product category, business type, and manner of operation, the unorganised retail industry in India can be further divided into various types. In India, peddlers, street vendors, hawkers, and fixed-shop sellers are a few examples of unorganised retailers. Hawkers are small-time retailers who carry their goods from one place to another and do not have a permanent place of business. They are often seen on busy streets and in public places, selling items such as vegetables, fruits, and household items. On the other hand, street vendors operate from a fixed location on a street or footpath and sell food, clothes, and accessories. Peddlers are mobile retailers operating from a small vehicle or pushcart, selling snacks, ice cream, and soft drinks. Fixed shop retailers operate from a permanent location and do not move from one place to another. Unstructured retail is a significant portion of the retail sector in India, accounting for around 90% of all retail sales. These retailers are small, independent businesses not part of a formal retail chain. They are crucial in providing customers with goods and services in urban and rural areas. Here are some common types of unstructured retailers in India:

1. Kirana Stores: Small, independent grocery stores usually located in residential areas. They offer a variety of household items, including groceries, toiletries, and other essentials. Kirana stores are often owned and operated by families and are an essential part of the local community.
2. Street vendors sell goods on the street or in public areas. They often sell fresh produce, snacks, and other inexpensive items. In cities, street sellers are

common and offer reasonably priced alternatives to consumers who might not otherwise have access to conventional retail establishments.

3. Mom-and-Pop Shops: These are small, family-run businesses that sell a variety of products, including groceries, clothing, and other household items. Mom-and-pop stores are common in small towns and rural areas, and they are often run by families that have been in business for multiple generations.
4. Convenience Stores: Convenience stores carry a variety of goods, such as food, drinks, medications, and personal hygiene products, and they are usually open around-the-clock. These shops offer quick and simple access to necessities and are frequently seen in crowded urban settings.
5. Hawkers are street vendors who move from place to place, selling their goods to customers on the street. They often sell items like clothes, accessories, and small household items. Hawkers are prevalent in urban areas and are often seen in busy marketplaces and tourist areas.
6. Pan Shops are small stores selling tobacco, cigarettes, and other smoking-related products. Pan shops are often located near busy marketplaces and transport hubs.

In India, a sizable portion of the retail industry is unstructured, with a wide variety of retail outlets catering to varied consumer demands. These tiny, unorganised retail shops are an essential part of the neighbourhood and are vital to the supply of goods and services that customers need in both urban and rural locations. Despite lacking supply chain management techniques and contemporary technology, this industry is essential to the Indian economy and offers millions of people jobs (Thakur, 2022).

1.6 TYPES OF RETAIL TECHNOLOGIES

Retail technology integration has become an essential part of contemporary retail businesses in India and around the world. The field of retail technology deals with the integration of new technologies and digitisation in both online and physical retail. This covers a range of features like order processing, inventory control, point-of-sale systems, and in-store customer support. Enhancing the customer experience and increasing operational effectiveness require the use of retail technology. One significant technology organised retailers adopt in India is mobile point-of-sale (mPOS) systems. These systems allow small retailers to accept payments through mobile devices, making it easier to process transactions and compete with larger retailers. In addition, larger organised retailers have also started adopting mobile point-of-sale (mPOS) systems to enhance the in-store shopping experience by enabling customers to pay using mobile devices (Thakur, 2022). Another technology adopted by organised retailers in India is the use of electronic shelf labels (ESLs). Electronic shelf labels (ESLs) are digital displays that replace traditional paper labels and allow retailers to update prices in real time. This technology benefits retailers because it saves time and reduces the risk of errors when manually updating prices. Additionally, using electronic shelf labels improves the customer experience by ensuring accurate and up-to-date prices (Thakur, 2022). Inventory management systems are another technology adopted by Organised Retailers in India. These systems use data analytics and artificial intelligence (A.I.) to help retailers optimize inventory levels, reduce waste, and increase sales. These technologies allow retailers to automatically replenish products when stock levels are low and track inventory levels in real time. Due to fierce competition and the requirement to complete orders promptly and precisely, inventory management systems have become more and more crucial for Indian online merchants (Gupta & Ramachandran, 2021). Finally, customer relationship management (CRM) systems are another technology, which retailers adopt in India. Retailers can use these technologies to watch consumer activity, maintain customer data, and develop tailored marketing strategies. CRM systems are used by organised retailers to send customers personalised offers and promotions based on their past purchases and preferences (Thakur, 2022). CRM systems are becoming increasingly important for retailers in India as they seek to differentiate themselves in a highly competitive market (Gupta & Ramachandran, 2021).

Table 1: Disruptive Technologies and their Adoption

Technology	Description	Adoption
Artificial Intelligence (A.I.)	A.I. is used to improve the customer experience and automate processes, resulting in more efficient retail operations (Cao, 2021).	Structured and Organised retailers are adopting A.I. in various aspects of their businesses. According to a report by Capgemini, over 50% of retailers in India plan to invest in A.I. by 2022 (Cao, 2021).
Mobile Payments	With the rise of mobile phone usage, retailers in India are increasingly adopting mobile payments to make transactions more convenient for customers (Papagiannis, 2023).	Structured and Organised retailers are adopting mobile payments. At the beginning of 2024, there were 1.12 billion cellular mobile connections in India, according to data from GSMA Intelligence. In January 2024, 78.0 percent of India's population had mobile connections, according to data from GSMA Intelligence. India saw a 23 million growth in the number of mobile connections. (Kemp, 2024; Sinha & Kar, 2009).
Inventory Management Systems	Retailers use inventory management systems to track and manage inventory levels more efficiently (Papagiannis, 2023).	Structured and Organised retailers are adopting inventory management systems. According to a report by a Big4 Firm, retailers in India are using inventory management systems to improve supply chain efficiency and reduce costs (Sinha & Kar, 2009).

Structured and Organised retailers in India have adopted various retail technologies to improve their businesses. These technologies include electronic shelf labels, inventory control, customer relationship management, and mobile point-of-sale systems. In order to stay competitive in a retail environment that is changing quickly, these technologies have become more and more crucial for Indian retailers.

1.7 TECHNOLOGY ADOPTION DURING THE PANDEMIC

Right now, the retail sector is at a turning moment. Adoption of technology by the retail outlets is changing significantly as a result of changes in the global macroeconomic environment. The driving force behind this change is disruptive technologies. This research explores how the industry is changing as a result of disruptive technologies. Mixed reality and advanced analytics have the potential to enhance operations, personalising situations, and even alter our perception of purchasing (Deloitte, 2024). It is inconceivable to exaggerate the COVID-19 pandemic's worldwide expansion and immediate impacts on our daily lives, politics, business, and health (Gupta & Ramachandran, 2021). One reaction to this "new normal" environment of mask-wearing, quarantine, and social isolation was from retailers (Khalifa, 2021). Since the procedure significantly decreased foot traffic, technological advancement and acceptance became essential in both organised and unorganised retail sectors. Robots, chatbots, augmented reality, virtual reality, and the Internet of Things are just a few examples of the AI-based tools and methods that are revolutionising both online and physical retailing (Gupta & Ramachandran, 2021).

1.8 FACTORS BRINGING CHANGES IN RETAIL INDUSTRY

Retailers in the modern day demonstrate a substantially higher level of concentration towards the process of selling goods in comparison to their ancestors. Retailers who sell at establishments anticipate receiving a business experience that is individualised and adapted to their own needs. Before making a purchase, consumers engage in information-seeking behavior by consulting multiple sources such as retail sales associates, acquaintances, family members, social media platforms, and online resources (Ramanan & Ramanakumar, 2014). With AI driving its rapid adoption, disrupting practices, and altering customer experiences, retail is poised for a tremendous revolution. Twenty percent of the leading international shops will use distributed AI technologies to achieve holistic outcomes by 2025. According to a recent survey, AI is the retail technology that will change the game the most in the next three years, according to 91% of CEOs. AI may help retailers with supply chain management, marketing, operations, personalisation, and more. Brands gain from personalisation in a number of ways, such as 18% cheaper acquisition costs, 20% higher customer spend, 30% higher customer happiness, etc. AI will change how people purchase and sell, from transforming marketing and sales to streamlining supply chains and operations (Deloitte, 2024).

A number of different ways are available for the customer to engage with the retailer. Because of this, businesses are required to offer a consistent and seamless experience for their customers across all platforms. Better customer service is one of the most effective ways for retailers to boost sales, cultivate customer loyalty, and portray a favourable image. Several factors influence the consumer experience: -

- Store proximity and layout
- Parking facilities, cafeteria, entertainment, children’s play area, restrooms, and so on
- Retailers’ desire to keep engaged with shoppers

- Quick and prompt service at retail outlets
- Uncomplicated return policy (Ramanan & Ramanakumar, 2014).

Since the dawn of human civilisation around 10,000 years ago, trade and commerce have existed. As previously indicated, organised retail, another name for the notion of retail, has an almost 150-year history. In many facets of modern society, this business has developed into a vehicle for significant change in the way we work and participate in the economy.

Economic Factor

The retail business has undergone a progressive metamorphosis over the course of many economic fluctuations, which gives rise to the obvious association that exists between the retail sector and a country's economy. In comparison to economies that are centred on production and agriculture, those that are driven by consumption have a significantly stronger link. When it comes to the majority of countries, the growth or dynamics of the retail industry substantially reflect future growth and existing market fiscal liquidity. There are several areas of the retail industry that are prone to varying slow-down and turnaround times. These aspects include vehicles, garments, and consumables, and they are a solid predictor of the most likely future situations. The essential contribution to the decision-making processes of business leaders and legislators in the retail sector regarding investment and action is to understand the economic influence and interconnections with other sectors and marketplaces.

Policy Factor

Government policies have an impact on the retail industry as well. Small local businesses comprise a significant portion of the grocery, pharma, footwear and apparel stores last mile in various locations. The government positively impacts prosperity by developing programs and resources to assist small businesses. Government policies can either enable or dissuade significant players. Large-format multinational supermarkets, for example, were not authorized in India, one of the world's most lucrative retail marketplaces. However, the government has liberalized the market in the past ten years. The area has seen an upsurge in foreign direct investment and allowed the construction of large multi-brand retail stores, which has led to the country's main international retail chains being established. At roughly 8% of employment and contributing around 10% to India's GDP, the retail industry is likewise quite important at home. The majority of market shares are held by foodstuffs and groceries merchants, hence the retail industry was expected to be worth 1.2 trillion US dollars. The retail sector in India is growing at an exponential rate, with expansion of retail taking place not only in major cities and metro areas additionally in tier II and tier III locations (statista.com, 2024). India's retail industry is poised for revolutionary expansion, with projections indicating a surge to an astounding $2 trillion over the next ten years. According to a study released by the BCG and the RAI, the retail surge was predicted to reach $820 billion in 2023 (livemint.com, 2024).

Demographic Factor

The demographic composition and changes in various enterprises significantly influence the retail industry, both of which have economic implications. Most developed economies exhibit a demographic trend characterized by an increasing proportion of elderly individuals, whereas most developing economies display a comparatively youthful population. The purchasing behaviors exhibited by various ethnic groups may exhibit a high degree of variability. There exist correlations between demography, economics, and consumer behavior. In highly industrialized and affluent countries, such as those in which the Millennial Generation, also known as Gen Y, resides, economic growth prioritizes consumerism and retail expenditure over savings. Nevertheless, the economic ramifications of age distribution within a given society do not provide a comprehensive understanding of its influence, as it entails a significantly more nuanced analysis. The growth of the retail industry in the economy has been significantly impacted by the increase in the middle-class population and the demographic upswing. The prevalence of multigenerational households in marketplaces that were formerly dominated by nuclear families changes the nature of domestic retail productivity. The retail industry will be significantly impacted by this.

Sustainability Factor

Retailers and governments have emphasized environmental protection throughout the retail value chain in the past six years; however, the degree of care is rising tremendously (Zaltman, 2003). Several factors motivate retailers to address environmental concerns. Retailers can implement measures at the organizational level, particularly for their facilities. However, they are susceptible to significant environmental impacts that occur remotely from their supply chains, frequently in jurisdictions with uncertain environmental regulations. The cost of conducting business is another contributing factor to this trend. Frequently, the utilization of renewable resources in a more sustainable manner can reduce costs. Several major retailers have leaders and groups dedicated to ensuring sustainability from beginning to end. Data monitoring and management are crucial to monitoring and maintaining supply chain sustainability.

Pandemic Factor

All industries have been profoundly affected by the start of the COVID-19 pandemic, while the retail industry has been especially heavily hit. This disruption is especially noticeable with unstructured shops, particularly those that were confronted with quick and considerable issues as a result of the implementation of lockdown measures in March of 2020. While these actions were essential to the public's health, they also caused a significant collapse in the conventional retail sector, which resulted in a sharp reduction in the number of customers who visited physical stores. Unstructured retailers, often limited in their digital presence and technological capabilities, found themselves at a distinct disadvantage. The shift toward social isolation and enforced lockdowns necessitated a pivot to digital platforms that many were unprepared for. As a result, even in the face of high demand, these retailers struggled to compete with more digitally savvy counterparts who could cater to consumers in a contactless, online environment. The longer-term economic effects of the recession brought on by the pandemic are likely to persist, with a sustained impact on consumer spending patterns. Unstructured retailers, therefore, not only have to contend with immediate operational challenges but also with a broader economic climate of reduced consumer spending. This environment demands a strategic reassessment and adoption of technology for unstructured retailers to navigate the ongoing crisis and its aftermath.

Technological Factor

The impact of technological advancements on unorganized retail outlets has become a focal point of discussion within the sector. Historically, these retailers have not been part of the mainstream push towards technologically driven marketing strategies, instead relying on direct customer interactions and conventional methods such as word-of-mouth and physical displays of their products (Zaltman, 2003). The advent of e-commerce has dramatically altered the commercial landscape, necessitating even the smallest unorganized retailers to consider an online presence (Lee, 2001). The rapid shift towards online platforms has left unorganized retailers grappling with a need to either establish a digital footprint or form alliances with larger entities that have already made the transition (Gulati et al., 2000). In this fast-paced market, unorganized retailers face the challenge of adapting to a new set of operational rules defined by technological innovation (Lee, 2000). The transition to e-commerce is not simply about adding an additional sales channel but represents a complete overhaul of their business model. The shift is not only in how they engage with customers but also in the underlying processes that govern their business operations. The crux of the matter for unorganized retailers is not the replication of successful e-commerce strategies but the fundamental change in how they traditionally conduct business. E-commerce introduces an entirely new paradigm that requires unorganized retailers to adopt innovative technologies or risk becoming obsolete. In scenarios where the unorganized retail sector remains small, embracing technology is not an option but a critical necessity for survival. These retailers may need to consider becoming technologically adept, aligning with larger e-commerce platforms, or transforming into delivery partners to remain viable. This research will focus on the repercussions of retail technologies on the distribution networks of unorganized retail outlets, examining the ways in which these technologies necessitate operational shifts. It will delve into the implications for unorganized retailers who must now navigate a landscape where technological integration can mean the difference between thriving and closing down.

1.9 STATEMENT OF THE PROBLEM

The retail industry's rapid adoption of technology has been essential to raising profitability and operational effectiveness. However, there are clear differences in how quickly these technologies are being adopted across various retail formats and sectors.

This discrepancy raises questions about the barriers to technology adoption faced by unorganised retailers and potential remedies. A comprehensive examination of the literature reveals a seismic shift in the retail landscape, with this transformation starkly highlighted during the Covid-19 pandemic's enforced nationwide lockdowns. The unorganized retail sector, characterized by its smaller scale and limited resources, has been particularly challenged in integrating new technological advancements.

Despite strides in some areas, such as adopting digital payment systems, these retailers continue to grapple with ensuring efficient delivery of goods and services. Unorganized retailers are noticeably lagging in digital transformation and supply chain optimization when contrasted with their online counterparts. As the market environment advances, it becomes imperative to forge a strong support system tailored to the unique needs of the unorganized retail sector.

This involves overcoming significant hurdles related to capital, workforce, infrastructure, and distribution networks, even when resources are constrained. Identifying and resolving the specific issues these retailers face in adopting technology is an immediate and critical step towards enhancing their competitive standing in an increasingly digital marketplace.

Kolkata has been chosen as the geographical area for the purpose of this research. Kolkata, a major metropolitan city in India, has a dense concentration of unorganized, small retailers. These businesses, typically family-run or sole proprietorships, reflect the characteristics of unorganized retail prevalent across the country. The city’s unique mix of traditional markets (e.g., Burrabazar, Kidderpore Bazar, New Market etc.) and neighbourhood stores makes it a microcosm for studying the challenges and opportunities of low technology adoption. Kolkata has a rich history of traditional trade and commerce but has been relatively slower in adopting technological advancements compared to other metropolitan cities like Bengaluru or Hyderabad or Mumbai. This cultural tendency to rely on established, low-tech methods of business operation align perfectly with the research focus on technology aversion among unorganized retailers. The city offers access to a diverse range of small retailers, from street vendors and neighbourhood kirana stores to semi-structured small businesses. This variety ensures a comprehensive analysis of the unorganized retail sector's technology adoption barriers across different business types. Small retailers in Kolkata often operate on tight margins and lack awareness of the benefits of digital tools like QR codes, UPI payments, and internet banking. The city's economic landscape provides a fertile ground to explore the link between financial literacy, technological exposure, and digital transformation. West Bengal, with Kolkata at its core, has been a key area for initiatives aimed at financial inclusion and digitalization, such as Pradhan Mantri Jan Dhan Yojana and Digital India. However, the apparent disconnect between policy efforts and on-ground adoption among small retailers presents a critical research gap. Kolkata remains underexplored in academic research on the digital transformation of unorganized retailers, with much of the existing literature focusing on cities with higher technology penetration. This research addresses a geographical and thematic gap by concentrating on Kolkata, providing perspectives on the unique possibilities and constraints that exist in this scenario. Kolkata, the capital of West Bengal and an economic centre in Eastern India, impacts business activities in adjacent areas. The findings of this study may be relevant to analogous urban and peri-urban regions throughout eastern India. As a researcher, being based in or having easier access to Kolkata ensures greater feasibility in terms of data collection, participant observation, and follow-up interactions. Proximity to the study area allows for richer qualitative insights through in-depth interviews and field visits. Many small retailers in Kolkata view technology as an unnecessary disruption to their traditional methods. The study can explore how cultural factors hinder technology adoption, offering actionable insights for intervention. Unorganized retailers in Kolkata often rely on informal networks for transactions, which may deter them from adopting formal digital tools. This socio-economic dynamic is worth investigating to tailor solutions. Low penetration of banking infrastructure and digital literacy in Kolkata's unorganized retail sector offers a contrasting perspective to tech-savvy urban hubs, highlighting unique challenges. Kolkata's consumers also tend to prefer cash transactions. Understanding this interplay between retailer practices and consumer preferences adds depth to the research. The findings could inform targeted government or private-sector initiatives to enhance technology adoption, providing a practical contribution beyond academic merit.

1.10 RESEARCH GAP

Technology adoption is an inextricable aspect of any industry, and its growth relies on it. Technology adoption is not new and can be seen to both organized and very limited extent in the unorganized retail sector.

Extensive literature reviews brought forward couple of interesting points: -

- Although technology adoption is greater in the organized retail sector, it is not uniform across all retail formats. According to the above-mentioned theory, new technology adoption is accompanied by a human behavior theory that considers various factors influencing the success and adoption of new technologies. There is a substantial void in the repository of knowledge regarding the unorganized retailers in India, from the perspective of technology adoption.

- Following the beginning of the pandemic that was caused by the Covid-19 virus, there was a noticeable movement towards the adoption of technology remedies. Given the enormous advancements in technology that are sweeping all around, the research that is being proposed would investigate the various theories that are now being used in the retail sector.
- The research currently in publication has neglected the adoption of technology in India's unorganised retail sector, particularly when considering poor, shallow digital footprints in the Eastern parts of India, including Kolkata.
- There is currently no research demonstrating the applicability of the UTAUT-2 Theory in India's unorganised retail industry. Therefore, from the standpoint of the UTAUT-2 Theory, no research has been conducted on unorganised retailers. No study is available regarding unorganized retailers in Kolkata city and their technology adoption.
- The unstructured retail sector in the Kolkata region has absolutely no research done. Furthermore, no research has been done on the retail technology digital divide in different places within the geography of Kolkata.

The study's target population was divided into six groups (mentioned hereunder) and based on the types of basic unstructured retailers, in Kolkata, that only sell manufactured goods:

1. Grocery / Kirana
2. Medicine / Ayurveda / Homeopathy / Yunani
3. Footwear
4. Ready-made Garments
5. Handicraft and Artisan
6. Electronics

1.11 RESEARCH QUESTIONS

- **Research Question 1:** What determinants affect the technology adoption by unorganised retailers?
- **Research Question 2:** In what ways do format and product category influence the technology adoption process among unorganised retailers?
- **Research Question 3:** What are the attitudes of unorganised retailers regarding technology adoption in their sector?
- **Research Question 4:** What is the incremental financial benefit realised by unorganised retailers from technology adoption?

1.12 RESEARCH OBJECTIVES

- **Objective 1**: To study the factors affecting technology adoption by unorganized retailers
- **Objective 2**: To study the impact of format and product category on the adoption of technology by unorganized retailers
- **Objective 3**: To understand the perception towards the adoption of technology in the unorganized retail industry
- **Objective 4**: To study the marginal financial gain of unorganized retailers in case they are adopting technology.

1.13 SIGNIFICANCE OF THE STUDY

In the year 2023, the retail market in India was estimated to be worth the equivalent of around 952 billion US dollars. 11.4% is the projected CAGR for expansion of the retail segment, which would bring it to a total value of USD 2,542 billion by the year 2032 (Sharma, 2024). The market comprises both organised and unorganised sectors, with the latter still holding a significant share due to the prevalence of small, local shops and informal vendors (Sharma, 2024).

The unorganised retail sector, encompassing traditional stores and local markets, plays a critical role in serving the diverse consumer base across urban and rural areas.Kirana stores account for nearly 75%-78% of all consumer goods sales in India (2023) (Sharma, 2024).

Retailing entails the sale of products and items from a stationary establishment, such as a store, in small amounts for direct customer consumption. India's retail industry is creating jobs as well as contributing to the country's GDP. Unorganised retail plays a significant role in developing countries. Unorganised merchants seek to remain competitive in the market against organised shops (Kesavan et al., 2019).

Traditional unorganised retailing gave rise to the Indian retail business of today. Small retail establishments that operate on a smaller scale with little to no standardisation and sell goods in small numbers within a constrained geographic area. Retail establishments that lack organisation don't use technology or follow procedures. Nonetheless, they have a great deal of room to expand and develop in India (Sangvikar et al., 2019).

The planned study is significant in a number of ways. First of all, the development and prosperity of any industry, including the retail sector, depend significantly on the adoption of technology. The factors influencing the adoption of emerging technologies in the retail industry, particularly in the unorganised sector, will be clarified by this study. It will help identify the challenges that merchants have while implementing emerging innovations and offer solutions.

Secondly, while technology adoption is relatively higher in the organized retail sector, there is a lack of uniformity in its adoption across all retail formats. This research will help identify the formats lagging in technology adoption and provide insights into the reasons for this lag. Thirdly, the research will investigate the human behaviour theory accompanying technology adoption. The outcomes of this research will provide insights into the variables that determine the success of new technologies introduced into the retail industry as well as the adoption of these technologies.

Fourthly, the shift towards embracing technological solutions has become more visible after the onset of the Pandemic due to Covid-19. As a result, this research is crucial and pertinent since it will provide insights on how this global epidemic has impacted the retail sector's embrace of technology. Finally, the study is going to concentrate on retail shops that sell only manufactured goods, such as grocery stores, pharmacies, clothing stores, and shoe stores. Because of this targeted approach, the research will be able to provide extensive insight into the challenges retailers face in these formats and recommend solutions. The planned study is significant because it will add to our understanding of how technology is being adopted in the retail sector, especially in the unorganised sector. It will give the lawmakers and the retailers access to crucial knowledge that will help them make decisions about technology adoption and how it will impact the growth and success of the industry.

1.14 SCOPE OF RESEARCH

The digital revolution also accelerates globalization. Even small businesses should benefit from global acquisitions and seek new clientele from other countries provided by digital advancements, particularly increased interconnectivity (Lituchy & Rail, 2000; Prasad et al., 2001). For specific retailers, increasing digitalization entails a variety of socially sensitive tasks, such as understanding different internet purchasing behavior or adapting online stores to the expectations of socially diverse crowds (Luna et al., 2002; Park & Jun, 2003).

Unorganized retailers are being forced to evaluate and adjust set-up procedures due to the increased disruption of plans of action brought about by digital improvements, and they see new opportunities and challenges (Bartikowski & Singh, 2014; Bartikowski et al 2016). As a result, we define digital transformation as the combination of the digitalization of already simple (administration) activities, methodology, credible errands, and administrative cycles to create an incentive for clients, representatives, and various partners, with the goal of gaining a competitive advantage (Mazaheri et al., 2014).

Digital transformation necessitates a re-evaluation of action plans, including determining whether previous cycles, products, or operations are still necessary and whether new digital options and options could supplant or improve them. Despite universal recognition of the importance of digital transformation, the scientific literature on the topic is extraordinarily splintered, with few connections between fields of study.

An overview of the literature on digital transformation is given in this article, paying specific attention to retailing, retail-facing features of digital advancements, and their crucial planning implications. A plan for productive future exploration in the industry, emphasizing complex advancements, developments, and patterns that retail showcasing executives will look at sooner rather than later by spreading the focus beyond retailing (Evanschitzky et al., 2020).

There is an absolute absence of comprehension of how new multisensory advances may assist with reproducing administration encounters through multisensory portrayal. How clients respond to digital conditions is muddled as to whether they can improve the general client experience. For instance, while it very well might be fun in the principal case to “contact” items essentially utilizing reverse electro-vibration advances, purchasers may quickly rediscover the estimation of genuine actual encounters, reject the previous, and pick the last whenever the situation allows. Also, it is hazy how digitization and the virtualization of item and administration contributions will change the idea of client brand connections (Evanschitzky et al., 2020).

Aside from the more imminent challenges from the research described in this article, digital disruption may have longer-term implications for the retail industry. New commitments to problematic developments and plans of action transformation have examined some of the characteristics that make up interruptions (Müller et al., 2020).

Dr Christensen proposed the interruption hypothesis that disruptors join the market at the low end of the cost and quality spectrum and that the disruption (fundamentally) causes (a few) existing enterprises to be disappointed (Christensen, 2013; Christensen, Raynor, & McDonald, 2015).

Regardless, continual interruptions have occurred without regard for a market’s passing point or the dissatisfaction of officeholders. Another innovation is detrimental if it eventually replaces the officeholder invention and profoundly alters the behavior of most partners, clients, suppliers, and competitors (Müller et al., 2020). As a result, digital disruption alters how clients interact with enterprises seeking to build trust; disruptors may enter the market at any point regarding cost and quality, and incumbent firms may not quit the market but modify their strategy.

Such a plan of action transformation can be fruitful if the redesigned offer is in line with sustained, fundamental changes in client behavior, the transformation isn’t limited to specific parts of the organization but rather the entire organization, and the representatives are viewed as capable change specialists (Rudolph & Schweizer, 2019).

The research focuses on the district of Kolkata. Only the unstructured retailers in the Kolkata district are identified.

- The research will be undertaken in the District of Kolkata, a metropolitan city in West Bengal, India,
- The target demographic of the study is split up into groups according to the kinds of fundamental unorganised retailers.:
  - Grocery / Kirana
  - Medicine / Ayurveda / Homeopathy / Yunani
  - Footwear
  - Ready-made Garments
  - Handicraft and Artisan
  - Electronics

The research methodology and design would include the above-mentioned six types of unorganized retailers in the District of Kolkata. Even among these six types of unorganized retailers, only those establishments that deal with manufactured goods (tangible items) would be considered.

1.15 STRUCTURE OF THESIS

1. **Introduction:** The fundamental framework is described in the opening chapter of the research, including the study's setting, issue statement, research aims, questions, significance, and limitations. This section provides a summary of the topic being examined and outlines the study's contextual structure. The statement gives a general overview of the research conundrum and outlines the main issues. The

research issue and its significance are outlined in the problem statement. The statement clarifies the specific goals of the study and the issues that will be looked at. The specific and quantifiable goals that the research seeks to achieve are referred to as the study's objectives. The study objectives and their relevance to the research quandary are outlined in this section. The specific questions that a research project aims to answer are known as research questions. Research objectives typically influence the formulation of research questions, which in turn directs the study's design.

Given the significance of the study, it is clear that it has the potential to make contributions to both academic and practical fields. The paragraph provides an explanation of the significance of the research as well as the potential impact that the findings could have in the future. The research parameters and the restrictions of the inquiry are delineated by the scope and limitations of the study, which help to delimit the parameters of the research. This research not only elaborates on the potential limitations of the study, but it also provides an explanation of the scope of its coverage and non-coverage respectively.

2. **Literature Review:** The literature review chapter rigorously examines the published research linked to the research subject. This chapter outlines the unorganised retail sector in India, highlights the importance of technology integration in retail, examines the elements affecting the industry's adoption of technology and provides a comprehensive assessment of the existing literature on technology adoption in retail.
3. **Research Methodology:** This chapter's goals are to give an outline of the research design, sampling strategy, sample size, data collection technique, and data analysis approach that was utilised in the study.

4. **Results and Discussion:** The outcomes of the investigation are presented in the chapter titled "Results and Discussion." It includes a study of the factors influencing the adoption of technology in the unorganised retail sector, together with descriptive statistics of the respondents. A discussion of the results obtained: The findings that were presented in the previous chapter is clarified and addressed in this section. The implications of the findings and the significance of those findings for the research problem are discussed in this section.
5. **Conclusion and Recommendations**: A summary of the most important findings from the investigation is presented in this chapter, coupled with a few suggestions derived from the study's objectives. The article includes a brief synopsis of the research findings, a conclusion drawn from the study's objectives, likely implications, recommendations for additional research, and strategies for integrating technology in the disorganised retail sector.

CHAPTER 2

Literature Review

CHAPTER 2

LITERATURE REVIEW

2.1 OVERVIEW OF RETAIL TECHNOLOGY

Our initial understanding prior to this research was that retailers are quick in adopting technology than other entrepreneurs. They are more obsessed with sales tactics, even though advanced technology can aid service delivery. As a result, retailing is seen as a service-oriented industry that is always changing. As a result, market knowledge of developing technologies in terms of emotion, behavioral purpose, and successful gadget use plays a key role in technology selection and adoption (Inman & Hristina , 2017). Retailers can simplify the difficulty of innovating by employing various approaches and tactics (Hopping, 2000). For example, the Concern Breakdown Structure is an effective method for evaluating the risks that are involved. The different sources of dangers are outlined in this structure, which starts with a root node that implies a common problem and then partitions it into deeper levels (Hillson, 2002). Although favoured for precise risk evaluation, The chance-impact matrix delivers a risk evaluation according to the impact's severity and possibilities of occurrence (Pantano & Viassone, 2015). Technology development and innovation management are inextricably intertwined, with studies concentrating on how to conceive, produce, and deploy an innovation based on technological advancements (Shankar et al., 2021). The implementation of cutting-edge technologies at the point of sale improved the system from multiple vantage points is closely linked to the governance of advanced technology in retailing. Numerous methods (such as acceptability models, usability, ethnography etc.) can be used to investigate this (Stieninger et al., 2021). Digitalization has significantly influenced retail (Hagberg et al., 2016). Retailers, specifically organized retailers now access various tools to improve logistics and the consumer experience (Fredriksson & Hagberg, 2023). It has been suggested that retailers who play and invent with these innovations would be the most effective (Grewal et al., 2020). Various technologies that improve the shopping journey and processes in stores have emerged in a recent study, with their distinguishing trait being that they are transparent (Quinones et al., 2023). Just a few examples encompass fit technologies (Chen et al., 2023). The existing literature on retail technology advancements is divided into three categories: offline and internet, consumer and firm viewpoints (Mathur & Mathur, 2019). The study of consumer acceptance of online applications focuses on mobile devices and software (Shekhawat, 2023). TAM in conjunction with one or more additional adoption models, is frequently used in these studies to investigate customers' performance expectations, utility, and attitudes towards the technologies (Davis. et al., 1989). The next phase of research emphasises on retail management strategies to determine the disruptive impact of offline and online technology on retail, especially multidimensional commerce (Hagberg et al., 2016). Despite the continuous evolution of technological advancements and shifting market demands, there is an emphasis on a select number of emerging and prospective innovations (Fredriksson & Hagberg, 2023). Even though technical advancement and market demands are continually changing, they do focus on a few emerging and future new inventions (Kampa, 2024).

However, opinions on how quickly fashion retailers are adopting in-store technology vary. Tracking the dissemination of technology, industry sources accuse retailers of being late adopters of in-store devices, while other academics praise them as innovators. (Briedis et al., 2020). However, there are varied perspectives regarding the rate at which fashion retailers adopt in-store technologies. While some scholars commend these retailers as innovators in tracking technology diffusion, industry sources often criticize them for delayed implementation of in-store advancements (Mukherjee & Wood, 2021). Given the sector's issues, such as changing customer attitudes toward technology and the rapid rate of technological advancement, it's vital to maintain track of retail innovation diffusion progress (Yadav & Pavlou, 2020). Comprehensive understanding of disruptive technologies—encompassing aspects such as emotional impact, behavioral intent, purpose, effort expectancy, perceived risks, and effective gadget usage—significantly influences technology selection and adoption in the retail sector, particularly among unorganized retailers (Suo et al., 2022).

2.2 TYPE OF RETAIL TECHNOLOGY

Businesses all throughout the world were smashed to their cores when the Covid-19 outbreak began two years ago. In order to mitigate this, though, these shifts have brought up some fascinating new advancements in both online and offline retailing. It's crucial to consider how retail technology developments may affect operations of all sizes.

2.3 POINT-OF-SALE AND INTERNET SHOPPING

Nowadays, a lot of stores provide same-day and overnight shipping and delivery choices in addition to BOPIS (buy online, pick up in-store). There are many novel methods to purchase goods, thus point of sale systems need to be updated carefully. What effect does an online purchase have on the physical store's inventory records? Does the number of products available for purchase drop when items are put on hold for customer pickup? Answers to these questions should be readily available in a modern Point of Sale System configuration. The movement in consumer preferences toward online shopping has not been universally successful for businesses. Microsoft has shut down all of its retail stores nationwide. However, retailers who were able to adapt to the changing retail environment, such as Walmart and Target, experienced notable growth. While it is necessary to have the ability to manage transactions both online and in person, it is even more crucial to have a unified and integrated system that interfaces with other technologies the firm uses. The need to synchronise sales, inventory, and promotional data across physical and virtual shopfronts is one of the many challenges faced by software engineers working on point-of-sale (PoS) systems for retail organisations.

2.4 INDOOR NAVIGATION SYSTEM

In order to improve user navigation in enclosed spaces where global positioning system (GPS) signals are either nonexistent or insufficient, indoor positioning systems (IPS) have gained popularity in recent years. The prospective applications of this technology are extensive. Indoor navigation presents significant potential for user orientation, successfully implemented in environments such as retail establishments, offices, airports, and hospitals. This innovation is behind the “HKG My Flight” smartphone app at Hong Kong International Airport. Lowe’s and Target are just two examples of retailers adopting this technique. Integrating in-store navigation technology is a considerable challenge for any retail organisation. Hardware serves as the foundational element. It is crucial to set up the proper network infrastructure, such as ultra-wideband (UWB), Wi-Fi RTT, or Bluetooth beacons. Lighting systems that connect to the internet using Bluetooth IoT are already available in many shops. Customers utilising the Target app on their mobile devices while in-store will have access to a map that precisely indicates their location inside the various departments and products of the store. In this method, the lighting systems above the sales floor of the store were equipped with

Bluetooth beacons. However, depending on the size and layout of the store, a number of options might be available. The next step is to create software that can fully exploit the system when the necessary hardware has been established. Applications for IPS technology go beyond just making selling easier for the retailers. There are three beneficial applications of understanding client purchasing locations within a store: personalised recommendations, foot traffic analysis, and product monitoring. More importantly, customer foot traffic information can help optimize product displays. When they walk into the business, where do customers go? Is there a section of the shop that they frequent more often than others? Which parts of the shop do customers avoid the most? IPS tracking provides the answers to all of these questions. While protecting user privacy with anonymized data is critical, these analytics may prove indispensable for some retailers in determining the best locations for their items. This information might be used as leverage with suppliers to get a better price for shelf space in a high-traffic section of the shop. The radio frequency identification (RFID) technology used to track store merchandise is helpful but has a limited range. When these systems advance, IPS can give shoppers more precise information about where items are on the store's shelves. Not only may this aid in bolstering efforts to safeguard assets, but it can also facilitate the safe return of goods that have been relocated. Even while Internet of Things (IoT) devices are becoming more affordable and smaller with time, their initial use may still be limited to a few high-value items. It can also be used to track personal devices used at work. Retail employees may quickly utilize IPS maps on their work devices to locate an item for duties like order fulfillment. As an alternative, they may use IPS tracking to find the object. If the object has been accidentally relocated, this will come in handy.

2.5 CONSUMERS AND EMPLOYEES AUGMENTED REALITY

By the year 2022, augmented reality in stores will be the standard. Those that don't provide augmented reality experiences, such as virtual try-on rooms, improved in-store AR navigation, and other services, are slipping behind the competition. This important technological development helps bridge the gap between online purchasing and traditional stores. Applications that allow customers to "try before they buy" are some of the most promising uses of virtual reality to aid digital shoppers in the retail sector. Virtual try-on rooms are a great illustration of this kind of innovation. Similarly, they may see the appearance of other things, such as furniture. Store employees may preview shelf placement using an augmented reality gadget before placing products.

2.6 APPLICATION OF ARTIFICIAL INTELLIGENCE IN THE RETAIL SECTOR

So far, AI has been mentioned in practically every single trend that has been explored. Today's augmented reality systems rely on artificial intelligence for scene interpretation. However, artificial intelligence has much more potential applications in the retail sector than this. In 2022, computers and large databases are more important than ever for the retail sector. However, many inefficiencies stemming from mistakes have emerged from these systems' intricacy. For businesses to save time and money, these problems must be resolved. There are several ways in which artificial intelligence might improve the efficiency with which we handle these stocks. Artificial intelligence (AI) may analyze consumer purchasing data to forecast when specific products on the sales floor will see increased foot traffic. Because of this, the system may decide that some regions need more attention than others regarding manual auditing. Auditing the entire company may seem overwhelming, but it is far more effective to concentrate on trouble areas. With this idea, Amazon Go Grocery, powered by Walk Out, goes one step farther. This research made use of deep learning, sensor fusion, and computer vision. Owing to the store's extensive network of cameras and Internet of Things sensors, it is possible to track the exact moment an item is removed from the shelf and added to a customer's shopping basket. When customers leave, the full price of their purchases is automatically charged to their credit cards. An online merchant may track a user's activities while they are there. Their origin, the items they hover their cursor over, and the amount of time users spend on a website. Online marketers that use Google Analytics are familiar with this type of data. But beneath all of this technology sits a powerful artificial intelligence that is faster than humans at finding patterns and relationships.

2.7 DEMAND FORECASTING POWERED BY AI

Some of the most well-known companies in the world rely on this effective method. Many firms were clearly unprepared for the unexpected spike in panic buying that occurred during the Covid-19 pandemic a few years ago. Businesses who were able to quickly adapt to changing consumer preferences and secure supplies of popular goods fared well. Demand forecasting fueled by machine learning became increasingly popular in response to the public's requirements during the epidemic. In this regard, Amazon is just one example of a corporation using machine learning. Technology like this also helps with logistics, production, advertising, and customer and supplier relationship management. Demand forecasting techniques can result in improved sustainability in both consumption and production. When customer demand can be forecast more precisely, just the required quantity may be manufactured and ordered. Approaches based on machine learning for demand forecasting are far more flexible and adaptable than their more conventional predecessors. Because of how rapidly it can be applied, machine learning can better respond to shifting consumer preferences.

2.8 SALES FLOOR ROBOTICS AND AUTOMATED SYSTEMS

Robotics hardware has a close relationship to AI. Delivery, stock control, and client support are just a few areas where this might be useful. Autonomous cars have advanced with AI in recent years. In 2022, autonomous delivery has become the standard, and this trend is expected to continue. Tortoise's autonomous delivery cart for Safeway stores debuted a year ago. Another company developing a delivery robot for Uber is Serve Robotics, formerly known as Postmates X. The importance of Grubhub's successful deployment of autonomous food delivery robots to university campuses, such as Ohio State University, is undeniable. Research has also been conducted on robots for customer service applications. In January of the previous year, Hyundai introduced its robotic assistant for automobile showrooms, DAL-e. The robot may meet and welcome clients and guide them to the perfect automobile. The robot can also recognize the customer's face using AI and facial recognition technology to determine if they are hiding their identity behind a mask and, if so, provide them with helpful guidance on the restrictions around mask use. When regular tools, such as cameras installed on the ceiling or shelves, aren't cutting it, specialized gear might be a huge help in inventory management. Machines like SmartSight can monitor stock levels and inform staff when essential products are running short, eliminating the need for manual inventory counts.

2.9 VOICE TRANSACTION RETAILING

In 2022, natural language processing will catch up to the advancements in artificial intelligence (NLP). Smart assistants such as Alexa, Google Assistant, Bixby, and Siri are continually enhancing their speech recognition and response capabilities. Their customer service competencies in the retail industry have significantly improved. Voice-activated purchasing offers significant potential for discovery from the convenience of one's home, regardless of screen usage. There is a massive market potential for firms to capitalize on since over 77 million American households are predicted to have smart home devices by 2025. Smart mirrors that support augmented reality are only one example of a useful type of consumer IoT gadget. Ensuring these gadgets don't invade people's privacy while providing true value is the most crucial step. It's amazing to see this technology used at retail giant Walmart with their Voice Ordering service. Voice ordering is possible through smart speakers by asking for items to be added to a shopping basket. Then, Walmart associates will be able to retrieve such things.

2.10 ADVANTAGES OF RETAIL TECHNOLOGY

- Retailers benefit greatly from the automation of processes. It decreases expenses, improves precision, shortens processing times, enables prompt decisions, and accelerates customer service.
- Individual shoppers' purchases are analyzed. Analysis of shopping trends informs product expansions and promotions. Loyalty card databases contain client demographics. Retail Technology provides transaction data for the loyalty card. This data can profile customers. It allows for targeted client offerings. All loyalty cardholders from the previous year may get a mail-order catalog. Internet and e-commerce businesses leverage prior purchases to customize their website for each customer by presenting comparable products. They welcome site visitors by name.

- Retail Technology allows consolidated data analysis which determines the impact of promotions, pricing, new items, and packaging changes. Retailers might examine shop layout or merchandising modifications based on category sales, competitive brands, gross profit, and store sales. Innovative product concepts may be tested in the market. Automation data analysis assists the organization in promotional evaluation, core and seasonal product price response, forecasting the impact of new policies, and promotional plans.
- Retailers can communicate well with vendors. Purchase orders, inventories, and sales information are sent across third-party networks. E-commerce is fast and cheap. Retailers can place orders one or two days in advance vs. seven days for paper-based purchases. Store computers provide automation data daily to the back office. So, the retailers can examine each sale and product group. Auto-replenishment occurs. The automated technology collects daily data from each sale, so the following day's supply needs are known. The technology automatically updates the inventory. The products which are low in stock can be immediately re-stocked. Effective communication reduces the delay between placing an order and getting the product.
- With advanced software, retailers can plan, budget, predict, find the best location, and oversee their business. Retailers can use model decision-making, sales forecasting, and data mining techniques. Retailers can utilize GIS. Sociodemographic data, firm transaction data, and analytical methods are utilized to anticipate shop sales.
- IT-assisted transactions are faster, more accurate, and more convenient than traditional retailing.

Online retailing has changed the rules for the outlets. Electronic sales include food, clothes, footwear, music, books, films, cameras, photographic products, computer hardware and software, pharmaceutical items, etc. Banking, insurance, financial services, real estate, stocks and shares, tourism, flowers, entertainment tickets, virtual education, information services, etc. Thus, retail technology is changing goods, processes, organizations, industries, and competition. Today, retail technology has remarkably reached globally.

2.11 LIMITATIONS OF RETAIL TECHNOLOGY

- Retailers utilized Retail Technology to automate finance, payroll, and management accounts. Only a few department retailers can afford electronic POS. The retail industry is greatly fragmented. Retailers spend a lot on technology equipment installation.
- There are a wide variety of things that may be sold in retail. A vast number of product lines necessitate the use of a complicated system.
- Routine automation process investments are quite expensive.
- Retailers have an unacceptably high failure rate when implementing new IT systems.
- Rather than focusing on transformative changes, many merchants, says Prof. John Sawson, are focused on operational ones. It hasn't delivered on its promise of financial gain. Small sums of money are spent on IT by retailers.
- It may take longer to get the full benefits of retail technology. The new mechanisms should be fully exploited by retailers. Investing in well-known retail systems is common, but just a handful effectively leverage consumer data.

Stock replenishment systems based on IT could only be developed by retailers that had made significant investments and had gained valuable knowledge.

- The retail sector has not experienced an enhancement in performance solely from a software perspective. Hardware updates are urgently required.

Table 2.1: Pros & Cons Summary Table

Pro	Citation	Con	Citation
Automation Process	Powell, T. C., & Dent-Micallef, A. (1997); Stieninger, Mark, et al. (2021)	Expensive installations	Gregory, J. (2015); Naeem, M., Ozuem, W., & Ward, P. (2022)
Customer Database & Shopping Patterns	Anderson, J. L., Jolly, L. D., & Fairhurst, A. E. (2007); Nica, Elvira, et al. (2022)	System Complexity & regular upgrades to match the technology market	Kalakota, R., & Whinston, A. B. (1997); Tidd, J., & Bessant, J. R. (2020)
Retailer & Customer Feedback – contributes to technology marketing and upgrade strategies	De Marco, Alberto, et al. (2012); Piotrowicz, W., & Cuthbertson, R. (2014); Bag, Surajit, et al. (2021); Alzoubi, H. et al. (2022)	Need for up-to-date technological training and knowledge with every upgrade	Morrison, B., Coventry, L., & Briggs, P. (2021); Kang, H. Y. (2022)
Allows effective communication between retailers and vendors to reduce the delay in re-stocking the inventory	Rowley, J. (1996); Goel, R. (2007); Chuang, H. H. C., Chou, Y. C., & Oliva, R. (2021)	Routine Maintenance and upgrades are expensive; Retailers avoid customized technology as per their needs; they go with what is famous in the market	Gupta, S., & Ramachandran, D. (2021); Kopalle, Praveen K., et al. (2022)
Intelligent Analytics provides a forecast for better	Cao, L. (2021); Awan, Usama, et al. (2021); Gupta, S., &	High Failure Rates	Kapuria, P., & Nalawade, H. S. (2021); Aminova, M., & Marchi, E. (2021);

Pro	Citation	Con	Citation
business decisions	Ramachandran, D. (2021)		Gong, T., Wang, C. Y., & Lee, K. (2022)
E-payments make transactions transparent	ELMS, D. (2021); Adeogun, C (2021); Khan, F., Ateeq, S., Ali, M., & Butt, N. (2021)	Developers only focus on operational improvement and hardly consider transformational improvements	Sovacool, B. K., Monyei, C. G., & Upham, P. (2022); Sneader, K., & Singhal, S. (2021)
Online Retailing has set up a systematic and easy shopping experience for both customers and retailers	Kim, Y. (2021); Kircova, I., Saglam, M. H., & Kose, S. G. (2021); Jiang, Y., & Stylos, N. (2021)	Only software upgrades will not upgrade the system. There is a compulsory need to upgrade both hardware and software together	Sookoo, A., Garg, L., & Chakraborty, C. (2021); Endres, H., Huesig, S., & Pesch, R. (2022)

As more sophisticated options become available, retailers are replacing antiquated inventory management software, point-of-sale systems, and other technologies. Nonetheless, significant delays are prevalent throughout such transitions. Occasionally, certain gaps and unforeseen events necessitate more attention. More significantly, these new systems must be managed to ensure they are a good fit for the organization (Pantano E. , 2014). The relationship between a retailer and the vendor creating new technology is crucial to its successful implementation in retail. Whether the technology is designed to help the business perform its responsibilities more efficiently or to help the customer directly, the product's success will depend on how well the team works together to create and maintain the solution.

2.12 RETAIL TECHNOLOGY ADOPTION

The use of technology in retail has increased dramatically since the Covid-19 contagion. Numerous conventional retailers have been compelled to shut down as a result of the contagion. Instead, they are now using more technologically advanced ways of conducting business, like click and collect, online ordering and fulfilment, and robot-assisted operations.

During the pandemic's outbreak, others with immediate access to data would have an advantage over others with less recent data and would even make better investment choices during a time when buying trends were radically shifting from week to week, if not day to day (Akram et al., 2021). Given the rapid rate at which technology is altering the retail industry, experts in the field are trying to get a handle on the full scope of the changes (Goswami & Chouhan, 2021). Retail companies and their supply chain partners are increasingly using cloud computing, which is a dispersed network of servers for data hosting, processing, and management (Goswami & Chouhan, 2021). Retailers of all sizes may take advantage of cloud computing since it is becoming less expensive, more scalable, and more secure than ever (Goswami & Chouhan, 2021). Cisco defines the Internet of Things (IoT) as an Internet-like structure for remote locating, sensing, and operating the components with real-time data/information flows between them: "a system of uniquely identifiable and connected constituents (referred to as" Internet-connected constituents ") capable of virtual representation and virtual accessibility" (Ng & Wakenshaw, 2017). . Synthetic intelligence is the driving force behind many innovations (AI). Artificial intelligence further complicates changes to the retail environment with these new technologies. The influence of these technologies on retailing is not well understood since there is a lack of in-depth evaluations and frameworks (Chu et al., 2024).

2.13 RETAIL TECHNOLOGY ADOPTION GLOBALLY

The retail sector is one of the many that has benefited from the fast growth of digital and automated technology (Skarbez et al., 2021). From point-of-sale to inventory control, fulfilment, and physical store infrastructure, retail technology includes advancements and digital solutions throughout the retail and e-commerce value chain. Technology in stores has become more important to the satisfaction of shoppers. Investing in various forms of retail technology is a common practice for both traditional stores and their virtual counterparts. Smart mirrors and automated checkout systems are just two examples of AI-enabled retail technology products that are now available. Online merchants have benefited greatly from retail technology in a number of ways, including the ability to offer a seamless shopping experience across several channels and customer relationship management (CRM) tools (Pantano E. , 2014).

In the last ten years, management, strategy, and information technology have paid greater attention to information standards. Information standards outline how organisations share and use data, allowing firms to collaborate more effectively (Ashraf et al., 2014).

Information standards guarantee interoperability throughout value chains (Adama & Okeke, 2024). The retail industry has seen a significant transformation, with supply-side and demand-side data becoming increasingly crucial and other capabilities and capacities frequently contracted from the market. This movement has resulted in a dramatic shift (Saarijärvi et al., 2024). Retailers, wholesalers, and manufacturers used to be more linked and coordinated. As a result, we have argued in this study that both the potential long-term effects of information standards on the power dynamics and structure of the retail value chain, as well as the significance of information standards in establishing the standards for information sharing and inter-organizational collaboration in the retail industry, must be understood by participants in the market. Therefore, we encourage retail research by expanding the scope of the retail literature beyond analysing the ways in which specific technologies impact different actors throughout the retail value chain. We specifically take into account the sector-level effects of information standards, especially the increasingly intricate systems of standards that are today run by numerous standard-setting organisations and consortia, as well as consultancies and technology suppliers throughout the globe.

The incorporation of technical advancements and various customer convenience considerations, particularly the transition from unorganised to organised merchants, are causing significant changes in the business model of the retail industry. According to a study, Dr. Harikrishnan found that new technologies have a number of effects on unorganised retailers and that they serve as catalysts for customers to switch from unorganised to organised stores (Harikrishnan et al., 2024).

2.14 RETAIL TECHNOLOGY ADOPTION IN INDIA

India's retail environment is distinct. With more than 12 million retail locations of all shapes and sizes, a large portion of it is in the unorganised sector. Nearly ninety-six percent of these stores are smaller than 500 square feet. India has the most outlets worldwide, with around nine per 100,000 people (Kesavan et al., 2019). Shopping centres' ability to provide value to customers was accelerated by the pandemic, which forced them to adopt new tactics and embrace online shopping. Sixty percent of retail expenditure occurs in these lower-tier cities, which are vital to business-to-business (B2B) e-commerce firms like ShopX and Udaan, said Anurag Mathur, partner & head - consumer & retail Business, Strategy8, part of the PwC network. Tier 2 and 3 cities had a triple-digit increase in online sales, while metro areas saw less than 2% growth. Tier 2 and tier 3 cities have attracted five times as many investments in retail infrastructure as metro areas, according to Mathur's remarks at the Phygital Retail Convention 2021 in Mumbai. It is anticipated that social commerce in India will reach $18 billion by 2025, contributing to the $104 billion in online retail sales in India as a whole (Chawla et al., 2024). The unorganized retailer market is still dominated by Kirana stores, which are widely distributed throughout the nation. These retailers are still dealing with difficult problems and tumultuous times due to the recent epidemic and the development of technology. Retailers have recognised the value and significance of developing strategies for utilising technology to communicate with and reach customers during these challenging times (Tabeck, et al., 2022). The retail industry has seen significant changes as a result of numerous recent technological advancements. The emergence and growth of the new economy have released powerful forces that have successfully and quickly changed the retail industry. Today's retailers run the danger of losing consumers if they don't offer a consistent and easy shopping experience across all platforms. The entire ecosystem of modern retail is technologically advanced. Businesses can experiment with a wide range of new tactics through technology, such as smart shelves, in-store services, interactive displays, home delivery, supply chain optimisation, logistics automation, and brand optimisation. Wallets, point-of-sale data, and social networking are sites where grievances and compliments can be sent directly. The merchant is responsible for all the apps customers use to try on the goods, learn more about them, and ultimately make a purchase. The retail industry's heavy hitters have welcomed new technologies with open arms, using them to their full potential to attract and retain consumers and grow their businesses. Small businesses have been slower to adopt technology in order to stay up with the quick changes in the market and advancements in technology, particularly those in the unorganised sector. Since 80 percent of India's retail industry is unorganised, its adoption of technology would provide the Indian economy with the necessary impetus and usher in a new era for the sector. Technology is the saviour that will bring success to the retail industry. In 2018, the term "Experiential Retail" became a buzzword. It became the buzzword of the day, whether it was presented through in-store features, quick access, ATL and BTL animation, or innovative fusion of the digital and physical worlds of shopping. Technology is capturing consumers' attention in both real and virtual retail environments. In the past, retail meant merely a storefront; now, thanks to technological advancements, consumers can shop multi-channel around the clock, comparing items and pricing online, posting reviews on social media, and even connecting online. People have developed strong attachments to their electronic devices. Customer service and in-store transactions are simplified by technological advancements, leading to operational excellence. Our company's success is predicated on the loyalty of our customers, and because of improvements in the speed with which merchants can respond to consumer comments and resolve customer questions, we can better nurture and keep these vital relationships. Online and offline stores now offer nearly identical customer service thanks to technological advances. SPAR India has implemented several technological solutions throughout our retail locations to serve our customers better.

2.15 RETAIL TECHNOLOGY ADOPTION BY STRUCTURED RETAILERS

In India, where the organized retail industry is still maturing, just a handful of companies are attempting to forge a new standard. The retail sector in India needs major investment from domestic and international firms to develop into a successful business.

Additionally, a number of challenges faced by organised retailing are highlighted (Rajesh, 2015). Compared to FY 2022-23's growth rate of 7.0%, real GDP (gross domestic product) is predicted to expand by 8.2% in FY 2023-24. Real GVA (gross value added) grew by 7.2% in 2023–2024 as opposed to 6.7% in 2022–2023. Real GDP, or GDP at Constant Prices, is expected to reach ₹173.82 lakh crore in 2023–2024, compared to the First Revised Estimates (FRE) of GDP for 2022–2023 of ₹160.71 lakh crore. Real GDP (Gross Domestic Product) is expected to expand at an 8.2% annual pace in 2023–2024, up from 7.0% in 2022–2023. In 2023–2024, nominal GDP, or GDP (Gross Domestic Product), at current prices is projected to reach ₹295.36 lakh crore, up from ₹269.50 lakh crore in 2022–2023, indicating a 9.6% growth rate. With a growth rate of 7.2% compared to 6.7% in 2022-23, real gross value added (GVA) is projected to reach ₹158.74 lakh crore in 2023-24, compared to the FRE of ₹148.05 lakh crore in 2022-23. With a growth rate of 8.5%, nominal GVA (gross value added) is predicted to reach ₹267.62 lakh crore in FY 2023–24 compared to ₹246.59 lakh crore in FY 2022–23 (Bureau, Govt of India, 2024).

India's retail sector is impressive, with a market size of over 10% and a fourth-place ranking globally. By 2027, the market is anticipated to have grown at a compound annual growth rate (CAGR) of more than 13% from its 2022 valuation of an incredible INR 91,891 billion (Sharma, 2024). Urban Indian consumers' purchasing power is increasing, and branded goods in sectors like attire, cosmetics, watches, footwear, beverages, food, and even jewellery are increasingly gaining traction with them for both their personal and professional use. By 2032, the retail industry in India is projected to be worth an astounding US$ 2 trillion, according to a recent analysis by the Boston Consulting Group (BCG Report, 2024).

In 2023–2025, it is anticipated that around 60 shopping centres with a combined retail capacity of 23.25 million square feet would open. India is among the best locations for retail real estate investments. As it enters the second phase of growth in the Indian market, Swedish furniture maker Ikea was looking to expand with a range of retail formats as of September 2023, in addition to starting online operations in Delhi-NCR by the end of 2024. To finance expansion, pay off debt, and be ready for the conglomerate's retail business's IPO, Reliance Industries is probably going to sell an additional 8–10% of its interest in Reliance Retail Ventures Ltd (RRVL). The finance minister claims that at a CAGR of 45%, the total volume of digital payments increased from 2,071 crore in FY 2017–18 to 13,462 crores in FY 2022–23. Between April 2000 and December 2023, US$ 4.56 billion in foreign direct investments were made in India's retail trading sector (Report, 2024).

India's retail sector is expected to increase at a rate of 9% between 2019 and 2030, from $779 billion in 2019 to $1,407 billion by 2026 and over US$ 1.8 trillion by 2030, according to Kearney Research. By the end of 2025, the direct selling market in India is projected to be worth $7.77 billion USD (Report, 2024).

2.16 RETAIL TECHNOLOGY ADOPTION BY UNSTRUCTURED RETAILERS

Unincorporated companies owned and operated by private citizens or households make up the unorganised sector. These companies are not legally separate from their owners, who are personally liable for all debts and obligations and raise capital at their own risk. Family members and casual workers without official contracts are frequently employed by informal companies. Traditional low-cost retailing types include paan or beedi shops, convenience stores, owner-manned general stores, local kirana shops, pavement and hand cart vendors, etc. Without a doubt, the majority of sales in India occur through unorganised retailers, also referred to as kirana stores, as approximately 96% of the retail industry is unorganised (Kesavan et al., 2019). Retail establishments that lack organisation don't use technology or follow procedures. Nonetheless, they have a great deal of room to expand and develop in India (Sangvikar, et al., 2019). Structured and unstructured merchants must adopt digital technologies and e-commerce methods to bridge the digital divide; small-format businesses may draw in more customers. Their creditworthiness has begun to gradually improve due to the growing use of digital payments.The gradual digitisation of unstructured retail enterprises includes digital/online payment systems, apps to manage business processes (inventory, billing, finance), and a potential collaboration with the e-commerce industry (Venkateswarlu & Kotni, 2022).

Unstructured retail stores like Kirana, footwear, readymade garment shops, and small pharmacy stores are cash-based, tiny convenience businesses in residential areas. A purchase at a store is considered “risk-free” since the buyer gets the opportunity to examine the merchandise and the service before committing to either (Singh et al., 2023).

Part of the reason for the ongoing popularity of unstructured merchants is that they are easily accessible to locals (Narang & Tiwari, 2024). Unstructured retail shops, which are specific businesses that are often family-run and satisfy emergency, fill-in, and stock-up requirements, account for a significant part of India’s food retail industry (Singh et al., 2023). However, most Indians still shop at unstructured retailers, rather than BigBasket and Blinkit (Kumar & Singh, 2023). Unstructured retailers face severe competition from supermarkets and other organized food retailers as their market expands (Narang & Tiwari, 2024). Unstructured retailers were the "new supermarket" during the COVID-19 shutdown, changing from their earlier iterations. Even though greater numbers of people shopped online as a result of the lockdown and coronavirus mitigation measures, e-commerce suffered greatly since it was not considered an essential service (and hence could not carry goods) and because of other problems, such as last-mile logistics (Karthik & Selvabaskar, 2023). Independent merchants may protect themselves against cybercriminals by moving their sales and activities online. Getting more customers who are tech savvy is difficult for unstructured retail stores since they are typically not equipped to handle internet orders (Bhardwaj & Srivastava, 2023).

Specifically, this study addresses how local merchants might be enticed to embrace digital tools and become part of the burgeoning e-commerce sector. It delves into unstructured retailers and other unorganized retailers' dominant role in India's retail industry and worries about the widespread adoption of new technologies. It also analyses how public and commercial organizations have contributed to the digitalization of unstructured retail shops. Finally, the report suggests that unstructured retailers adopt digital strategies by putting either the "phygital" (combining the digital and physical; where brick-and-mortar stores accept digital payments, manage store operations digitally, and have an online presence) or convergence (collaborations between large retailers, unstructured retailers, and e-commerce platforms) models into practice (Karthik & Selvabaskar, 2023). The digitalisation of unorganised retail enterprises in emerging markets positively influences the socio-economic conditions of subsistence consumer-merchants, who simultaneously fulfil the roles of consumers supporting their families and managers of micro-unorganized retail businesses. Innovations in sustainable company models facilitate socio-economic developments similar to those observed in unorganised retail sectors within rising Asian countries (Mukherjee & Wood, 2021).

2.17 TECHNOLOGY ADOPTION DURING THE PANDEMIC

Retail innovation is still not well studied, despite the fact that constant change has long been recognised as a fundamental component of commerce and that its current acceleration is unmatched (Mukherjee & Wood, 2021). The potential application and deployment of wearable gadgets in experiential retailing has recently generated huge attention in the retail industry (Goswami & Chouhan, 2021). As a result of this predicament, questions regarding how the effects of digital technology have irreversibly transformed sectors arise (Akram et al., 2021). Reduced market entry barriers, disintermediation of established suppliers, access to a global digital labor pool, and consumer empowerment through knowledge and new distribution channels are all potential implications (Bharti et al., 2022).

All facets of society have been negatively impacted by COVID-19, but unorganised shops have been particularly hard hit. An extended unplanned lockdown had a significant negative impact on the Indian economy in terms of containing the virus's spread (Narang & Tiwari, 2024). This lockdown period had a major effect on the unorganised retail industry. The scope of the Covid-19 pandemic's global spread and its immediate impacts on our daily lives, politics, business, and health cannot be overstated (Kapasi, 2021). The unplanned total shutdown, transportation system failure, and rising debt collection negatively impacted the unorganised retail sector's profitability in India (Tabeck, et al., 2022). As everyone has seen, the unexpected total shutdown and the serious transportation system failure resulted in a sharp decline in the number of customers visiting retail establishments. As a result, both organised and unorganised retail segments found that technological change and acceptance were crucial. In nations with more mobile penetration, changes were less noticeable (Auer et al., 2023).

In India, the COVID-19 epidemic has had a profound impact on tiny and unorganised firms, causing long-lasting changes in how they use technology. These changes are especially crucial for comprehending how companies, such as those in the unorganised retail sector of Kolkata, have adapted to new possibilities and problems. The pandemic forced many small businesses to adopt digital solutions to stay afloat. According to research, the crisis acted as a catalyst for digital transformation, as businesses shifted to digital payments, e-commerce platforms, and online customer engagement tools (Dun & Bradstreet, 2021; BusinessToday, 2024).

This aligns with findings from this research, where retailers in certain sectors, like electronics and ready-made garments, were more willing to embrace digital tools as part of their survival strategy. Despite this, widespread adoption remained slow, particularly in sectors where traditional practices dominate, such as kirana stores and handicraft businesses (Sadiq et al., 2020). The post-COVID recovery of small businesses in India has highlighted the urgent need for increased technological infrastructure. While some businesses have bounced back with improved digital capabilities, the overall recovery in employment and establishment growth in informal sectors, like those in unorganized retail, has been slow (Mehrotra, 2024). Many small retailers continue to face barriers such as limited access to credit, technology, and digital tools, which affects their long-term ability to integrate new technologies into their operations. This underscores the need for continued policy intervention to support digital upskilling and infrastructure development for small retailers (Dun & Bradstreet, 2021). Although there was an increase in technology adoption among small businesses, many still struggle with financial constraints and lack of awareness regarding the full benefits of technology. Studies show that small businesses in India are particularly hindered by factors such as poor internet access and high costs associated with adopting digital solutions (BusinessToday, 2024). These findings were evident in the Kolkata unorganized retail study, where only a fraction of retailers reported a clear understanding of how technology could benefit their operations beyond basic digital payments. The post-pandemic recovery efforts highlight the importance of targeted government support for MSMEs and small businesses, including subsidies for digital tools, training programs, and better access to finance (Dun & Bradstreet, 2021). In Kolkata, this support could bridge the digital divide, providing small retailers with the tools they need to enhance efficiency and compete in an increasingly digital marketplace.

2.18 SUMMARY OF THE REVIEW OF LITERATURE

Table 2.2: Summary of Literature Review and Research Gaps

Sr. No.	Authors	Research Design	Context	The gap in the Literature
1	Pantano & Viassone, (2015)	Cross-sectional, qualitative, observations	Acceptance and spread of technology among a variety of merchants on a shopping avenue	Focused on organized retail only
2	Andreu et al., (2010)	Review of Literature	Market understanding of their position in the process is still minimal, even though retailers recognize the importance of customers in the process	Consumer attitudes about the adoption of new technology are disregarded.
3	Adhiarna et al., (2011)	Literature review	RFID uptake and spread in poor nations	Firm-level analysis

Sr. No.	Authors	Research Design	Context	The gap in the Literature
4	Tsai et al., (2010)	Cross-sectional, Quantitative	Effects of innovation, organization and supply chain integration on RFID retail adoption in Taiwan	Firm-level analysis
5	Cao et al., (2018)	Longitudinal, (8 years), Quantitative	Retailer cross-channel integration from the perspective of innovation diffusion	Firm-level analysis
6	Tao et al., (2018)	Cross-sectional, Qualitative	Consumers' perceptions and adoption intentions of fashion subscription service retailing	Customer-centric analysis
7	Natarajan et al., (2017)	Cross-sectional, Quantitative	Uses TAM and DOI theory to propose a new model orientated to the intention to use mobile apps for shopping	Customer-centric analysis
8	Jahanmir et al., (2018)	Cross-sectional, Quantitative	Determinants of late adoption of digital innovations by consumers	Customer Level
9	Lee, (2014)	Cross-sectional, quantitative	Factors influencing early adopter smartphone adoption	Customer level analysis
10	Goodell, (2020)	Cross-sectional, quantitative	Studied the impact of the new normal business environment	Customer level study

Sr. No.	Authors	Research Design	Context	The gap in the Literature
11	Dehghani et al., (2020)	Cross-sectional, Quantitative	Studied the impact of AI on retail business	Firm level study
12	Wood et al., (2020)	Cross-sectional, Quantitative	Studies of the new normal distribution channel	Firm level study
13	Pagano et al., (2021)	Cross-sectional, Quantitative	To what extent does social distancing impact in-person shopping?	Customer level study
14	Mishra et al., (2021)	Semi-Structural Qualitative interview	Unstructured retailers' technology adoption in India results in non-adoption	Types of Unstructured retailers are not explored
15	Adhikary et al., (2021)	Literature Review	Financial gain with the adoption of POS technology in unstructured retailers	Other retail technologies not explored
16	Ram et al., (2022)	Cross-Sectional Quantitative	E-Payment adoption in Unstructured retailers in India	Need for low-cost retail technologies for small retailers
17	Tabeck et al., (2022)	Literature Review	Technology adoption for unstructured retail business transformation in India	Only Kirana stores are considered, and other small retailers are neglected
18	Kumar et al., (2022)	Cross-Sectional Quantitative	E-payment systems adopted by Unstructured retailers in India using the TAM model	Vulnerabilities, risk, and security training towards technology adoption not addressed
19	Kapuria et al., (2021)	Qualitative Literature Review	Based on TAM, Kirana stores and internet grocery businesses were compared.	Only one sector of small retailers explored
20	Choudhary et al., (2022)	Qualitative Research with Thematic Analysis	Mapping the emergence of Low-Cost e-commerce technology	Non-E-commerce low-cost retail technology not explored

Sr. No.	Authors	Research Design	Context	The gap in the Literature
			adopted by small Kirana stores in India	
21	Kakar, (2021)	Descriptive Statistics	Comparing modest Kirana stores with other small companies that provide electronic payment methods amid the pandemic lockdown in India's four largest cities	Small towns and small rural retailers were not taken into consideration; only point-of-sale systems were investigated
22	Koul, (2021)	Cross-Sectional Quantitative research analyzed using SEM	Adoption of M-commerce in Indian Suburban small retailers using the UTAUT model	Only M-commerce was explored, and other retail technologies neglected
23	Kannan, (2021)	Literature Review	M-commerce adoption in Structured vs. Unstructured retailers in Inda, Unstructured fall behind	No other retail technologies were considered for comparison
24	Gupta et al., (2021)	Literature Review	Structured vs. unstructured retailers' technology transformation based on customer response and product-centric	Practical approach not considered, which may change the outcome of the paper
25	Khaled et al., (2021)	Cross-Sectional Quantitative	The fast transition of technology adoption for operational purposes in the Indian retail industry	Retailers' perspectives are not considered; only metro cities are considered; Sub Urban and rural retailers not considered
26	Aithal et al., (2022)	Qualitative	Small retailers may become more competitive if they	Eight factors affecting technology adoption in small

Sr. No.	Authors	Research Design	Context	The gap in the Literature
			implement technology more widely	retail businesses have been identified
27	Ram et al., (2022)	survey based	Automation technologies in retail are very useful and effective for unorganized retailers	The text does not mention any specific gaps in the literature
28	Ram and Selvabaskar, (2022)	survey based	More technology should be developed by the unorganised retailer's payment platforms, aggregators, and digital marketing apps to help them manage their inventory and vendors and help them establish a reputation among their customers	Focusses on how unorganised sellers use social media, online markets, and payment networks.
29	Sehgal et al., (2022)	a case study	Local retailers, now enhanced by technology, can better service their customers than previously	How much of the retail industry is made up of unorganised retailers?
30	Ram et al., (2023)	survey based	Unorganised retailers use business-related mobile applications	A new framework for unorganised shops to embrace mobile applications is suggested in the paper

Retailers' perceptions of their use, for instance, are likely to be influenced by individual experiences, risk tolerance, and service provider support. However, the little study done in the organised retail sector found that conducive conditions and use context were important determinants because of India's high scores in the unorganised retail sector (Bharti et al., 2022). Factors such as individual experiences, risk tolerance, and the support provided by service providers are critical in shaping retailers' perceptions of technology usage. From the Indian context, the unorganized retail sector has a massive domination; the facilitating conditions and the specific context of use have emerged as decisive factors, as demonstrated by findings from significantly limited studies conducted and that too focussed on the organised retail sector in India (Narang & Tiwari, 2024).

To summarize the review table, India's retail industry has undergone a massive transformation during the pandemic lockdown. The retailer has little experience implementing technology, as seen by the paucity of real-world surveys and interview techniques. Compared to the metro's and certain large cities' rapid adoption of technology, the difficulties faced by small retailers in suburban and rural India are not examined (Gupta et al., 2023).

2.19 TECHNOLOGY ADOPTION MODELS

For decades, retailing has been marked by constant transition, which has aroused scholarly attention with the development of various hypotheses that seek to model and forecast retail change (Hollander, 1960). Foundational studies on the evolution of institutional change in retailing, such as the "wheel of retailing" and the "retail accordion," have sparked research on the factors driving and trends in retail model innovation (Hart, 1999). Understanding whether technologies are implemented is important for innovation theory and practice (Mostaghel et al., 2022). The theory of reasoned action (TRA), TAM the technology readiness index (TRI) and the unified theory of acceptance and use of technology (UTAUT) have all been influenced by DOI theory (Venkatesh et al., 2003). Diffusion is "the mechanism by which an innovation is embraced by persons, communities, or organisations throughout time," according to

DOI, while invention is "a thought, method, or item that is judged novel by a person or another unit of adoption" (Rogers, 1995).

According to Alexander & Kent (2021), there are three types of emerging technology adoption: macro, domain, and market/industry. Many research experiments concentrate on determining the causes and probability of customer acceptance of emerging technical technologies (Alexander & Kent, 2021). To determine the factors influencing the intention to utilise cross-border QRIS, the TAM, UTAUT2, user system trust theories (perceived trust and perceived security), and financial literacy are merged (Bestari & Dony, 2024).

2.20 TECHNOLOGY ADOPTION IN RETAILING: THEORIES

Retailers embraced new technology by guessing how much customers would use it and how managers would acquire precise data for projecting future demand patterns (Parasuraman, 2000). As a result, one crucial area of research concentrated on consumers' acceptance of contemporary technology rather than the efficient implementation or adoption by businesses and employees (Shekhawat, 2023). Businesses might embrace innovation in one of two ways: either to prepare for or react to environmental changes (Gopalakrishnan & Fariborz, 1997). The productivity of businesses may be impacted by retail technology, and new technologies are always being created (Heins, 2023). Innovation in technology encompasses new concepts, plans, actions, or outcomes of new goods for the industry or the general public (Grossova, 2023) (Christensen et al., 2013). The adaptation of retailers and consumers to innovative, disruptive technologies is examined (Metcalfe et al., 2023). Process innovation is the main connection between these different types of innovation. Aggregation level can be used to categorise innovation. Enhancement at the individual level, process adaptation or refinement at the functional level, product and service innovation, new business models at the organisational level, and technological advancements as innovation systems at the industry level are all examples of how innovation can appear (Edquist 1997). The diffusion of innovations, grounded in sociology and psychology, examines the adoption and execution of novel inventions (Yadegari et al., 2024). The most recognised and frequently utilised theories and models of technology adoption. These theories were established to analyse human technology adoption and to illustrate their ability to assimilate new technology, grounded in the principles of behavioural sciences from psychology and sociology, along with their consequences on technology utilisation. These hypotheses have developed over the years and have sprung from one another. Following is an overview of the 14 most significant and widely known theories: The TPB was developed into the Decomposed Theory of Planned Behaviour, and was an extension of the TRA (1988) (Yadegari et al., 2024). Information systems contributed to the development of the Technology Acceptance Model (1989), which is an extension of the Technology Readiness Assessment; TAM has a further extension, TAM2 (Venkatesh et al., 2003). In addition to the combined form of TAM and TPB (C-TAM-TPB), we also provide TAM and TPB separately. UTAUT is the extension of TAM and is further extended to UTAUT-2 (Venkatesh. et al., 2012). Several scientific and social fields have generated the Model of PC Utilisation (MPCU), Innovation Diffusion Theory (IDT), Motivational Model (MM), and Social Cognitive Theory (SCT), which are also reviewed (Emon, 2023).

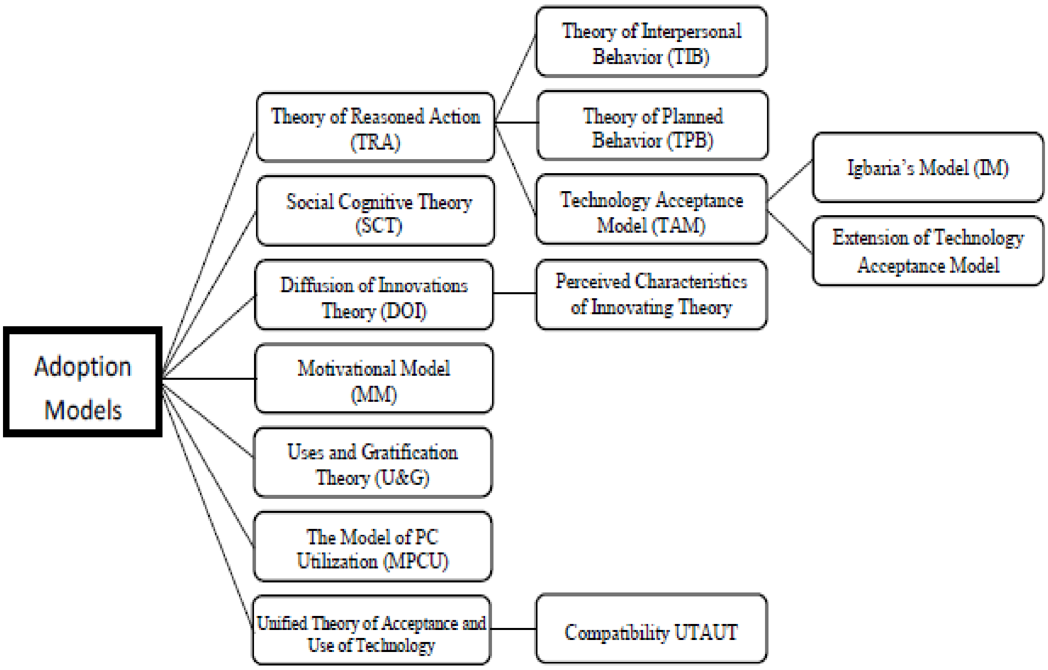

Figure 2.1: Overview of Adoption Models: Created by Researcher

2.21 THEORY OF REASONED ACTION (TRA)

One of the most widely applied ideas is the Theory of Reasonable Action (1988). It concerns a factor that influences an individual's intention to behave depending on their perceptions of that behaviour. "Belief" was described as a relationship between an object and some attribute, "attitude" as a person's evaluation of an item, and "behaviour" as a result or objective. Emotional in nature, attitudes are based on assumptions about the behaviour's object (e.g., POS payments are convenient). The second component is the individual's subjective norms about how they believe their local community feels about a specific retail industry activity.

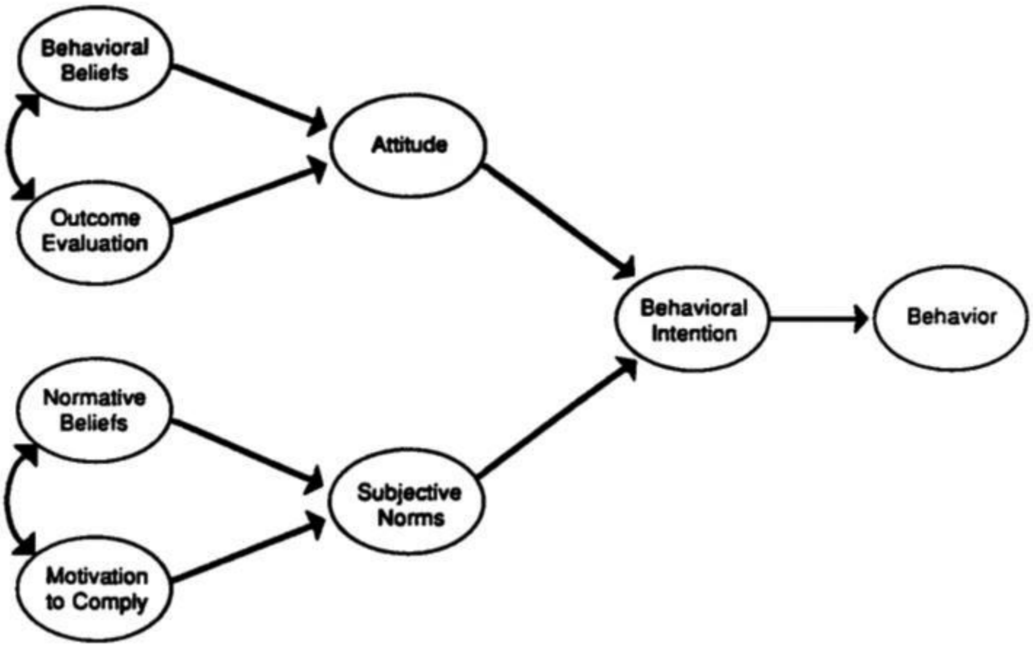

Figure 2.2: The Theory of Reasonable Action (Ajzen & Fishbein, 1988)

An individual's attitude towards behaviour is what defines their good or negative thoughts (evaluative impact) about carrying out a particular activity (Ajzen & Fishbein, 1988). What the majority of people who care about a person think about whether or not he should engage in a particular activity is his subjective norm. There is a connection between normative views and subjective norms. This suggests that if someone feels pressured to do something because they believe most people around them do it, they will be subject to social pressure. To sum up, a variety of academic disciplines employ the Theory of Reasoned Action (TRA). This researcher ultimately concluded that there were several problems with this concept. TRA is limited as it assumes that actions are fully controlled by will, according to (Irimia-Diéguez et al., 2023). This assumption does not consider that systemic restriction may influence people’s actions. The Theory of Reasoned Action (TRA) is widely applicable, according to (Davis. et al., 1989). TRA is a broad model that does not describe the active beliefs for a given activity. Researchers utilizing TRA must first identify subjects’ views about the conduct under examination (Yadegari et al., 2024). Ajzen & Fishbein (1988) added the variable "perceived behavioural control" to his preexisting TPB in order to solve these limitations. The Theory of Planned Behaviour posits that an increased impression of behavioural control in an agent correlates with a higher likelihood of intending to act on the matter (She. et al., 2024).

2.22 THEORY OF PLANNED BEHAVIOUR (TPB)

As depicted in Figure 2-3, Ajzen & Fishbein (1988) Theory of Planned Behaviour focuses on a component that defines a person's behavioural intentions based on their attitudes about the behaviour in question. The initial two components are congruent with those in the Theory of Reasoned Action. The third factor, perceived control behaviour, pertains to the extent to which customers believe they can regulate their actions (e.g., "Am I able to apply for a QR code for UPI payment, and what are the prerequisites?").

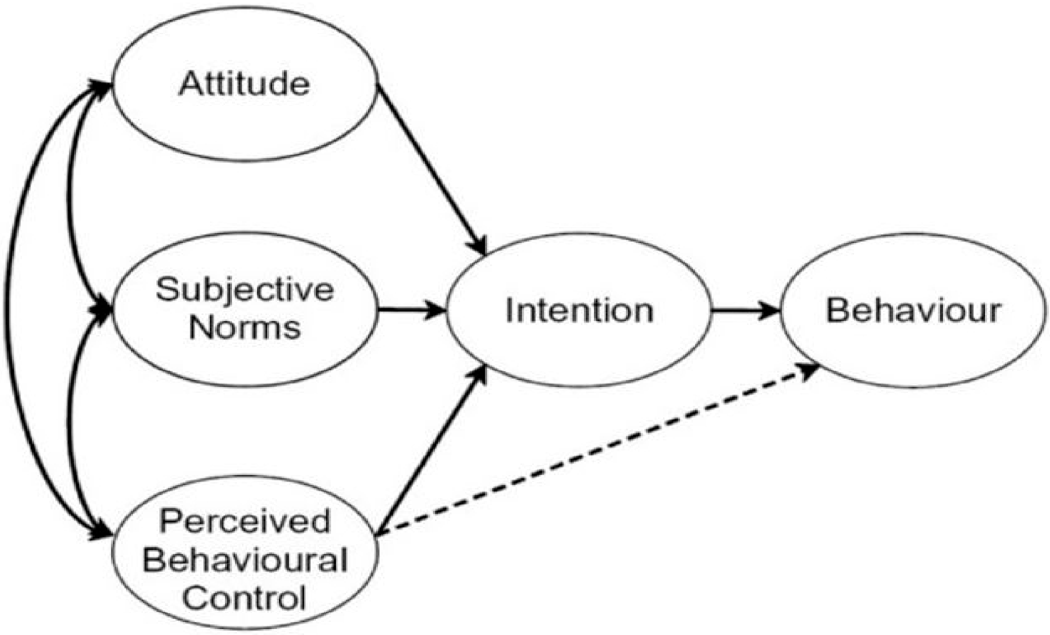

Figure 2.3: The Theory of Planned Behaviour (Ajzen, 1991)

According to Venkatesh et al., (2003) (2012) the Theory of Planned Behaviour (TPB) included the concept of perceived behavioural control into the TRA. The TPB posits that perceived behavioural control serves as an extra predictor of intention and activity. According to the paradigm of the Theory of Planned Conduct (2023), attitudes, subjective norms, and perceived behavioural control forecast intention, which then forecasts behaviour. It is expected that background traits, such demographics, will influence conduct through the three determinants and the objective. Prior to the activity, attitudes, subjective norms, and perceived behavioural control all contribute to the explanation of the behavioural purpose. A trustworthy predictor of behaviour is the purpose. Theoretically, perceived behavioural control is also a measure of the capacity to overcome barriers and the skills needed to exhibit the behaviour. Thus, it is assumed that perceived behavioural control directly affects behaviour—the actual conduct results in feedback regarding the behaviour's expectations. The Theory of Planned Behaviour posits that consumers make decisions by assessing the costs and benefits of many options and choosing the one that optimises their expected net gains. In 1985, Fred Davis proposed the technology acceptance model (TAM). It investigates the mediating function of performance expectancy and perceived usefulness in the relationship between system attributes (external variables) and the likelihood of system utilisation (an indicator of system success). Davis has offered an updated version of his model: TAM2. It encompasses subjective norms and was evaluated using longitudinal research methodologies. Collectively, they account for around 40% of the system's utilisation. The analysis of empirical studies utilising the Technology Acceptance Model (TAM) indicates that the findings are neither entirely consistent nor unequivocal. This indicates that crucial variables are omitted from the models (Legris et al., 2003). Taylor and Todd's study suggests that organisations should account for users' levels of competence when developing and implementing IT systems, as less experienced users tend to depend more on different factors, such as perceived utility, compared to their more experienced counterparts (Yadegari et al., 2024). The hypothesis is depicted in the figure 2-4 as a structural diagram.

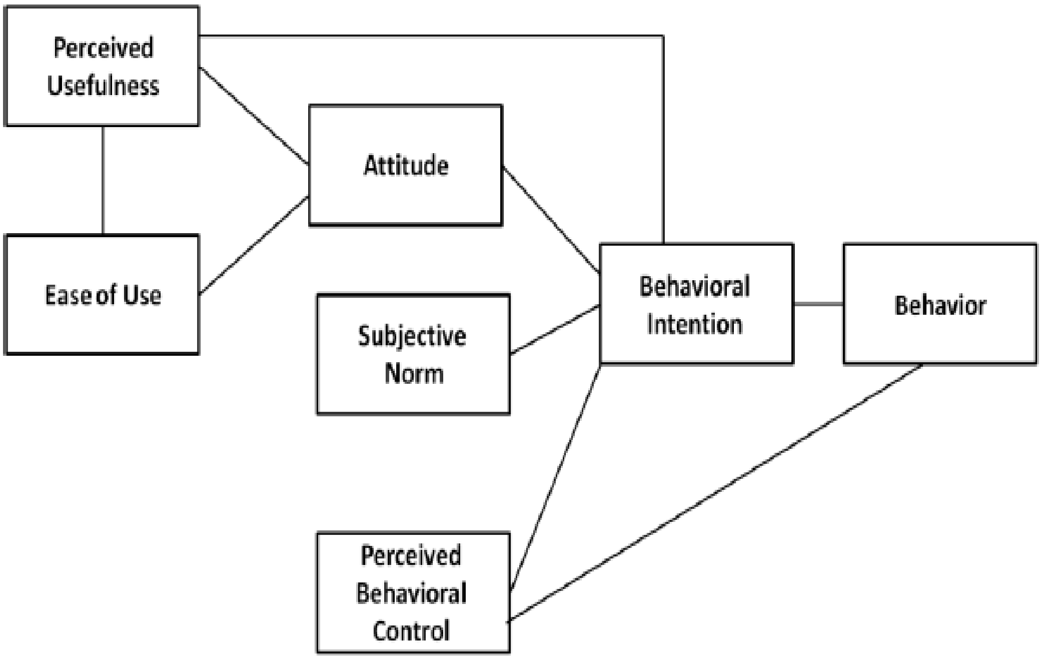

Figure 2.4: Combined TAM-TPB (Thompson et al., 2006)

The fundamental premise of the theory of reasoned action (TRA) and the theory of planned behaviour (TPB) is that individuals engage in rational analysis of their actions and the resultant consequences (decision-making) (Ruiz-Herrera et al., 2023). The concept of planned behaviour centres on actions and intentions. The concept of Planned Behaviour is categorised as one of the 'rational decision models' in specific contexts; nonetheless, the application of the system is necessary. The users lack the option to utilise the system.

2.23 DIFFUSION OF INNOVATION (DOI)

An efficient methodical framework for explaining the acceptance or non-adoption of new technology is the theory of innovation adoption and dissemination. Diffusion happens gradually within a market (a system of users) when potential users share knowledge and opinions about new technology through communication channels (Rogers, Diffusion of innovations, 1995). In this way, users get a personal look at emerging technologies. The first step in Rogers' five-stage adoption process is knowledge. Persuasion, decision (whether to accept or reject new technology), implementation, and confirmation are the final four stages. According to this perspective, non-adoption could be interpreted as the outcome of an unsuccessful adoption procedure. According to Rogers, a variety of factors (such as the intended user's own limitations) and outside obstacles (such as ineffective communication channels) could make the adoption process less successful (Rogers, 1995). The goal of the diffusion theory of innovations is to explain how, why, and how quickly new concepts and technology proliferate throughout societies. The communications cover new ideas, making it a special kind of communication. The four essential components of innovation dissemination are time, social structure, communication routes, and innovation itself (Rogers, Diffusion of innovations, 1995). Several factors influence how quickly an invention is adopted, according to Rogers. Relative advantage, compatibility difficulty, trial ability, and absorbability account for 49% to 87% of the range in adoption rates. The figure depicts the factors influencing the rate at which new ideas are adopted (Rogers, 1995).

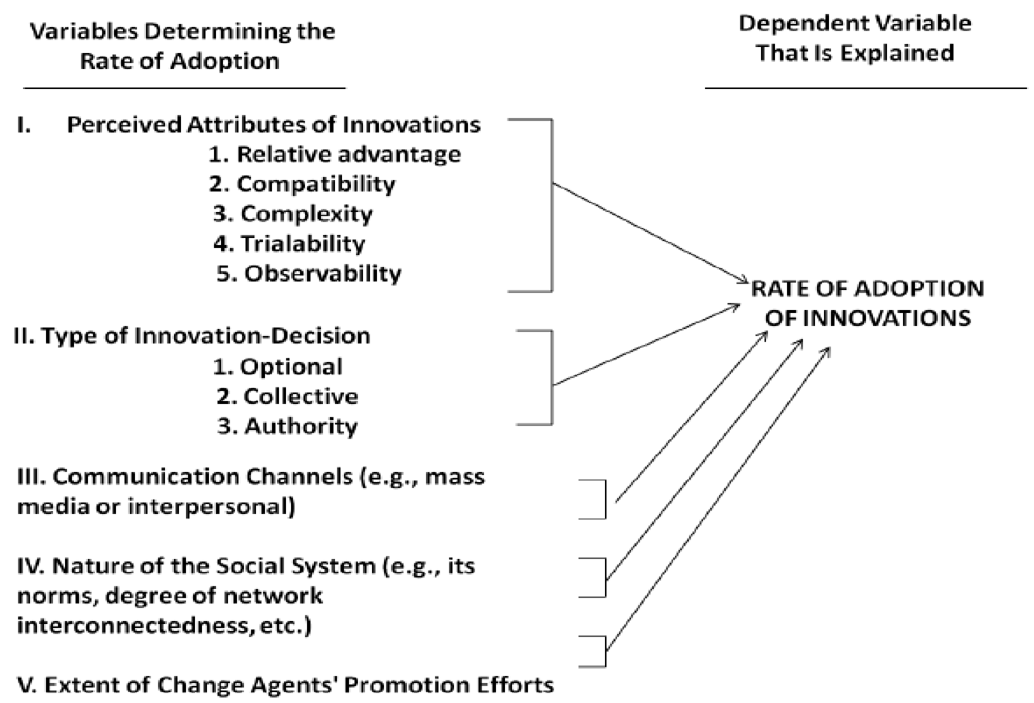

Figure 2.5: Variables Determining the Rate of Adoption Innovations (Rogers, Diffusion of innovations, 1995)

By concentrating on a single idea or product and ignoring other factors like socioeconomics or societal norms, DOI theory generally has a tendency to oversimplify matters. However, according to Yadegari et al. (2024), numerous research have been conducted on using the diffusion model to predict how people and organisations would behave. The Diffusion of Innovation (DOI) Theory applies to businesses, not to people (Yadegari et al., 2024).

2.24 DECOMPOSED THEORY OF PLANNED BEHAVIOUR (DTPB)

As per Kanimozhi & Selvarani (2019) three major factors that affect behaviour intention and actual behaviour adoption are attitude, subjective norms, and perceived behaviour control, according to the Decomposed Theory of Planned Behaviour. She. et al. (2024) studied the TPB and Decomposed TPB for the adoption of technology. Though they took into account the opinions of the community, the TRA, TPB, and Decomposed Theory of Planned Behaviour were primarily applied to items that were already on the market. This model uses the relationship between ideas, attitudes, intentions, and behaviour to explain user behaviour. Although the goal is thought to be the best indicator of behaviour, this model also includes attitudes, subjective standards, and the sense of behavioural control (Yadegari et al., 2024). DTPB focusses on factors that influence behavioural outcomes, including attitudes, subjective standards, and perceived behavioural control. The three elements of attitude in this paradigm are perceived utility, usability, and compatibility, which are taken from Rogers' diffusion of innovation theory (Rogers, Diffusion of innovations, 1995). "The extent to which [an] invention is perceived as congruent with existing values, prior experiences, and future consumer demands" is what is meant by compatibility (Rogers, Diffusion of innovations, 1995). Compatibility is frequently cited as a factor in determining one's outlook. This Model is based on these two theories. Chen et al., (2023) found that compatibility is an antecedent of attitude among perceived utility, Performance expectancy, trust, and perceived service quality in a study aiming to identify the major success determinants for online retailers. The more compatible an online store is, the more likely it is to be adopted. Furthermore, compatibility influences attitudes on the acceptability of the internet as a tool (Yadegari et al., 2024).

2.25 TECHNOLOGY READINESS ASSESSMENT (TRA)

Critical Technology Elements (CTEs) are technologies that are essential to the operation of a system, and a TRA is a methodical, metric-based procedure and accompanying report for evaluating CTE maturity. The Department of Defence Technology Readiness Assessment Deskbook, 2003 (TRA). The TRA evaluates the level of progress made in the field of technology. This is neither a graded assignment nor is it meant to serve as an evaluation of the technology's creators or the development program's efficacy (Mankins, 2009).

What a TRA can do

- Determine what information and processes are needed to get the technology up to the level of readiness necessary for successful inclusion in the project and where testing, demonstration, and knowledge gaps exist.
- Recognize vulnerable technologies that require more oversight from upper management or more funding for research and development.
- Identifying essential technologies that have been proved to work or emphasizing immature or untested technologies that can result in higher project risk, can raise the openness of management choices.

The Technology Readiness Level (TRL) scale was developed by NASA in the 1980s and is now used by TRAs to assess the development stage of technologies. TRL of technology reveals its level of development. The TRLs' significance in the context of DOE-EM initiatives is illustrated in Figure 1 below. The TRL scale goes from 1 (basic concepts observed) to 9 (very advanced) (the total system used successfully in project operations). There is no correlation between TRL and the quality of a technology's implementation in a design (Mankins, 2009).

However, the outcomes of the tests performed on the technology are crucial in establishing the TRL. The right conditions must be met for testing, and the technology used in the experiment must be of sufficient size and detail. Definitions and specifications for TRL testing terms like "scale," "system fidelity," and "environment".

2.26 MODEL OF PC UTILIZATION (MPCU)

As per Thompson et al. (1991) interpersonal behaviour is the foundation of the Model of Personal Computer Use (MPCU). According to an IS perspective, the Model of PC Utilisation can be used to forecast the uptake and use of personal computers (PCs). The authors choose to exclude behaviour intention from the MPCU model since it assesses actual behaviour, such as using a computer. In addition, habits aren't factored in because their link to current usage is tautological in the context of PC use (Seibold & Roy , 1979). The MPCU examines the direct behavioural effects of mood, task difficulty, perceived consequences, ease of use, social pressure, and job fit. Significant predictors of PC use were complexity, long-term consequences, social repercussions, and job-related features. Despite being a trustworthy predictor of behaviour, routines have not been included in MPCU (Thompson et al., 1991). In addition to the relationships in this framework, other factors that influence behavioural intention and conduct include favourable conditions, pertinent arousal, and an individual's assessment of the traits of subjective culture (Yadegari et al., 2024).

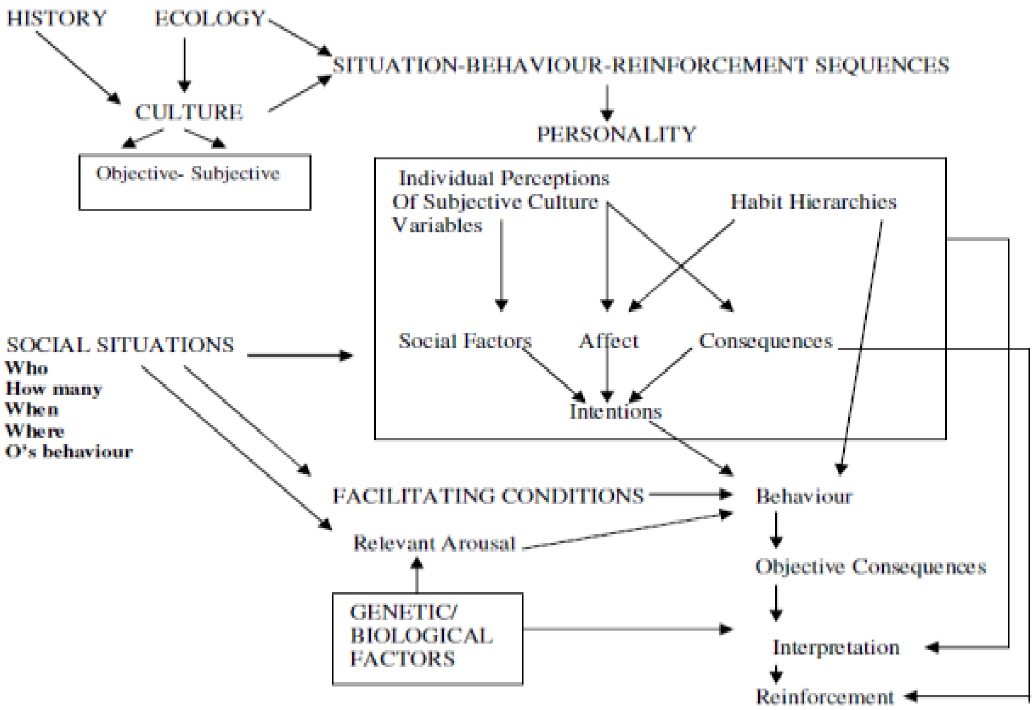

Figure 2.6: Triandis' framework (Seibold & Roy , 1979)

Because of its features, this theoretical model can be used to predict how many information technologies will be adopted and used by specific consumers. The MPCU Figure demonstrates that the following factors influence PC usage behaviour: people's attitudes (affect) towards PC use, social norms surrounding workplace PC use, general computer usage habits, expected consequences for individual PC use, and the degree of facilitating conditions available at work to assist using PCs (Seibold & Roy , 1979). Due to measurement issues, the authors excluded the habit variable and concentrated on user conduct (actual) rather than intention (predictive).

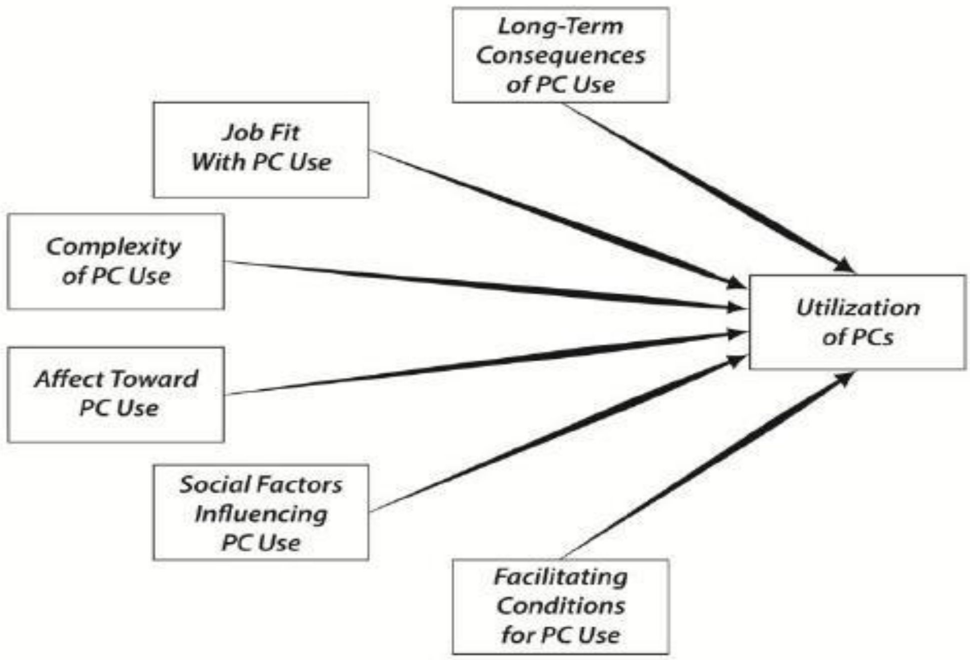

Figure 2.7: Model of Personal Computer Utilization (Seibold & Roy , 1979)

The MPCU model has faced criticism about its effectiveness as a theoretical framework for elucidating and understanding computer usage behaviour in voluntary contexts. The limited explanatory power (24%) is the primary disadvantage of employing this model (Seibold & Roy , 1979).

2.27 INNOVATION DIFFUSION THEORY (IDT)

Rogers (1995) sociologically informed theory has been employed to analyse recent advancements in the field since the 1960s. The diffusion of innovations (DOI) model, a prominent framework in information systems and technology literature, elucidates the process by which consumers acclimatise to new technologies. Rogers differentiated between the diffusion and adoption processes due to their essential role in the theory's emphasis on the dissemination of innovation throughout society at both individual and organisational levels. (Rogers, 1995) Adoption is defined as "the decision to fully utilise innovation as the optimal course of action," while diffusion refers to " the process through which an invention is spread via specific channels over time among members of a social system." The innovation-decision process, innovation characteristics, and adopter characteristics are all included in the DOI/IDT theory as essential components to clarify the barriers and enablers of technology adoption and dissemination. Knowledge, persuasion, choice, execution, and confirmation are the five steps in the model of the innovation-decision process Figure 2-8 (Rogers, 1995). Rogers et al. (2014) proposed categorisation of individuals into five groups according to their rate of acceptance of new technologies: innovators, early adopters, early majority, late majority, and laggards.

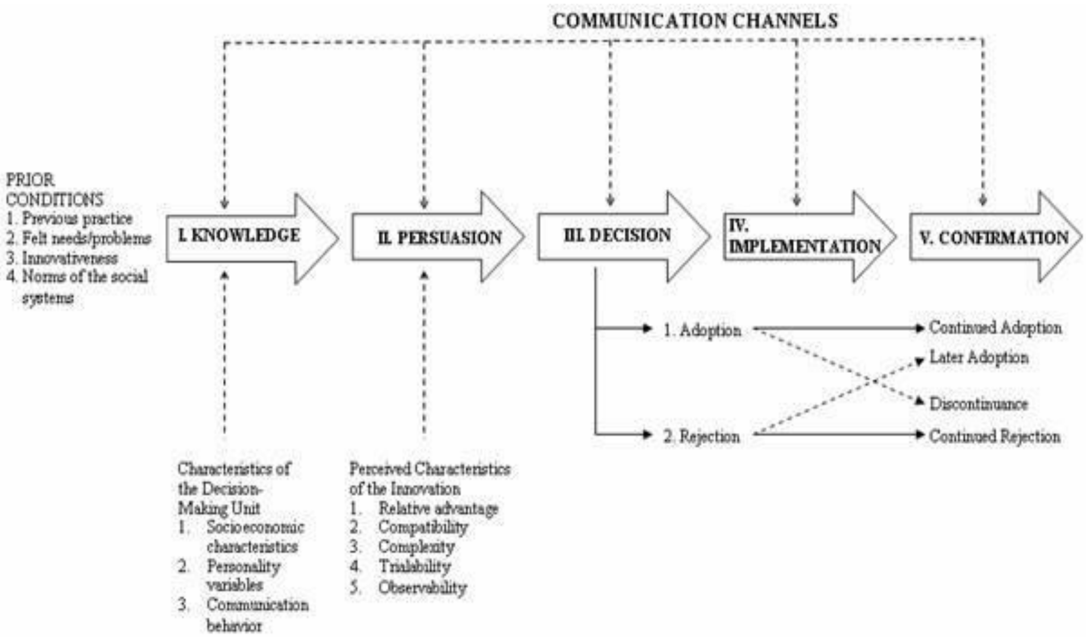

Figure 2.8: A Model of Five Steps of the Innovation-Decision Process (Rogers et al., 2014)

Advantage, compatibility, intricacy, observability, and try-ability are some of the specified qualities of innovations. Moore & Izak (1991) added an expanded set of factors pertaining to people's adoption of technologies in order to modify Roger's qualities for usage in the IT/IS setting.

These factors include of people's readiness to utilise the technology, its accessibility, its perceived worth, and its performance expectations. The hypothesis was used with an eye on the dissemination of IT across communities. The theory offered by DOI/IDT is only partially comprehensive in terms of cultural significance. Academic study may also need to take the social context into account in order to improve the usefulness of DOI theory.

2.28 MOTIVATIONAL MODEL (MM)

According to Davis et al. (1989), many psychological theories are grounded in studies of intrinsic motivation. Self-Determination Theory (SDT) posits that the self-determination process is a fundamental aspect of human functioning, involving the experience of decision-making, the availability of options, and the act of choosing (Deci & Ryan, 2008). According to Deci et al., (1991), the regulatory process is a discretion when factors dictate an individual's behaviour outside the individual's control. The motivation hypothesis has been studied extensively, and variations on it have been developed to explain various human behaviours in different settings. The Motivation Model (MM) literature argues that people's actions are driven either by internal or external factors. The impact of social factors on a person's motivations was another topic covered by SDT. Deci et al. (1991) propose that a tertiary component (i.e., motivation) must be recognised to comprehensively elucidate individual behaviours beyond the two generally accepted kinds of motivation (intrinsic and extrinsic). Davis

(1989) Expanded the Motivational Model to the domain of Information Technology, expanding upon the research of Deci et al., and demonstrated that both extrinsic and intrinsic motivations significantly influence individuals' intentions for their IT usage behaviour. The model established by Davis et al. differentiates between extrinsic and intrinsic factors affecting PC utilisation in the workplace (Davis. et al., 1989). Instances of extrinsic motivation encompass a computer's perceived usefulness (PU), peer approbation (subjective norms), and the perception of its ease of use (PEOU). An affirmative correlation between enjoyment and perceived usefulness of the information system indicates that enjoyment substantially influences intention when the system is regarded as more beneficial. In other words, individuals are becoming more receptive to the advantageous IS due to its enhanced delight.

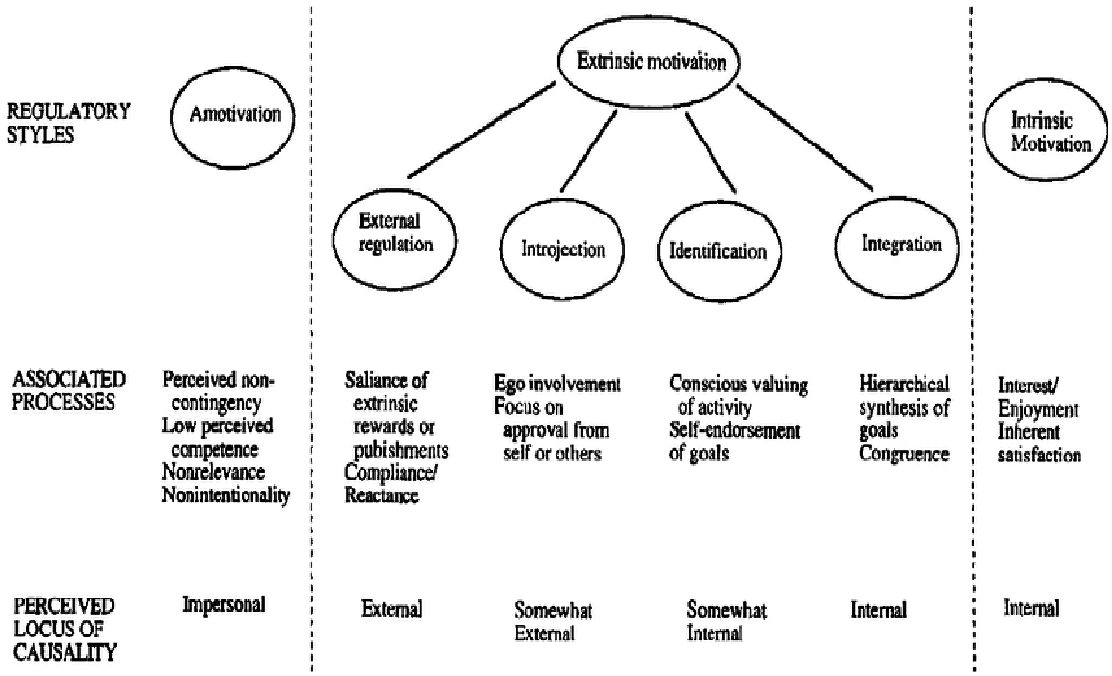

Figure 2.9: Self-Determination Theory "Taxonomy of Human Motivation (Ford & Nichols, 2019)

2.29 SOCIAL COGNITIVE THEORY (SCT)

Numerous explanations have been proposed over the years to elucidate the developmental changes individuals undergo. These theories vary in their interpretations of human nature and their viewpoints on the essential causes and mechanisms of human motivation and action. Bandura formulated the Social Cognitive Theory (SCT). The SCT characterises human conduct as a triadic, dynamic, and reciprocal interaction among personal characteristics, behaviour, and the environment. This concept posits that each of the three elements distinctly influences an individual's behaviour. The SCT upholds the behaviourist principle that the consequences of responses influence behaviour, yet contends that cognitive processes predominantly regulate actions prior to their manifestation. Thus, the implications of a response to an action are employed to establish expectations regarding its results. The ability to formulate these expectations allows individuals to anticipate the consequences of their actions prior to their implementation. Furthermore, the SCT posits that the majority of the behaviour is replicated.

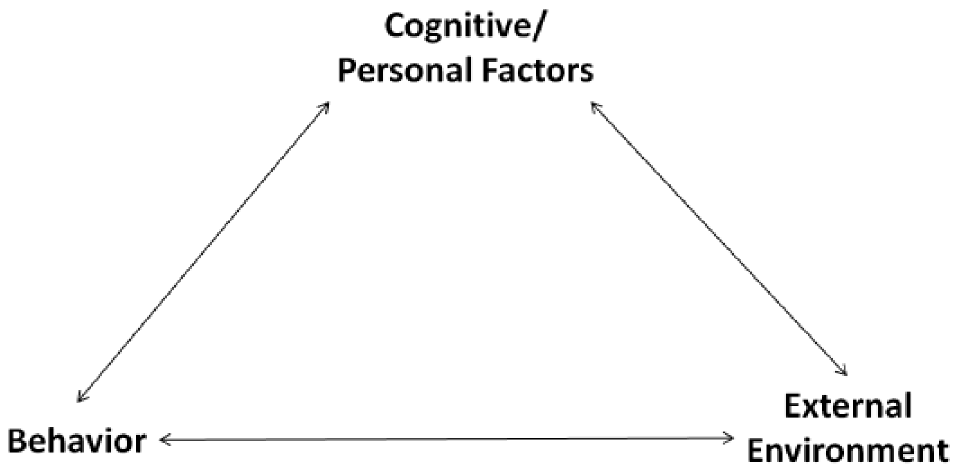

Figure 2.10: Social Cognitive Theory (Bandura, 2003) (Wood & Bandura, 1989)

Social Cognitive Theory (SCT), according to Venkateswarlu & Kotni (2022), is one of the most influential human behaviour theories. The SCT consists of five essential constructs: result expectancies, performance, personal expectations, self-efficacy, affect, and anxiety. (Venkatesh. et al., 2012). Compeau & Higgins (1995) defined result expectancies performance as the performance-related outcomes of an action. Performance expectations are concerned with job-related outcomes. The effect is defined as a person's preference for specific conduct (e.g., computer use) (Venkatesh et al., 2003). Igbaria & Juhani (1995) describe computer anxiety as the propensity for an individual to feel unpleasant, apprehensive, and phobic about the present or future computer use in general. Numerous research domains, including human functioning such as career choice, athletics, organisational behaviour, and mental and physical health, have made use of Social Cognitive Theory (SCT). It has been used to classroom behaviour as well as motivation, education, and achievement. Although the Social Cognitive Theory (SCT) offers innovative concepts of self-efficacy, experience, study time, training, and social impact—later used as subjective standards—the theory is difficult to generalise. Although SCT can be used as a general framework to extend its ideas and structures to a specific model and objective, putting the theory into practice is extremely difficult. As previously said, SCT is not a theory designed specifically for examining human behaviour in particular contexts. But because of its universality and scope, it may be used generally to a variety of areas, such as computer use, Internet use, and leisure. The dynamic interplay between an individual, their conduct, and their surroundings forms the foundation of social cognitive theory. It is unclear whether of these factors has a greater influence on actual behaviour and to what extent. It is possible to extend the notions of social cognitive theory, but implementing the theory itself is extremely challenging. Moreover, this viewpoint relates more to education and motivation.

2.30 THEORY OF TAM – TECHNOLOGY ADOPTION MODEL

There has been much research on the Technology Acceptance Model (TAM), which was developed with the original objective of forecasting Internet user behaviour based on four important constructs: performance expectancy, perceived utility, mood, and behavioural intention (Davis. et al., 1989). All of these constructs influence the attitude that reflects the subject's evaluation of the system and the behaviour that follows. Performance expectancy is the extent to which a participant thinks that utilising a specific system would be easy, and perceived usefulness is the extent to which a participant feels that using a specific system would (Pantano & Loredana, 2012). TAM is founded on the TRA, which posits that A person's attitude towards a conduct and subjective norms, which show how much other people's opinions affect their behaviour, affect their intention to engage in that behaviour (Ajzen & Fishbein, 1988). Acceptance of particular technologies by retailers, such self-service technologies (Yadegari et al., 2024). Consequently, previous research used the traditional TAM method, designing expanded models that add more variables capable of explaining better the reasons to implement a given technology, considering the various technologies examined. Pantano & Loredana, (2012) categorised the extensive array of potential constructions into four primary categories: technological safety and cost, and individual consumer characteristics.

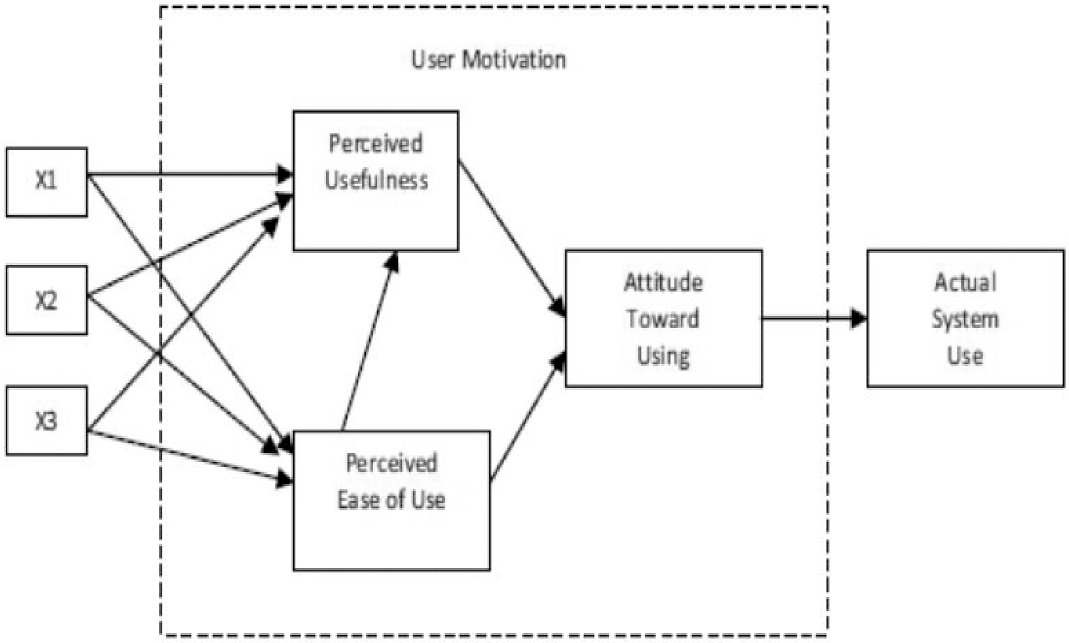

Figure 2.11: Original Technology Acceptance Model (Davis F. , 1986)

In 1989, the computer usage activity depicted in the graphic below was explained by Davis using TAM. TAM aims to clarify the basic factors that affect user behaviour across a wide range of user demographics and end-user computer platforms (Davis. et al., 1989). First, perceived utility and ease of use (PU and PEI) were the main focus of the TAM model (PEU). The subjective likelihood that a particular system (such as a single platform e-payment system) will enhance the potential user's action is known as perceived utility, while performance expectancy is the extent to which the potential user thinks the target system will be simple (Davis. et al., 1989). Other outside factors, referred to as external variables in TAM, may have an impact on an individual's belief in a system.

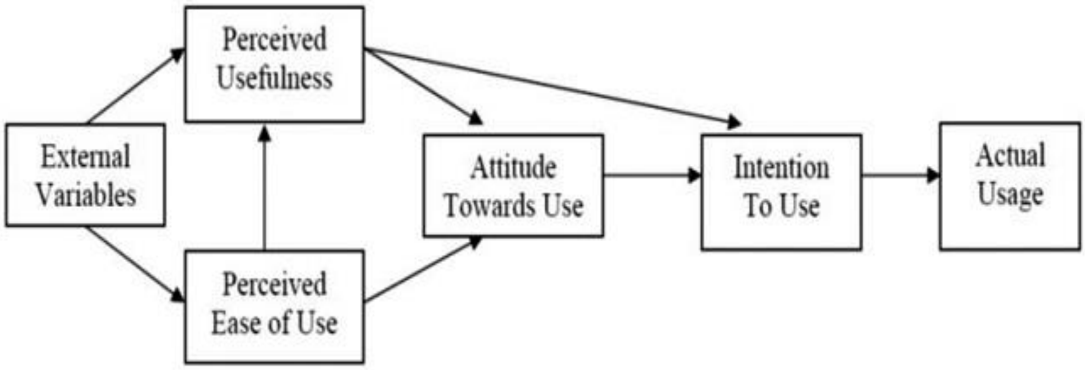

Figure 2.12: First modified version of the Technology Acceptance Model (TAM) (Davis F. , 1986) (Davis. et al., 1989)

As seen in Figure 2-12, created the final iteration of the Technology Acceptance Model after realising that behaviour intention was directly driven by perceived utility and ease of use, negating the need for an attitude construct (Davis & Venkatesh, 1996).

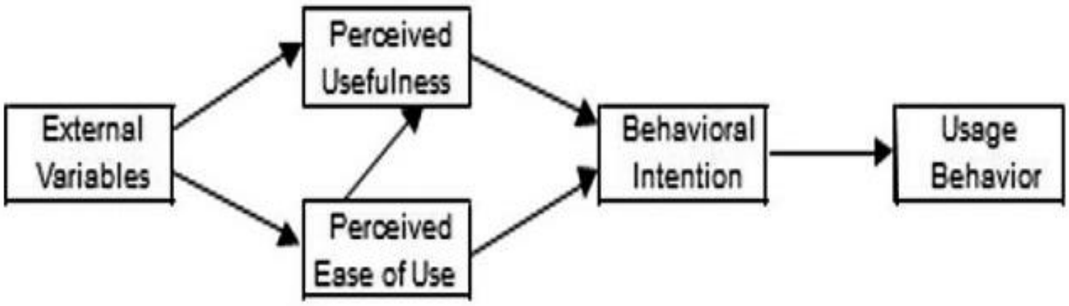

Figure 2.13: Final version of the Technology Acceptance Model (TAM) (Venkatesh and Davis, 1996)

2.31 TAM-2

The TAM 2 suggested by is seen in the figure 2-13 (Venkatesh & Davis, 2000). The current research examined the factors that led consumers to believe that a particular system was beneficial at three different times, one month after the launch and three months later. Based on their subjective evaluation of how well work-related objectives match the system's ability to assist them in achieving those objectives, users form opinions of a system's usefulness (Venkatesh & Davis, 2000). The research showed that TAM 2 performed well in both the obligatory and optional settings.

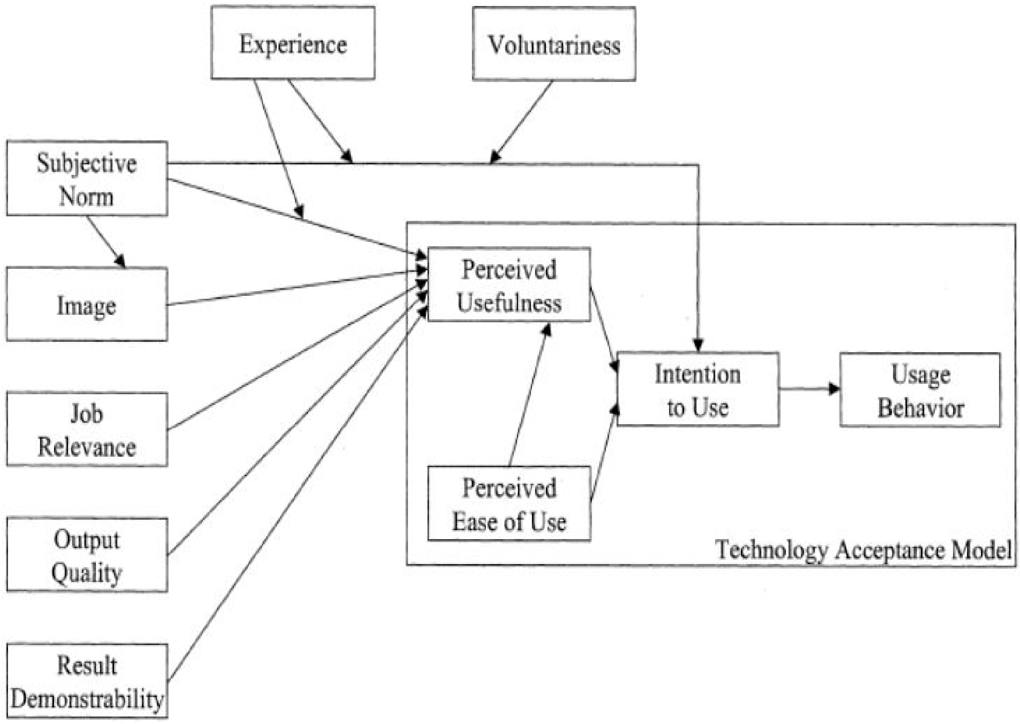

Figure 2.14: Technology Acceptance Model (TAM 2) (Venkatesh & Davis, 2000)

2.32 TAM-3

Venkatesh & Bala (2008) incorporated the TAM2 Model of technological acceptance and built an integrated model known as TAM3 seen in the figure (Venkatesh & Davis, 2000). The authors developed the TAM3 using four unique categories of variables related to perceived utility and performance expectancy: individual differences, system characteristics, social influence, and facilitating conditions. In the TAM3 study paradigm, computer anxiety was associated with performance expectancy, which in turn was correlated with behavioural intention. Investigations into the TAM3 Model were performed in real-world technological implementations.

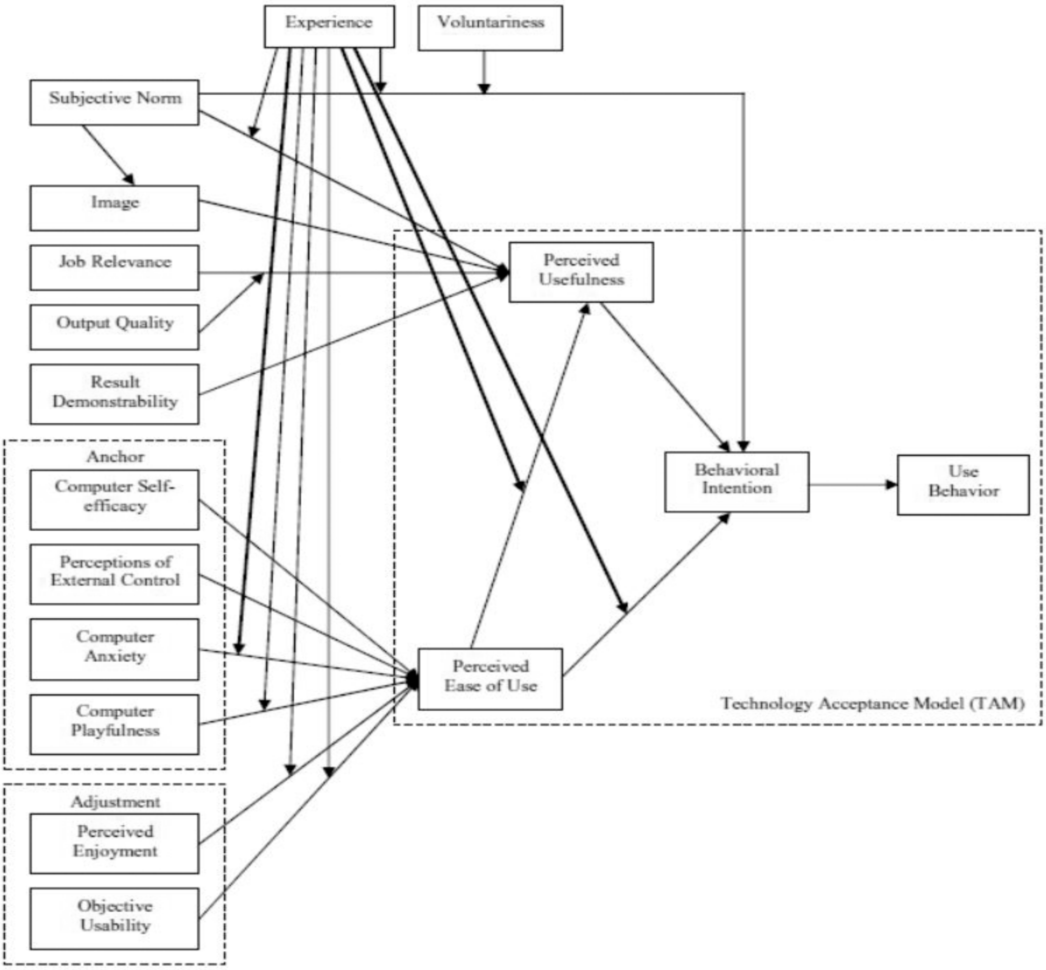

Figure 2.15: Technology Acceptance Model (TAM 3) (Venkatesh & Bala, 2008)

2.33 THEORY OF UTAUT - UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY

Venkatesh et al. (2012) formulated the Unified Theory of adoption and Use of Technology (UTAUT) as a model for technology adoption in "User Acceptance of Information Technology: Towards a Unified Vision." A recent study highlighted the elements influencing shops' acceptance of mobile payment. Numerous variables affecting mobile payments encompass social influence, performance expectancy, facilitating conditions, effort expectancy, habit, privacy, perceived security, and intentions, as articulated in the UTAUT model (Ariffin et al., 2020). The UTAUT strives to explain users' intentions regarding how they can take advantage of an information system and how they engage with it. The theory comprises four fundamental constructs: 1) Facilitating Conditions 2) Social Influence 3) Effort Expectancy; 4) Performance Expectancy (Wijaya & Noviaristanti, 2024). Gender, age, experience, and voluntary usage are proposed to attenuate the influence of the four primary constructs on usage intention and behaviour (Oyetade et al., 2024). In order to develop the theory, the constructs of eight models—the theory of reasoned action, the technology acceptance model, the motivational model, the theory of planned behaviour, a combined theory of planned behavior/technology acceptance model, the model of personal computer use, the diffusion of innovations theory, and the social cognitive theory—that had been used in previous research to explain information systems usage behaviour were reviewed and consolidated.

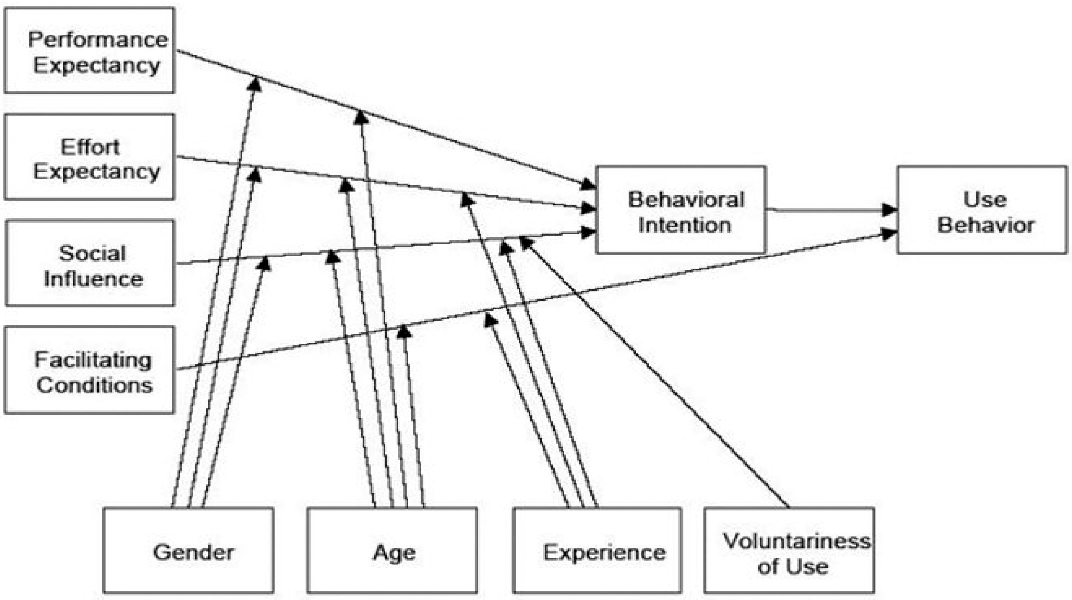

Figure 2.16: Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003)

Two further variables were added to the Unified Theory of Acceptance and Use of Technology (UTAUT) model: perceived risk (PR) and trust. According to the results, the retailers' behavioural intentions to adopt m-payment (BIU) are significantly influenced by performance expectancy, effort expectancy, social influences (SI), trust, and public relations (Nguyen, 2024). The research indicated that the augmented UTAUT model might enhance comprehension of the influences of trust, perceived risk, perceived privacy, perceived ease of use, facilitating conditions, and social influence on mobile payment acceptance among Egyptian retailers (Esawe, 2022). Digital technology has revolutionised information, communication, and connectivity as the world has changed. Industry 4.0 technologies, of which cloud computing is a prime example, have played a major role. Data storage and transmission via the internet are made possible by cloud computing, which offers significant advantages to businesses, particularly Micro, Small, and Medium-Sized Enterprises (MSMEs), by enabling them to handle data efficiently and independently. Micro, Small, and Medium Enterprises (MSMEs) utilising cloud computing services were solicited to participate in the study employing UTAUT2 theory. Partial Least Squares-Structural Equation Modelling (PLS-SEM) was employed to analyse the data. The findings showed that MSMEs' intentions to embrace cloud computing are positively impacted by performance expectancy, effort expectancy, facilitating conditions, habit, and optimism (Lee et al., 2024). Additionally, behavioural intention has a positive impact on actual usage. According to the study, MSMEs are more likely to integrate cloud computing into their everyday operations if they have a strong goal to do so (Valencia, 2024).

2.34 THEORY OF UTAUT2

According to UTAUT2, in addition to the UTAUT constructs, hedonic motivation—the degree to which the technology is viewed as enjoyable—price value—the cognitive trade-off between the perceived advantages and monetary costs of technology usage—and habit—defined as the amount of time that has passed since the first time using the technology—all have an impact on the intention to use it (Venkatesh. et al., 2012). Venkatesh et al. (2012) expanded their UTAUT framework for the consumer context, highlighting the hedonic value (intrinsic motivation) of technology users. The augmented version of UTAUT is referred regarded as UTAUT2, which integrates three more constructs: hedonic motivation, price value, and habit into the original UTAUT framework (Venkatesh et al., 2003). In UTAUT2, the voluntariness of usage was omitted as a moderator due to the absence of an institutional mandate for customers, as consumer activity is often discretionary (Venkatesh et al., 2012). Tamilmani et al. (2017) emphasised that the Unified Theory of Acceptance and Use of Technology (UTAUT) is regarded as the most complete theory in Information Systems (IS) research for comprehending technology acceptance across many use settings (Tamilmani et al., 2017). The theory was expanded to the consumer environment by integrating three external constructs. The expanded version is known as UTAUT2. Despite its recent introduction, the growing citation count attests to UTAUT2's popularity among IS academics, particularly in the analysis of consumer-oriented matters. The UTAUT theory posits that performance expectancy, effort expectancy, and social influence serve as indirect drivers of usage behaviour via behavioural intention, while behavioural intention and facilitating factors directly affect usage behaviour. The theory posits that the relationships among the constructs are affected by various combinations of moderators, specifically: gender, age, experience, and voluntariness of usage (Tamilmani et al., 2017). Research indicates that the UTAUT2 dimensions of performance expectancy, effort expectancy, social influence, enabling conditions, and hedonic incentive are associated with behavioural intention (Hasselwander & Daniel, 2024). The evidence supports a significant influence of Performance expectancy on perceived usefulness (Gupta et al., 2024). The paper indicates a lack of understanding of the correlation among adaptation alternatives, performance, effort expectancy, and hedonic motivation. Higher levels of positive attitudes, perceived utility ratings, and social norms correlate with improved outcomes (Droogenbroeck & Hove, 2021). A study found a number of characteristics that influence consumers' behavioural intention to use mobile payments using quick response codes (QR-codes). This study adds the personal innovativeness construct to the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and finds that behavioural intention to adopt QR-code mobile payment is significantly correlated with performance expectancy, social influence, habit, price value, and personal innovativeness in information technology (Suo et al., 2022). The UTAUT2 theoretical model was evaluated in a quantitative study employing structural equation modelling, done in the United States with a sample sourced via Qualtrics. The results indicate that the intention to utilise mobile payments varies by payment type, with performance expectancy and habit serving as significant determinants of both intention and usage behaviour. Social influence and effort anticipation were inadequate predictors of intention. Furthermore, enabling conditions did not influence usage behaviour. The findings assist clothes retailers in identifying the mobile payment solution that aligns with the preferences and requirements of their target market (Martinez & McAndrews, 2023). The research identified beneficial impacts of enabling conditions on effort expectation and hedonic motivation; however, facilitating conditions showed no correlation with performance expectancy (Min. & Jo, 2024). “Smart Retailing has become the dominant business strategy in the retail sector. Therefore, comprehending the mechanics of augmented reality adoption is essential for organisations to successfully encourage client acceptance of this innovative technology (Kumar & Usman, 2024). For application in low-income nations, the authors therefore suggest and assess a more thorough model that combines the task-technology fit (TTF) and unified theory of acceptance and use of technology (UTUAT2) models (Khashan et al., 2023). The new financial and commercial landscape has rapidly changed in recent years due to technological breakthroughs (Tang & Tsai, 2024). Innovation-driven new payment methods are altering consumers' perceptions of money and payment habits. The goal of this study is to develop an analysis of biometric payments based on two related studies. In the first, a comprehensive model that integrates the concepts of the General Risk Theory, the Trust Theory, and the UTAUT2 model is used to identify the factors that predict the intention to use this technology using a variety of artificial intelligence feature selection techniques on a sample of 1905 potential users (Zarco et al., 2024). Jo & Bang, (2024) shown in a study that while social influence had no significant effect on purchasing intention, it did have a high association with continuance intention. Without affecting the intention to shop, facilitating conditions mostly guided the intention to continue. The study also confirmed the link between shopping intention and continuance intention, emphasising the role of innovativeness as a crucial moderator in the interaction between continuance intention and social influence. Sankaran & Chakraborty (2021) examined the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), taking into account the moderating influence of gender as well as social, monetary, emotional, and quality values. Performance expectation (PE) and social value (SV) were not shown to have a significant impact on behavioural intent (BI), but effort expectancy (EE), monetary value (MV), emotional value (EV), quality value (QV), and trust (TR) were. The study combines UTAUT2 with perceived value and trust components to provide a thorough model for analysing the uptake of mobile banking. Additionally, this study demonstrated the significance and influence of recently included variables in elucidating consumers' intention to utilise e-banking services (Sankaran & Chakraborty, 2021). In their study, Chauhan, et al. (2022) adopted UTAUT2 model with constructs including customer innovativeness, perceived risk, and the availability of security knowledge. This study examines the relationship between UTAUT2 predictors—Performance Expectancy, Effort Expectancy, Facilitating Conditions, Habit, Social Influence, and Hedonic Motivation—and the intention to utilise healthcare technologies, based on a survey of 298 US residents, while evaluating the impact of privacy concerns on these associations. Performance expectancy, effort expectancy, and habit all have a favourable effect on adoption intent, according to regression research, with privacy concerns considerably reducing the association between effort expectancy and usage intention (Raman & Don, 2013). By highlighting the critical significance of privacy issues, the study enhances the UTAUT2 model, promoting theoretical knowledge and improving model predictability in the context of healthcare technology (Ghnaimeh, 2024).

Table 2.3: Pro & Cons summary of Technology Adoption Models

No.	Theories	Citation	Pro	Cons
1	Theory of Reasoned Action (TRA)	Ajzen & Fishbein, (1988)	Explains Attitude & Behavioural	Behaviour performances are not considered
2	Theory of Planned Behaviour (TPB)	Ajzen & Fishbein, (1988)	Recommended forecast model	Fails to identify gaps between behaviour and intension
3	Diffusion of Innovation (DOI)	Rogers, Diffusion of innovations, (1995)	Emphasises distinct components, such as innovations or products.	Neglects social and socio-economic. Behavioural elements
4	Decomposed Theory of Planned Behaviour (DTPB)	Kanimozhi & Selvarani, (2019)	Focusses on identifying causes and beliefs; suggested for e-	Strictly need hardware and software infrastructure

No.	Theories	Citation	Pro	Cons
			commerce solutions	
5	Technology Acceptance Model (TAM)	Davis et al., Technology acceptance model, (1989)	Focuses on attitude towards adoption of technology	Lacks consideration of social and subjective elements
6	TAM -2	(Davis & Venkatesh, 1996; Venkatesh & Bala, 2008)	Extends inclusion of social and external factors	With so many variables, it is quite difficult to understand.
7	TAM – 3	Venkatesh & Bala, (2008)	Combination of TAM 1 & 2 Covers internal and external factors	With so many variables, it is quite difficult to understand.
8	C-TAM-TPB	Yadegari et al., (2024)	Predicts behavioural control & social norms for both experienced and non-experienced users	External factors are not considered
9	Technology Readiness Assessment (TRA)	Mankins, (2009)	Evaluates individual character and decision-making abilities	Needs support of TAM to prove adaptability
10	Model of PC Utilization (MPCU)	Thompson et al., (1991)	Predicts Technology Utilization behaviour	Uncertainties are excepted
11	Innovation Diffusion Theory (IDT)	Rogers, Diffusion of innovations, (1995)	Focuses on Ethical elements of technology diffusion and adoption	Social and Political influence is neglected

No.	Theories	Citation	Pro	Cons
12	Motivational Model (MM)	Li, (2010)	intrinsic and extrinsic motivation to adopt technology	Change of Motivation is not considered
13	Social Cognitive Theory (SCT)	Bandura, (2003)	Focused on Self-learning for technology adoption	Self-regulation and self-efficacy cannot be regulated
14	UTAUT	Venkatesh et al., (2003)	Focuses on intention and behaviour evolution	Lacks consideration of external factors
15	UTAUT -2	Venkatesh et al., (2012)	Combination of eight recommended models covering all acceptance levels	Lacks consideration of external factors

Recognizing that these models make numerous assumptions about the factors influencing user behavior is essential. There are several limitations to TAM in capturing the complex dynamics of technology adoption in contemporary settings. We observe significant contrasts between TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT), highlighting UTAUT's advantages in comprehensiveness (Kampa, 2024). Another recent study illustrated the expanding corpus of research, particularly with the moderating influence of students' gender and study discipline on their adoption and use of ChatGPT during their educational journey. This study added gender and academic disciplines as moderators to the Unified Theory of Acceptance and Use of Technology (UTAUT). A structural model employing Smart PLS revealed that gender significantly moderated the association between performance expectancy and ChatGPT use (Elshaer et al., 2024). Due to the rapid advancement of technology, small and medium-sized enterprises (SMEs) are playing a significant role in the digital transformation of various industries. By combining well-known theories and models of technology adoption, such as the DOI, Technology-Organization-Environment (TOE) framework, TAM, and UTAUT, a study has been conducted to fill a critical gap (Ofaletse et al., 2024). The effectiveness of Monsoon SIM in raising student proficiency in the Accounting Information Systems (AIS) course has been examined from the perspectives of TAM and UTAUT theory. Students can experience running a business online with Monsoon SIM, a platform that offers business simulations packaged as web-based games. According to the research study, when it comes to using Monsoon SIM, performance expectations, conducive environments, and social influence have a good and significant impact on students' AIS competence. However, students' opinions about the value or fun of Monsoon SIM have little bearing on their AIS skill (Mahmudi et al., 2024). Additionally, the prediction value of these models varies based on their relevant benefits and drawbacks. According to this study, the well-liked theoretical models were chosen because they could provide an explanation (like UTAUT) or because their theoretical framework was convincing (like TAM). The alternate strategy (like UTAUT2) balances the two points of view. Even though UTAUT2, the most recent Model in the research of technology adoption, is not widely utilised in the field, the review suggests that it could make a substantial contribution if applied and expanded. This can be explained by its durability, great predictive power (it explains 74% of the variation in usage behavioural intention), and broad theoretical foundation (nine IT acceptance models). Incorporating the relevant settings factors can be applied to a variety of IT usage scenarios, including those involving various countries and technology Castanha et al. (2020) noted that the UTAUT2 model's content analysis results show that it is more predictive than previous models (Castanha et al., 2020).

According to this thesis, UTAUT2 could be helpful in the future for determining how to measure people's responses to innovative technologies (Wu & Liu, 2023). Given that standard accepted theoretical models are limited in their ability to explain the event under study, a thorough and dynamic theoretical model that considers cultural, social, technical, and other relevant behavioural elements would be highly beneficial (Yadegari et al., 2024).

2.35 RESEARCH GAP

Technology adoption is an inextricable aspect of any industry, and its growth relies on it. Technology adoption is not new and can be seen to both organized and very limited extent in the unorganized retail sector. Extensive literature reviews brought forward couple of interesting points. Extensive literature reviews brought forward couple of interesting points: -

- Although technology adoption is greater in the organized retail sector, it is not uniform across all retail formats. According to the above-mentioned theory, new technology adoption is accompanied by a human behavior theory that considers various factors influencing the success and adoption of new technologies. There is a significant gap in existing available literature on the unorganized retailers in India, from the perspective of technology adoption.
- The shift to embrace technological solutions became more visible after the onset of the pandemic due to Covid-19. As a result of the significant Digital Transformations happening around us, the proposed research would investigate existing theories in the retail industry.
- Technology Adoption in Unorganized Retail sector in India has been ignored in the existing literature and more so from the perspective of low, shallow digital footprints in the Eastern parts of India, including Kolkata.

- No study is available showing how the UTAUT – 2 Theory is applicable in the unorganized retail sector in India. Hence, no study has been done on the unorganized retailers, from the perspective of the UTAUT – 2 Theory.
- No study is available regarding unorganized retailers in Kolkata city and their technology adoption. No study is available regarding the plight of the unorganized retailers in Kolkata; especially since they have been struggling since innovative technologies have been ushered in the Eastern part of India.
- The unstructured retail sector in the Kolkata region has absolutely no research done. Furthermore, no research has been done on the retail technology digital divide in different places within the geography of Kolkata.

The study's target population was divided into six groups (mentioned hereunder) and based on the types of the basic unstructured retailers, in Kolkata, that only sell manufactured goods:

- Grocery / Kirana
- Medicine / Ayurveda / Homeopathy / Yunani
- Footwear
- Ready-made Garments
- Handicraft and Artisan
- Electronics

2.36 RESEARCH QUESTIONS

- **Research Question 1:** What determinants affect the technology adoption by unorganised retailers?
- **Research Question 2:** In what ways do format and product category influence the technology adoption process among unorganised retailers?

- **Research Question 3:** What are the attitudes of unorganised retailers regarding technology adoption in their sector?
- **Research Question 4:** What is the incremental financial benefit realised by unorganised retailers from technology adoption?

2.37 CONCEPTUAL FRAMEWORK

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) serves as the foundation for the conceptual framework and describes the elements that affect individual retailers' acceptance of new technology in the unorganised retail industry**.**

The framework consists of several constructs or variables that are thought to affect technology adoption. These constructs are Hedonic Motivation (HM), Performance Expectancy (PE), Social Influence (SI), Perceived Risk (PR), Facilitating Conditions (FC), Effort Expectancy (EE), and Behavioural Intention (BI). The conceptual diagram depicts how these variables are interconnected and how they impact the adoption of technology by retailers.

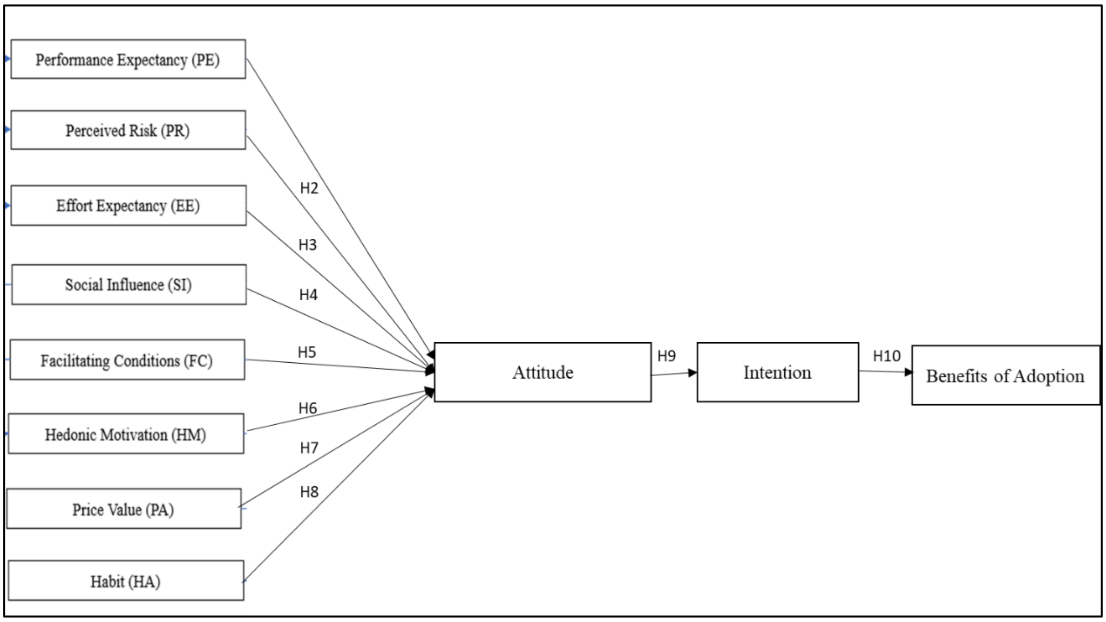

Figure 2.17: Conceptual Framework created by the researcher, based on the UTAUT-2 Model

2.38 RESEARCH HYPOTHESIS FORMULATION

Hypothesis for Retail Technology

The phrase "research hypothesis" is used when a hypothesis or prediction is investigated using scientific procedures. Research hypotheses predict the relationship between two variables. Gender, age, and education have all been demonstrated to significantly impact whether or not a person adopts and uses new technology. Numerous earlier studies have demonstrated that demographic traits influence adoption and use decisions. Thus, the impact of demographic traits on consumer awareness and retail technology use has been investigated in this study. The research additionally examines characteristics such as technical awareness, readiness for technological adaptation, understanding of retail and payment technologies, supply chain technology, and attitudes towards the willingness to learn and apply these technologies for successful business operations. The hypothesis is proposed below:

Hypothesis of Research

The current research primarily aims to investigate the factors affecting technology adoption among unorganised merchants. These retailers, typically defined by their casual, small-scale operations, encounter distinct obstacles and opportunities in the incorporation of new technologies into their business practices. The study provides eleven hypotheses to carefully examine these influences. Each hypothesis investigates the potential influence of a specific variable on the technology adoption process among these retailers, encompassing performance expectations, perceived risks, social influences, and demographic considerations. Comprehending these characteristics is essential for formulating strategies to facilitate the digital transformation of unstructured retail sectors. Following are the hypothesis carried in present research:

H1: Performance expectancy has a significant effect on the attitude of unorganized retailers.

H2: Perceived risk has a significant effect on the attitude of unorganized retailers.

H3: Effort expectancy has a significant effect on the attitude of unorganized retailers

H4: Social influence has a significant effect on the attitude of unorganized retailers.

H5: Facilitating Conditions has a significant effect on the attitude of unorganized retailers.

H6: Hedonic motivation has a significant effect on the attitude of unorganized retailers.

H7: Price value has a significant effect on the attitude of unorganized retailers.

H8: Habit has a significant effect on the attitude of unorganized retailers.

H9: Attitude has a significant effect on the intention of adopting technology by unorganized retailers.

H10: Behavioural Intention has a significant effect on the benefits of adopting technology by unorganized retailers.

H11: There is a significant difference of opinion existing among the retailers in the unorganized retail segment based on their demographic characteristics.

The research seeks to elucidate the many aspects influencing technology adoption among unorganised retailers through hypothesis testing. The insights obtained will illuminate the particular obstacles and incentives these enterprises face, while also informing the creation of tailored actions and policies to promote technical progress in this essential industry.

2.39 SUMMARY

To summarize, the presentation here is based on several distinct interpretations and points of view drawn from a thorough assessment of the literature. The review on retailer technology, types of retail technology. The adoption of technology by Indian retail stores in both structured and unstructured manners. The significant evolution of technology-driven retailing in India during the Covid-19 pandemic. It is usual to encounter several technology adoption models and hypotheses in literature reviews. A new theoretical research framework will be built based on the study's difficulties, target market, gap analysis, objectives, the organization's aims, and an understanding of technology adoption models and theories relative to available resources. Unorganised retail stores must comprehend both the academic and practical aspects of technology adoption models and theories. These evaluations assist a researcher in comprehending the foundational concepts of the evolution of technology adoption and the potential implications of these theories for future endeavours in this domain.

CHAPTER 3

Research Methodology

CHAPTER 3

RESEARCH METHODOLOGY

3.1 INTRODUCTION

This chapter centres on the detailed research strategy, which entails formulating research questions derived from the research topic and establishing research objectives based on these questions. A research hypothesis is formulated and assessed to meet the objectives. This chapter elucidates the research methodologies employed in this study. A methodology is a collection of directives designed to address a research topic. The research methodology elucidates the rationale behind the selection of a certain method or strategy, enabling both the researcher and others to evaluate the research outcomes. It examines the research approaches and the rationale for their selection. A research methodology is a system of models, processes, and techniques employed to derive the outcomes of a research problem. The research approach is separate from the research techniques employed (Panneerselvam, 2014). Researchers employ many tactics and methodologies to execute their study. This chapter will elucidate the study design, data sources, sampling design, research instruments utilised for data collection, and analytical techniques. Researchers in Kolkata aimed to identify the parameters influencing the adoption of retail digital technology systems by unstructured retailers. This study employs a descriptive research design.

3.2 RESEARCH GAP

Technology adoption is an inextricable aspect of any industry, and its growth relies on it. Technology adoption is not new and can be seen to both organized and very limited extent in the unorganized retail sector. Extensive literature reviews brought forward couple of interesting points: -

Extensive literature reviews brought forward couple of interesting points: -

- Although technology adoption is greater in the organized retail sector, it is not uniform across all retail formats. According to the above-mentioned theory, new technology adoption is accompanied by a human behavior theory that considers various factors influencing the success and adoption of new technologies. There is a significant gap in existing available literature on the unorganized retailers in India, from the perspective of technology adoption.
- The shift to embrace technological solutions became more visible after the onset of the contagion, due to Covid-19. As a result of the significant Digital Transformations happening around us, the proposed research would investigate existing theories in the retail industry.
- Technology Adoption in Unorganized Retail sector in India has been ignored in the existing literature and more so from the perspective of low, shallow digital footprints in the Eastern parts of India, including Kolkata.
- No study is available showing how the UTAUT – 2 Theory is applicable in the unorganized retail sector in India. Hence, no study has been done on the unorganized retailers, from the perspective of the UTAUT – 2 Theory.
- No study is available regarding unorganized retailers in Kolkata city and their technology adoption. No study is available regarding the plight of the unorganized retailers in Kolkata; especially since they have been struggling since innovative technologies have been ushered in the Eastern part of India.
- The unstructured retail sector in the Kolkata region has absolutely no research done. Furthermore, no research has been done on the retail technology digital divide in different places within the geography of Kolkata.

The study's target population was divided into six groups (mentioned hereunder) and based on the types of the basic unstructured retailers, in Kolkata, that only sell manufactured goods:

i. Grocery / Kirana
ii. Medicine / Ayurveda / Homeopathy / Yunani
iii. Footwear
iv. Ready-made Garments
v. Handicraft and Artisan
vi. Electronics

3.3 RESEARCH QUESTIONS

- **Research Question 1:** What determinants affect the technology adoption by unorganised retailers?
- **Research Question 2:** In what ways do format and product category influence the technology adoption process among unorganised retailers?
- **Research Question 3:** What are the attitudes of unorganised retailers regarding technology adoption in their sector?
- **Research Question 4:** What is the incremental financial benefit realised by unorganised retailers from technology adoption?

3.4 RESEARCH OBJECTIVES

- **Objective 1**: To study the factors affecting technology adoption by unorganized retailers
- **Objective 2**: To study the impact of format and product category on the adoption of technology by unorganized retailers

- **Objective 3**: To understand the perception towards the adoption of technology in the unorganized retail industry
- **Objective 4**: To study the marginal financial gain of unorganized retailers in case they are adopting technology.

3.5 QUANTITATIVE RESEARCH

Research, in its broadest sense, can be categorized based on its methodology, purpose, or the nature of the information it seeks. Quantitative research plays a pivotal role in academic thesis writing, particularly within fields that prioritize measurable data and statistical analysis. This methodology relies on numerical data collection, interpretation, and presentation to validate or refute hypotheses. The systematic methodology characteristic of quantitative research facilitates objective and generalisable results, essential for robust academic conclusions. Quantitative research is a methodical approach that employs statistical, mathematical, or computational approaches to collect and interpret data. The objective is to measure variables, discern patterns, and forecast correlations among variables. This approach is optimal for research intended to evaluate hypotheses or ideas using empirical evidence. Quantitative research depends on standardised tools and methodologies to guarantee data uniformity and comparability.

Quantitative Research: The researcher deployed quantitative research during his study on the unorganised retailers in Kolkata as a structured method is necessary which deals with numerical data. It seeks to understand patterns and establish relationships between variables through statistical analysis. In light of our investigation on unorganised retailers in Kolkata, we have opted for a Quantitative Research methodology. The aim is to acquire quantitative data concerning the technology adoption trends, preferences, and obstacles faced by these retailers. This method facilitates a more systematic and quantitative examination of the data, yielding objective and generalisable outcomes. Using quantitative research, we aim to produce statistically significant findings which can be used to infer patterns across the larger population of unstructured retailers in Kolkata.

3.6 DESCRIPTIVE RESEARCH DESIGN

Descriptive research design is a non-experimental, observational approach that aims to systematically capture and outline the characteristics of a specific phenomenon, population, or context (Nassaji, (2015). This approach is frequently used in academic thesis writing to provide readers a thorough grasp of the topic and allow researchers to respond to "what" queries without looking into causality (Creswell & Creswell, 2018). Studies that need a clear representation of current conditions or relationships might benefit greatly from descriptive research since it observes the variables and records them in their natural state (Creswell, 2014). Surveys, observations, and case studies are often used data gathering techniques in descriptive research, and they all aid in describing frequencies, averages, and other quantitative data (Saunders et al., 2019). Recent study indicates that descriptive research offers a fundamental empirical basis that enables researchers to record the state of affairs at the moment, which can subsequently serve as support for additional analytical or experimental investigations (Babbie, 2020). Using a descriptive design in a thesis guarantees a trustworthy representation of the topic being studied, improving the rigour and applicability of findings by closely matching them with real-world applications (Rahi, 2017).

In order to guarantee high-quality research free from bias on the primary data gathered by the researcher, this study has chosen to use a descriptive research design that includes a structured questionnaire, in-person interviews, and primary data collecting.

3.7 RESEARCH PROCESS

Many steps are required to carry out a successful research project, including understanding the research problem and reviewing prior literature to gain insight into the topic and identify the research gap, developing an appropriate research design, collecting data, analysing responses from the collected data, and finally interpreting and reporting the results (Khalid et al., 2012). The figure below illustrates the steps involved in the research process (Gunter, 2013).

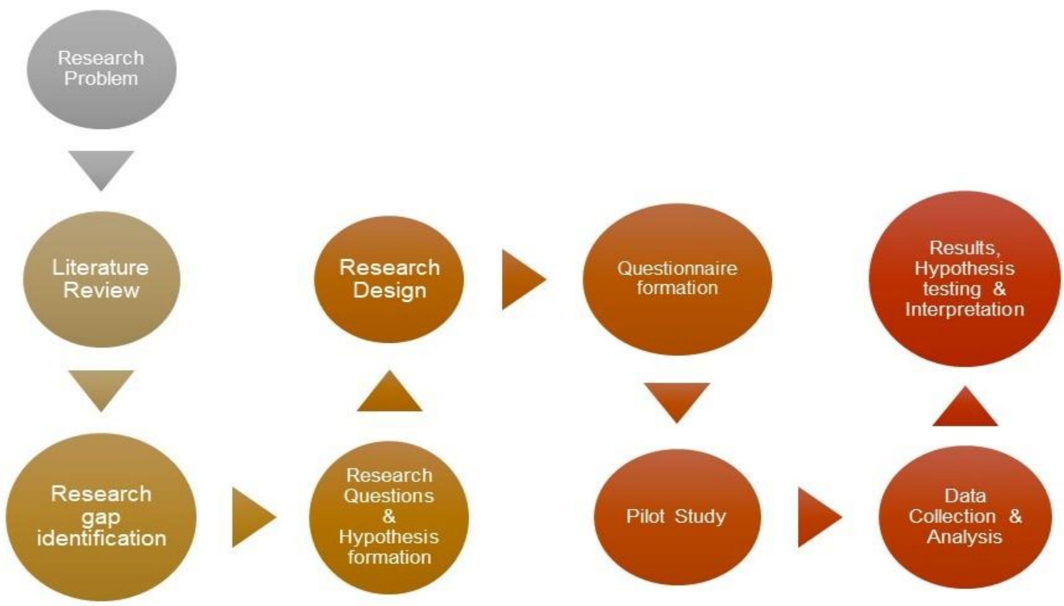

Figure 3.1 : Research Process Stages: Author Created

3.8 RESEARCH APPROACH

In the topic of information studies, several scholars have tried to assess and arrange different research methodologies. The best option for evaluating a group of precisely defined variables is to use a quantitative research technique. A quantitative research strategy is necessary for doing quantitative studies (Amaratunga et al., 2002). When it comes to thesis projects that aim to offer tangible, data-driven insights, quantitative research is invaluable. Strong arguments can be supported by a well-organised quantitative approach, which can also significantly add to the body of academic literature and give legitimacy to study findings. Getting data that can be expressed quantitatively is the main goal of quantitative research. According to Creswell, quantitative research must initially perform a literature review to ascertain the research problem and formulate a hypothesis or hypotheses (Creswell & Creswell, 1994). Quantitative research relies heavily on surveys as a primary source of data. To conduct this study, researchers used the quantitative technique. We reviewed the literature to come up with this set of factors. A paper-based questionnaire was chosen as the survey method for gathering primary data. To examine all of the data, statistical tests were used.

3.9 RESEARCH METHOD

Occasionally, "research method" and "research technique" are used interchangeably. The research method encompasses a variety of approaches to studying a topic or problem. methodologies for gathering data, statistical approaches for analysing the data, and procedures for assessing the accuracy of the findings are the three categories of research methodologies (Williams, 2007). Surveys and case studies are the most utilized methodologies in research, with interviews and experiments coming in a close second. The research approach in this study was a survey (Johnson & Onwuegbuzie, 2004). In descriptive research, surveys are a common approach (Palmié et al., 2020). According to the definition, sample population data may be obtained by well-structured printed questionnaires. Quantitative approaches to research both involve surveys (Hole et al., 2019).. The survey approach has been used extensively by researchers in retail technology (Shankar, 2021). Several retail technologies and disruptive innovations have used a survey approach by retail domain researcher, example, (Cheah et al., 2018).

To guarantee superior study quality and mitigate data bias, the researcher employed a Descriptive study Design in conjunction with a Quantitative Research Methodology.

3.10 POPULATION FOR THE STUDY

A "universe" or "population" might be the sum of everything being studied in a certain area (Guo, 2013). A census inquiry is a comprehensive enumeration of all the 'population' objects (Sukamolson, 2007). Due to the multitude of sampling strategies and their diverse forms, researchers must possess a comprehensive awareness of the distinctions among these techniques to choose the most suitable strategy for their study (Rahman, 2023). The survey participants are disorganised, unstructured retailers. The target respondents are unorganised retailers in several markets within the city of Kolkata.

3.11 SAMPLING FRAME

A sample design is detailed strategy researchers employ to choose a representative sample of the target population (Tambay & Catlin, 1995 ; Majid, 2018). A sample frame is an essential notion in research technique. It denotes the specific list or database from which a study sample is extracted. The sampling frame must accurately reflect the whole population under investigation, guaranteeing that each member has a known and non-zero probability of inclusion in the sample. An exemplary sampling frame precisely reflects the attributes of the target population, hence reducing the likelihood of sampling bias (Majid, 2018).

Sampling design delineates the procedure for selecting samples from the sampling frame. This design is a systematic methodology that delineates the process for selecting the study sample to guarantee representativeness and reliability. The primary objective of an effective sampling design is to minimise bias and guarantee that the sample accurately represents the population (Majid, 2018).

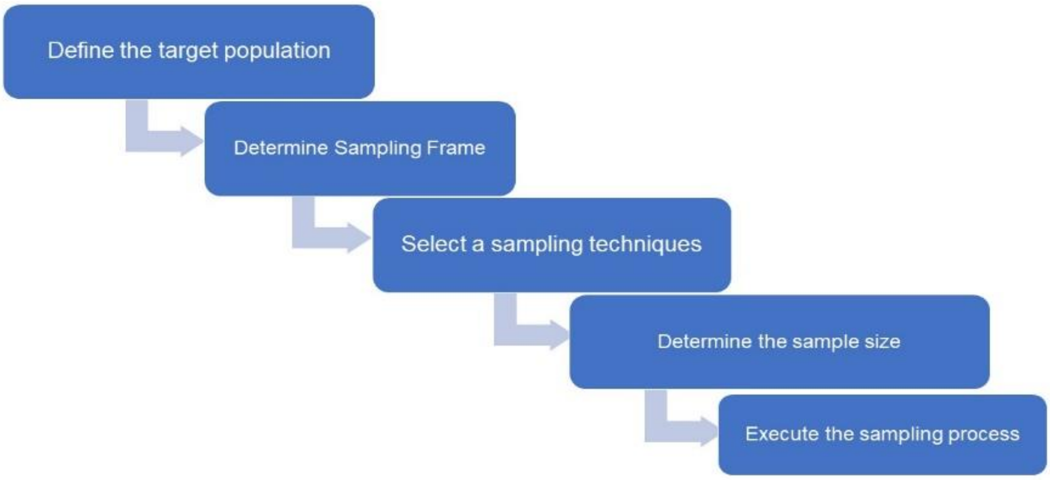

Figure 3.2: Sampling Design Steps: Author Created

The study's target population was divided into six groups (mentioned hereunder) and based on the types of the basic unorganised retailers, in Kolkata, that only sell manufactured goods:

- Grocery / Kirana
- Medicine / Ayurveda / Homeopathy / Yunani
- Footwear
- Ready-made Garments
- Handicraft and Artisan
- Electronics

3.12 SAMPLING UNIT AND FRAME

In the context of sampling, a sampling frame serves as a representation of the target population of unstructured retailers. A sampling unit is the basic element or set of elements considered for selection in some stage of sampling. It represents the smallest entity from which data can be collected in a study. Depending on the research design, a sampling unit can vary significantly—it could be an individual, a household, an organization, or any defined entity relevant to the study. People above the age of 18 were eligible to participate in this study. Kolkata's unstructured merchants are the study's sample units (Majid, 2018).

3.13 SAMPLING TECHNIQUE

A multitude of individuals in Kolkata were questioned to yield a varied spectrum of perspectives. The Stratified Sampling approach was utilised to collect data from the specified locations (Barreiro & Albandoz, 2001). Stratified sampling is a method wherein researchers divide a population into smaller subpopulations known as strata (Alvi, 2016). Strata are formed based on shared, distinguishing characteristics of the members, such as age, income, race, or educational level. Researchers utilising stratified sampling classify the population into groups based on age, religion, ethnicity, or income level and randomly choose from these strata to form a sample (Simkus, 2022).

Stratified sampling is a robust and effective method for collecting data, particularly in research focusing on diverse populations like unorganized retailers in Kolkata. The unorganized retail sector in Kolkata comprises various subgroups, such as retailers differentiated by location (urban, suburban, rural), size of operation (micro, small), and type of goods sold (groceries, apparel, electronics, etc.). Stratified sampling ensures that these diverse subgroups are sufficiently represented in the sample, yielding a more thorough and nuanced comprehension of the population. According to Etikan and Bala (2017), stratified sampling is especially advantageous in research requiring the separate analysis of specific subpopulations. In a varied population such as unorganised shops, simple random sampling may disproportionately represent certain groups while inadequately representing others. Stratified sampling mitigates this risk by categorising the population into strata and selecting samples proportionately, so ensuring representation of all groups. Saunders et al. (2019) emphasised that stratified sampling improves the accuracy of estimates by diminishing variability within each stratum. Stratified sampling enhances the accuracy of statistical metrics such as mean, variance, and correlation coefficients by guaranteeing proportional representation. In a study on technology adoption, stratified sampling facilitates enhanced understanding of the variations in adoption rates across several strata, such as geographic area or kind of business. Research by Cochran (1977) highlights that stratified sampling often leads to lower standard errors compared to simple random sampling, making it more reliable for complex studies. Stratified sampling allows researchers to explore specific behaviors and challenges unique to subgroups, such as technology adoption barriers faced by grocery retailers versus apparel sellers. This is crucial for studies aiming to provide actionable insights tailored to each subgroup, aligning with recommendations by Creswell and Creswell (2017) for qualitative and mixed-methods research. In a densely populated and varied urban environment like Kolkata, stratified sampling allows for targeted data collection, reducing the need for exhaustive surveys. The method enhances cost-efficiency by focusing resources on representative samples rather than attempting to survey the entire population. Kothari (2004) supports stratified sampling for its balance between accuracy and cost-effectiveness in large-scale surveys.

Since your study aims to examine technology adoption patterns among diverse unorganized retailers, stratified sampling aligns well with the goal of capturing variations across subgroups. It facilitates comparative analysis, enabling you to identify trends, barriers, and opportunities within different retailer categories.

The prioritization of the specific categories—grocery/kirana, medicine (Ayurveda, homeopathy, Yunani), footwear, ready-made garments, handicrafts/artisan, and electronics—for studying unorganized retailers was guided by their market share, relevance to technology adoption, and socio-economic significance.

Table: 3.1: Category-wise Analysis vis-à-vis Technology Adoption

Sr	Category	Market Share	Relevance to Technology Adoption
1	**Grocery / Kirana**	Grocery/kirana stores form the backbone of India's unorganized retail sector, contributing a significant portion of total retail trade. As of 2023, traditional grocery retailers account for nearly 75% of India's food and grocery market, making them the largest segment in unorganized retail.	Kirana stores are crucial in examining technology adoption due to their ubiquitous presence and direct customer interactions. Post-COVID, there was an increase in the use of UPI and QR codes among grocers, but adoption remains fragmented due to challenges like low digital literacy.
2	**Medicine (Ayurveda, Homeopathy, Yunani)**	The pharmaceutical retail sector, including traditional medicines, is a high-growth category. Post-COVID, the demand for health-related products surged, making these retailers pivotal in the economy.	Medicine retailers showed a relatively higher adoption of digital tools due to the demand for online consultations and cashless transactions during the pandemic. However, Ayurveda and homeopathy segments remain largely unorganized, highlighting gaps in digital integration.

Sr	Category	Market Share	Relevance to Technology Adoption
3	**Footwear**	Footwear retail is a significant component of the unorganized market, particularly in cities like Kolkata, which has a long history of traditional leather craftsmanship. This segment bridges daily essentials and artisan products, making it a diverse category to study.	Footwear retailers are moderately impacted by e-commerce and digital payment trends. Studying them provides insights into how semi-organized categories are coping with the technology gap compared to highly traditional retailers.
4	**Ready-Made Garments**	Ready-made garments represent a prominent unorganized retail segment in India, catering to daily essentials and seasonal trends. In Kolkata, the city's cultural focus on fashion and festivals amplifies the importance of this sector.	Garment retailers are increasingly exposed to online marketplaces and social media marketing. The degree of adoption varies significantly, providing a fertile ground for understanding the interplay of traditional and digital retail practices.
5	**Handicrafts and Artisans**	Kolkata has a rich tradition of handicrafts and artisan goods, contributing significantly to local livelihoods and cultural identity. This sector is vital for socio-economic studies, given its reliance on micro-scale production and sales.	Artisans are among the least digitally integrated due to infrastructural and educational barriers. Studying this segment highlights extreme cases of non-adoption, shedding light on systemic challenges.
6	**Electronics**	Electronics retail, including mobile devices, small appliances, and repairs, represents an evolving segment of unorganized retail. These businesses cater to growing consumer demand in urban and semi-urban areas	Electronics retailers are likely early adopters of technology given their exposure to tech-savvy consumers and product familiarity. Understanding their challenges and successes offers a benchmark for other categories

Ten of the most well-known hotspots for unstructured, unorganised retail market availability were selected, and this study visited heavily populated retail market regions for primary data collection. Necessary care and adequate precautions were taken to cover the entire geography of Kolkata, with specific emphasis on the pockets which are known as hub of unorganised retailers in the city.

1. Hatibagan Market
2. Orphangunge Market in Kidderpore (also known as Kidderpore Market, Kidderpore Bazaar)
3. Maidan Bidhan Market
4. Burrabazar Wholesale Market
5. Bagri Market
6. Koley Market
7. Nager Bazaar Market
8. College Street Market
9. Sealdah Market
10. Manicktala Market

3.14 SAMPLE SIZE

Sample size denotes the quantity of observations or individuals incorporated in a study. It is a fundamental element of research technique, affecting the accuracy, reliability, and relevance of the research findings. Selecting an appropriate sample size ensures that the results accurately represent the target population and produce meaningful conclusions. A total of 698 people from Kolkata are included in this study's sample size, with a split between unstructured, unorganised retailers of different categories like Kirana, Pharmacy, Footwear, Handicrafts, Electronics and readymade garments. A sample size of n subjects was determined by applying Slovin's formula (Isip). The equation is:

$$n = N/\{1 + N(e)^2\}$$

Here, N = total population

e = margin of error

n = sample size

The population of Kolkata is 44,96,694, so total population (N)= 44,96,694 and we have taken 5% as margin of error (e).

$n = 4496694/\ (1+4496694*0.05^2)$

n = 4496694/233829

n = 399.98

So, we get sample size (n) as 400 after rounding off.

3.15 DATA COLLECTION

To answer research questions, test the hypothesis using a deductive approach, and evaluate the findings, it's critical to gather information from all pertinent sources (Bar-Ilan, 2001).

3.16 METHODS OF DATA COLLECTION

Data acquired for the very initial period and data collected thereafter are the two categories of primary data. Secondary data refers to information that has been previously subjected to statistical processing, analysis, and collecting by an external entity. To provide novel insights, data may be repurposed from alternative sources or gathered anew (Grove & Fisk, 1992). The study's aims have been achieved through the utilisation of both primary and secondary data sources. To address the information gaps, we mostly utilised pre-existing secondary materials, including research papers, articles, survey results, and theses (McDonald & Adam, 2003). It was feasible to have a deeper comprehension of the factors influencing the acceptability of mobile payments as well as the methodologies used in their research. Primary data information was then used to assess the study hypothesis. Schedules, questionnaires, interviews, and observation techniques can all be used to collect primary data. Data from the survey of respondents was examined. A questionnaire was the tool used to get information from the respondents (Radhakrishna, 2007).

3.17 QUESTIONNAIRE DESIGNING PROCESS

The questionnaire and in-person interviews served as the primary data collection methods. Because it facilitates the collection of data from a large number of respondents, a structured questionnaire is the most important and successful way of quantitative research tool. A 5-point Likert scale was employed to collect the data. A five-point Likert scale, from strongly disagree to strongly agree, was used in the survey. Because it affects the larger market, it is essential to comprehend how technology is being adopted in the unorganised retail sector. With a focus on demographics, motivations, and barriers, this survey seeks to understand how these retailers view, use, or reject technology. Age, gender, education, business type, and income are among the demographic and business information gathered from unorganised retail stores in the Questionnaire for Demographics & Business Profile Section. The study approach is enhanced by this data, which makes trend analysis within groups possible and offers context on how organisations view and use technology. Respondents' knowledge and utilisation of technical tools, ranging from ordinary smartphone use to specialised tools like point-of-sale systems, are evaluated via the Technology Awareness & Usage Section of the questionnaire. The structured questions indicate areas that require more attention or funding by revealing the unorganised retail sector's present level of technological knowledge and usage. Using a Likert scale, the Questionnaire for Technology Adoption (Section A) investigates retailers' opinions and experiences with technology adoption. By examining factors like cost, societal impact, and ease of use, it offers a comprehensive understanding of what encourages or hinders technology integration. The primary objective is to identify the factors that contribute to and hinder adoption, offering data on both positive and negative responses.

The questionnaire details these concerns using a Likert scale. The objective is to offer information that will assist policymakers and stakeholders in addressing these issues and creating focused plans to promote the adoption of technology in the unorganised retail industry. A questionnaire was used in this study since it is the most methodical way to get information from participants (Phellas et al., 2011).

Since a questionnaire was an inexpensive and effective way to gather primary data, it was used. The English version of the survey was written in a way that was easy for everyone to understand (Joshi et al., 2015).

3.18 PILOT STUDY

In Kolkata, a pilot study was carried out with efficacy. The primary questionnaire for the final data collection was modified as needed in response to the respondents' feedback. The pilot study was carried out as an initial stage of the investigation. The purpose of this pilot was to:

- Test the clarity and understandability of the questionnaire.
- Identify any potential issues with the data collection process.
- Evaluate the time required to complete the questionnaire.
- Ensure the questionnaire effectively addresses the research objectives.

The researcher has utilised the results of the pilot study to pinpoint the deficiencies in the current technique. Conducting a pilot study is crucial as it helps in significant savings of both cost and effort, for the researcher. Two factors to examine in the pilot project are the appropriateness of the variables identified through experimental investigations and literature review, and the reliability and validity of the variables used in the questionnaire. Preliminary research examines these issues utilising a constrained yet representative sample size. The technique is employed prior to conducting the final study to discover and rectify any discrepancies beforehand.

- The questionnaire's reliability and validity are frequently employed in conducting pilot research.
- The questionnaire's reliability and validity must be evaluated, as it is the only instrument that encompasses all relevant study variables.
- This study primarily investigates the collection of elements included in the third portion of the questionnaire using a pilot study.

The researcher enlisted the assistance of a total of 66 respondents from various regions within the Kolkata geographical markets for the present research. The pilot study yielded significant insights that informed the refinement of the final questionnaire for the primary data gathering phase. The pilot study was essential in validating the efficacy of the final questionnaire.

Participation in the survey was entirely optional and it was assured that the respondents (unorganised retailers) gave informed permission without any coercion. All acquired data were thoroughly anonymised, ensuring that individual responders could not be personally identified, so protecting their privacy. The researcher certifies that all replies were utilised solely for research purposes and were not disclosed to any third party for commercial or non-research activities. Throughout the process, the researcher aimed to respect the Kolkata retailer community's cultural, social, and professional sensitivities. The researcher recognized and demonstrated the importance of transparent communication that ensured that all participants clearly understood the survey's objectives, and the fact that their feedback and their information would be used from the perspective of academic research, and that data protection and data privacy measures were well in place. Furthermore, all participants were adequately informed during the personal interviews about the data protection and privacy protocols, assuring that confidentiality and anonymity would be upheld indefinitely, so securing a transparent and reliable survey procedure. Moreover, researchers are acknowledged for their contributions to research through citations and references, when applicable.

3.19 DATA ANALYSIS

The study's analysis involved examining 698 datasets to fulfil the research aims. The methodology for data analysis is elaborated in the subsequent chapter. The essential methodologies employed are summarized in Table, which outlines the Data Analysis Tools utilized during the study:

Table 3.2: Data Analysis Methods

Step	Purpose	Tools Used
Coding and Cleaning	Identification of variables; elimination of discrepancies	Data cleaning (Excel) (Smith & Doe, 2020)
Measurement of Central Tendency	Assessment of data dispersion	Descriptive Statistics (SPSS) (Jones, 2019)
Confirmatory Factor Analysis (CFA)	Measurement approach for assessing the validity and reliability of constructs	Structural Equation Modelling (SEM Smart PLS) (Wilson, 2021)
Reliability	To assess the reliability and viability of data	Cronbach alpha (more than 0.7) SPSS (Khan, 2019)
Path Analysis	Structural Model	Structural Equation Modelling (SEM Smart PLS) (Wilson, 2021)

This table now incorporates citations for each phase of the data analysis process, clearly associating the approaches and tools employed with their corresponding sources. This study utilised the Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) paradigm to study the determinants affecting the acceptance and use of new technology.

3.20 UTAUT-2 MODEL

The UTAUT-2 model offers a thorough framework for analysing technology adoption, encompassing multiple variables that reflect diverse aspects of user experience and motivation. The model incorporates numerous factors as outlined below (Mookerjee & Chattopadhyay, 2022).

- **Performance Expectancy (PE):** Individuals believe that adopting a technology can boost what they accomplish or augment their performance in specific tasks.
- **Effort Expectancy (EE):** The convenience inherent in the utilisation of the technology.
- **Social Influence (SI):** The degree to which individuals sense that significant others expect them to utilise the new technology.
- **Facilitating Conditions (FC):** The extent to which an individual perceives the presence of organisational and technological infrastructure that facilitates the utilisation of the technology.
- **Hedonic Motivation (HM):** The enjoyment or satisfaction obtained from utilising the technology.
- **Price Value (PV):** The cost-benefit analysis evaluated by users concerning the utilisation of the technology.
- **Habit (H):** The degree to which individuals display behaviours automatically as an outcome of learning.

The original UTAUT model, which was created to comprehend technology use and user adoption, is further developed upon by the UTAUT-2. UTAUT-2, which was first presented by Venkatesh, Thong, and Xu in 2012, attempts to improve the original framework by adding more variables that take consumer-focused situations into consideration (Venkatesh et al., 2012). UTAUT-2's fundamental objective aims to provide a thorough model that explains the variables affecting a person's intention to use and adoption of technology. By addressing factors that more accurately reflect user conduct outside of work settings, it develops upon the original UTAUT, which was more geared towards organisational use (Mookerjee & Chattopadhyay, 2022). To analyse the data collected on these **UTAUT-2 constructs**, a series of statistical tests were selected as appropriate methodologies for this research. The following sections outline the statistical techniques applied to each construct within the UTAUT-2 framework (Mookerjee & Chattopadhyay, 2022).

3.21 CONFIRMATORY FACTOR ANALYSIS (CFA)

Confirmatory Factor Analysis (CFA) has become the primary and validated method for assessing Common Method Variance (CMV) (Becker, 1994). Conceived as the initial phase in the two-tier Structural Equation Modelling (SEM) framework by Anderson and Gerbing (1988), Confirmatory Factor Analysis (CFA) enables researchers to assess the reliability and validity of the employed survey instrument. Confirmatory Factor Analysis (CFA) assesses the associations between latent constructs and their corresponding indicator variables Hair et al (2006) outline a systematic four-stage approach to conducting CFA:

- **Defining Individual Constructs:** Specify the constructs included in the model.
- **Developing the Measurement Model:** Create an overall measurement model that depicts the indicator items associated with each construct.
- **Designing the Study:** Structure the research to yield relevant empirical data.

- **Assessing Measurement Model Reliability and Validity:** Assess the reliability and validity of the measurement model by estimating factor loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT), among other metrics.,

A series of hypotheses has been established to examine the factors affecting technology adoption among unorganised retailers, with each hypothesis targeting a specific possible influence on their decision-making process. Below is a detailed discussion on how the hypotheses were tested:

To test the hypotheses on the adoption of retail technologies by unorganized retailers, researcher used Descriptive Statistics with SPSS and Structural Equation Modelling (SEM) with Smart PLS. Descriptive Statistics in SPSS has provided an overview of our data, summarizing key metrics like mean, standard deviation, and frequency distributions. This will help us understand the general characteristics and attitudes of the surveyed retailers in Kolkata, including their technology adoption levels and educational backgrounds.

Next, SEM using Smart PLS was applied to analyse the relationships among UTAUT2 constructs. Smart PLS is ideal for this due to its robustness in handling complex models. Structural Equation Modelling (SEM) will enable us to assess the robustness and importance of these correlations, providing a comprehensive validation of our ideas. This integrated methodology allows us to articulate and systematically evaluate the theoretical model, yielding an in-depth comprehension of the determinants affecting technology adoption among unorganised retailers. Through thorough testing of these hypotheses, researchers can reveal significant insights into the variables influencing or obstructing technology adoption among unorganised retailers. This understanding can help tailor interventions and strategies to support more effective technology integration in this sector.

3.22 RELIABILITY TEST

A reliability study assesses whether the initial variables chosen during the literature review are adequate for conducting the research and whether these variables demonstrate internal consistency. Various ways exist for testing reliability, but the most effective way to assess it is by utilising Cronbach's alpha value. Variables are internally consistent if the alpha value exceeds 0.70. The reliability test evaluates the temporal consistency of a measurement instrument, with Cronbach's alpha (α) serving as a prevalent statistic for assessing the internal consistency of a collection of items, such as survey questions. A threshold of $\alpha \geq 0.7$ is typically seen as indicative of acceptable dependability, but this may differ depending on the research environment (Cronbach, 1951).

3.23 OUTCOME OF THE PILOT STUDY

A pilot study was well executed across Kolkata having 66 respondents from across all the unorganised retail markets in Kolkata. Based on the feedback taken from the respondents (unorganised retailers), necessary improvements and several necessary modifications were done in the main questionnaire for the final primary data collection.

Table: 3.3: Reliability Test: Cronbach's Alpha

Reliability Test: N= 38 Questions asked about technology acceptance		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.834	0.834	38

Table: 3.4: Action Taken Post Pilot Study

Aspect Evaluated	Findings from Pilot Study	Actions Taken Post-Pilot Study
Clarity and Understandability	Some questions were identified as too complex or ambiguous for respondents.	Simplified the wording of ambiguous questions to improve clarity and respondent comprehension.
Questionnaire Length	Respondents found the questionnaire slightly lengthy, leading to potential fatigue.	Reduced the number of redundant or less relevant questions to streamline completion time without compromising data.
Data Collection Process	Logistical challenges in reaching certain respondents and uneven response rates across categories were noted.	Enhanced logistical planning and ensured better representation across all categories of unorganized retailers.
Relevance of Variables	Certain variables appeared less aligned with the research objectives after preliminary analysis.	Refined variable selection to ensure stronger alignment with the objectives and removed irrelevant variables.
Reliability of Variables	High Cronbach's Alpha scores confirmed acceptable internal consistency for key question groups.	Retained reliable question sets and ensured alignment with the validated constructs in the main questionnaire.
Validity of Variables	Some variables needed better framing to reflect real-world scenarios effectively.	Rephrased or redesigned specific questions to improve construct and content validity.
Response Time	Average time for completion exceeded initial estimates by a small margin.	Adjusted estimated response times and communicated this clearly to respondents in the final data collection phase.
Category-Specific Insights	Variations in responses across retailer categories highlighted the need for tailored questioning.	Introduced minor category-specific adjustments to ensure relevant data collection for each group.
Technological Terms and Concepts	Some respondents struggled to understand technical terms related to retail technology.	Included explanatory notes or examples for key terms to improve understanding and response accuracy.

The pilot study helped the researcher in the following ways: -

- Helped in testing the clarity and understandability of the questionnaire.
- Helped the researcher in verifying the questionnaire's reliability and validity.
- Helped in identifying any potential issues with the primary data collection process.
- Helped in evaluating the time required to complete the questionnaire.
- Helped in ensuring that the questionnaire effectively addresses all the research objectives and covers all aspects of the research.
- The pilot study was done with online Google Form, and it was observed that the unorganised retailers were not at all comfortable with this methodology of research. The unorganised retailers requested printed questionnaire, which was subsequently prepared for the final primary data collection.
- The insights obtained during the pilot study process was invaluable and significantly helped the researcher in improving the questionnaire, arranging a printed questionnaire form for personal interviews, to understand the time required to cover the entire geographical area as well as all the categories required from the perspective of stratified sampling methodology.

The researcher enlisted the assistance of a total of 66 respondents from various regions within the Kolkata geographical markets for the present research. The pilot study yielded important insights and deficiencies that influenced the refinement of the final questionnaire for the primary data gathering phase.

Descriptive Analysis

Descriptive analysis provides a detailed summary of data characteristics, often serving as the initial phase of data exploration in research. This analysis involves calculating measures of central tendency, such as the mean (μ), median (M), and mode, alongside measures of variability or dispersion, including the standard deviation (σ), variance (σ^2), range, and interquartile range (IQR).

The mean is computed as:

$$\mu = \frac{\sum_{i=1}^{N} x_i}{N},$$

where x_i represents each value in the dataset and N is the total number of values. The standard deviation, an indicator of the variability of data points relative to the mean, is computed as:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \mu)^2}{N}}.$$

These statistical measurements offer insights into the data's central tendency and dispersion and the spread of values, essential for understanding the dataset's general characteristics. Descriptive statistics are pivotal for summarizing large datasets in a meaningful way, enabling researchers to present data concisely and informatively. This study employed Descriptive Statistics to determine the mean and standard deviation of Facilitating Conditions, Performance Expectancy, Behavioural Intention, Effort Expectancy, Hedonic Motivation, Perceived Risks, Social Influence, Price Value, Habit, Benefits of Adoption, and Attitude.

3.24 INFERENTIAL STATISTICS - DESCRIPTIVE STATISTICS

Inferential statistics are utilized to generalize from a sample to a population, providing insights beyond the immediate data. This methodology encompasses many statistical tests and metrics to infer conclusions or provide predictions on population parameters derived from sample data. Two fundamental methods in inferential statistics are analysis of variance (ANOVA) and the t-test for significance of difference between means. In this study, t-test and ANOVA were used to test the divergence in perspectives among respondents according to age, gender, Hedonic Motivation, Education, Performance Expectancy, Perceived Risks, Effort Expectancy, Social Influence, Price Value, Facilitating Conditions, Behaviour Intention, Habit, Benefits of Adoption, Attitude.

3.25 T-TEST FOR SIGNIFICANCE OF DIFFERENCE BETWEEN MEANS

An essential inferential statistical test for determining the significance of a difference between two means is the t-test. The present research utilised an independent sample t-test to analyse the differences in respondents' opinions according to their gender based on Performance Expectancy (PE), Effort Expectancy (EE), Perceived Risk (PR), Price Value (PV), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), and Behavioral Intention (BI) and benefits. The formula for the t-test varies based on the test type but generally follows the principle:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{s_{\bar{X}_1 - \bar{X}_2}}$$

where $\bar{X}_1$ and $\bar{X}_2$ are the sample means of the two groups, and $s_{\bar{X}_1 - \bar{X}_2}$ is the standard error of the difference between the means (Kim, 2015). The t-value obtained is compared against a critical value from the t-distribution to determine if the difference is statistically significant (Mishra et al., 2019).

3.26 ANALYSIS OF VARIANCE (ANOVA)

ANOVA is a statistical method used to compare the means of three or more groups to ascertain whether at least one mean significantly differs from the others. The core concept of ANOVA is the analysis of variation within each group relative to the variance among groups. The formula for the F-statistic in one-way ANOVA is:

$$F = \frac{MS_{between}}{MS_{\text{within}}}$$

where MS_{between} (Mean Square Between) represents the variance among the group means and MS_{within} (Mean Square Within) denotes the average variance within the groups. A substantial F value indicates notable variances among the group means (Shaw & Mitchell-Olds, 1993). When independent variables consist of many categories of nominal data and the dependent variable is continuous, Analysis of Variance (ANOVA) is utilised to assess the significance of the difference between two means (LaMotte, 2023). It was utilized to ascertain the divergence of perspectives among retailers regarding variables such as Hedonic Motivation (HM), Performance Expectancy (PE), Behavioural Intention (BI), Perceived Risk (PR), Facilitating Conditions (FC), Effort Expectancy (EE), Social Influence (SI), and the advantages of technology adoption.

3.27 MULTI-COLLINEARITY TEST:

In statistical modelling, a situation where two or more independent variables in a regression model show a strong association is referred to as multi-collinearity. This correlation suggests that the variables provide redundant information about the dependent variable's variability. Increased standard errors for the regression coefficients are one of the numerous problems that multi-collinearity can bring about, and they may make it more difficult to assess the true significance of each predictor variable. Moreover, it can lead to precarious estimations of the coefficients, rendering them susceptible to minor alterations in the model or data. Various tests and metrics can be employed to identify multi-collinearity. The Variance Inflation Factor (VIF) quantifies the extent to which collinearity increases the variance of an estimated regression coefficient and is a widely utilised approach. It is generally accepted that significant multi-collinearity is indicated by a VIF score more than 10. The measure of tolerance has an inverse relationship with VIF. Tolerance values that are typically below 0.1 imply a high degree of collinearity. The Condition Index can also be utilized for evaluating multi-collinearity. Elevated numbers (often exceeding 30) indicate possible problems with collinearity. To mitigate the issue of multi-collinearity, various solutions can be utilized. An effective strategy involves eliminating variables with strong correlations from the model, resulting in a simplified and less redundant model. Alternatively, combining variables or creating composite variables—which entails combining related predictors into a single variable—can both reduce collinearity. Another technique for resolving collinearity concerns is Principal Component Analysis (PCA), which converts the original variables into a collection of uncorrelated components.

3.28 R-SQUARED TEST:

The R-squared test, or coefficient of determination, is a statistical metric employed to assess the quality of fit of a regression model. The coefficient of determination quantifies the proportion of variance in the dependent variable that is elucidated by the independent variables within the model. It is a value that spans from 0 to 1. An R-squared number of 1 denotes a perfect fit, signifying that the model explains all variability, whereas an R-squared value of 0 indicates that the model explains none of the variability. Although R-squared is a valuable metric, it has limits, such as its inclination to rise when additional predictors are added, potentially resulting in overfitting. Furthermore, it fails to specify the suitability of the model or whether the assumptions of the regression analysis have been satisfied. To address these issues, one may employ the Adjusted R-squared metric, which considers the number of predictors and provides a more accurate assessment of the model's adequacy. While R-squared is beneficial for evaluating the degree to which a model explains the variation in the data, it should be analysed alongside other diagnostic metrics for a comprehensive evaluation. The formula for R-squared is:

- Sum of Squared Residuals (SSR): Measures the total deviation of the observed values from the values forecasted by the model.
- Total Sum of Squares (TSS): Measures the total divergence of the observed values from their average.

3.29 PATH ANALYSIS USING STRUCTURED EQUATION MODELLING

Path analysis, an element of structural equation modelling (SEM), offers a sophisticated statistical technique for simulating the interactions among several variables, accounting for both direct and indirect effects. Structural Equation Modelling (SEM) integrates factor analysis and multiple regression to analyse the structural relationships between observable and latent variables, providing a comprehensive view of causal linkages within a theoretical framework. Path analysis within the SEM framework enables researchers to graphically depict these correlations through diagrams and quantify them using standardised coefficients. A crucial element of performing route analysis with SEM is model specification, which entails delineating the causal relationships among variables grounded in theoretical frameworks. An optimal model fit signifies that the designated model sufficiently encapsulates the data. The mathematical framework of SEM includes the measurement model, linking latent variables to observable indicators, and the structural model, outlining the relationships among latent variables. The structural model may be depicted as:

$$\eta = \mathbf{B}\eta + \mathbf{\Gamma}\xi + \zeta$$

where η represents the vector of dependent latent variables, ξ represents the vector of independent latent variables, $\mathbf{B}$ and $\mathbf{\Gamma}$ are matrices of coefficients representing the relationships among latent variables, and ζ is the equations' vector of errors (Hoyle, 1995). SEM and path analysis require a large sample size and assume multivariate normality of the data (Maruyama, 1997). SEM is a potent yet rigorous technique in terms of the data and expertise necessary for its application and interpretation due to the model's complexity and the assumptions required (Kline, 2023).

3.30 MEASUREMENT MODEL

A key element of structural equation modelling (SEM) is the measurement model, which outlines how observed variables suggest and measure latent variables. It basically defines how constructs are operationalised in a study and provides the basis for comprehending the connections between theoretical constructions (latent variables) and their empirical indicators (observed variables). The Confirmatory Factor Analysis (CFA) framework can be used to conceptualise the measurement model. In CFA, each latent variable is associated with certain observable variables through factor loadings, which measure the direction and strength of these correlations. Mathematically, the measurement model for a latent construct η with observed indicators $x_1, x_2, \ldots, x_n$ can be represented as:

$$x = \Lambda_x \eta + \delta$$

where x is the vector of observed variables, Λ_x is the matrix of factor loadings relating each observed variable to the latent variable η, and δ signifies the measurement error for every variable that has been observed. This formula emphasises the presumption that distinct error terms and the latent variables they are meant to assess both have an impact on the observed variables. Evaluating the validity and reliability of the constructs is integral to assessing the measuring methods. Validity pertains to the extent to which indicators accurately represent the underlying components, whereas reliability refers to the consistency of the assessment (Hair et al, 2006). Commonly used criteria for evaluating the measurement model include the average variance extracted (AVE), construct reliability (CR), and factor loadings. To ensure that the SEM analysis is grounded in robust theoretical and empirical underpinnings, it is imperative to develop and assess the measurement model (Hair et al., 2012). A measurement model that is properly specified enables the meaningful interpretation of the connections between latent constructs and serves as a foundation for the empirical testing of theoretical hypotheses (Brown, 2015).

3.31 STRUCTURAL MODEL

Within the context of structural equation modelling (SEM), the structural model delineates the hypothesised relationships among latent variables, which constitute the theoretical basis for the study. In contrast to the measurement model, which emphasises the relationship between latent variables and their indicators, the structural model concentrates on the causal pathways and interactions among the latent constructs themselves. This model is essential to SEM's capacity to evaluate intricate theoretical models with numerous independent, dependent, and mediating variables, offering a thorough comprehension of the concepts being studied. The structural model can be expressed mathematically as follows:

$$\eta = B\eta + \Gamma\xi + \zeta$$

where η represents the vector of dependent latent variables, ξ represents the vector of independent latent variables, B and Γ are the matrices of coefficients which represent the relationships among dependent latent variables and between independent and dependent latent variables., respectively, and ζ is the vector of errors or disturbances in predicting the dependent latent variables (Kline, 2023). To assess the structural model, the calculated path coefficients are analysed to determine the significance and strength of the hypothesised relationships. This involves evaluating the model's direct, indirect (mediated), and total effects (Bentler, 1990).

3.32 ETHICAL CONSIDERATION

A survey was conducted among the unstructured retailers in Kolkata, and the researcher ensured highest ethical standards. It had been ensured that the respondents (unorganised retailers) gave their informed agreement free from compulsion and that participation in the study was completely voluntary. In order to protect respondents' privacy, all information gathered was fully anonymised, and it was made sure that no respondent could be recognised by name. The researcher guarantees that the answers will only be used for study and won't be shared with outside parties for non-research or commercial purposes. Throughout the process, the researcher aimed to respect the Kolkata retailer community's cultural, social, and professional sensitivities. The researcher recognized and demonstrated the importance of transparent communication that ensured that all participants clearly understood the survey's objectives, and the fact that their feedback and their information would be used from the perspective of academic research, and that data protection and data privacy measures were well in place. A transparent and reliable survey process was also ensured by appropriately informing all respondents during the in-person interviews about the data protection and privacy safeguards and assuring that total confidentiality and anonymity would be maintained indefinitely. Additionally, when appropriate, citations and references are used to acknowledge researchers for their contributions to the field of study.

3.33 SUMMARY OF RESEARCH METHODOLOGY

Research design, research methodology, sampling have been discussed in this chapter to get the intended outcomes. The rationales for selecting factors, variables, sample size, and data collection techniques have been summarized. The results of the pilot research have been given, and the adjustments made to the final questionnaire have been reported.

We will subsequently analyse how this knowledge was employed in our assessment of future outcomes in the following chapter. The following chapter provides the analysis and interpretation of the gathered data.

CHAPTER 4

Data Analysis and Interpretation

CHAPTER 4

DATA ANALYSIS AND INTERPRETATION

In accordance with the goals of the study, this chapter analyses and evaluates the collected data. It involves conducting a simple percentage analysis of the respondents' demographic data to detect any discernible discrepancies in their views on the utilisation of technology in the unorganised retail sector. Beginning with a thorough demographic analysis, the study dissects various retailer profiles, highlighting how age, gender, education, and income levels interplay with their readiness and ability to embrace technological solutions. By integrating theoretical models with empirical data, the study aims to unravel how unorganized retailers in Kolkata interact with technology, offering insightful conclusions and strategic recommendations tailored to enhance digital empowerment and economic progress in the region. ANOVA and t-tests are two statistical methods employed to assess the significance of these differences. Structural Equation Modelling (SEM) was employed in the analysis. This sophisticated statistical method is utilised to elucidate the intricate elements affecting technology adoption, clarifying retailers' motivations, problems, and actions in this dynamic city.

4.1 DEMOGRAPHIC PROFILE

The demographic data suggests that middle-aged, male, primary school-educated retailers, predominantly in the grocery and apparel sectors, are the most engaged in the technology adoption process in Kolkata's unorganized retail market. The low representation of younger and highly educated individuals might indicate untapped potential or barriers to entry. The predominance of lower-income brackets suggests that cost-effective and accessible technological solutions are critical for wider adoption.

Understanding these demographic nuances is crucial for tailoring interventions, training, and support services to enhance technology adoption among these retailers.

Table 4.1: Demographic Profile of respondents (n=698)

Age	**Count**	**Percentage**
18 to 25	46	7%
25 to 35	104	15%
35 to 45	182	26%
45 to 55	189	27%
55 & above	177	25%
Gender		
Female	117	17%
Male	581	83%
Education		
Graduate	74	11%
High School	153	22%
Postgraduate and above	4	1%
Primary School	265	38%
Uneducated	202	29%
Income		
25,000 to 49,999	123	18%
50,000 to 74,999	122	18%
75,000 to 99,999	19	3%
< 25,000	432	62%
> 1 Lakh	2	0.3%
Type		
Ayurveda / Homeopathy / Yunani / Small Medicine Shop	94	13%
Electronics	54	8%
Footwear	119	17%
Grocery / Kirana	219	31%
Handicrafts & Artisan	48	7%
Medicine / Ayurveda / Homeopathy / Yunani	9	1%
Other Manufacturing	16	2%
Readymade Garments	139	20%

Age: The majority of retailers (27%) are between the ages of 45 and 55, with those between the ages of 35 and 45 coming in second (26%). Given that middle-aged people make up the largest portion of the market, this suggests that corporate operations may be more mature and stable. At 7%, the younger age group of 18 to 25 years old makes up the lowest sector, which may indicate less involvement or a more recent entry into the retail industry. Gender: There is a significant gender inequality, with males (83%) vastly outnumbering females (17%). This skew suggests that male retailers are more predominant in Kolkata's unorganized retail sector or potentially more receptive to adopting technology. Education: The highest percentage of retailers have only completed primary school (38%), followed by those with a high school education (22%). Only a small fraction (1%) has postgraduate or higher qualifications. This spread might influence the types of technology adopted and the ease with which new systems are learned and integrated. Income: Most retailers (62%) earn less than 25,000 INR, pointing towards a segment that might be price-sensitive and cautious about investments, including technology. Those earning between 25,000 and 49,999 INR and 50,000 and 74,999 INR are relatively balanced (18% and 17%, respectively), suggesting a middle-income bracket possibly more capable of adopting cost-incurring technologies. Type of Business: The most common business type among respondents is Grocery/Kirana stores, accounting for 31% of the sample. This is followed by Readymade Garments (20%) and Footwear (17%), indicating these sectors might be more inclined or positioned to adopt innovative technologies. Ayurveda/Homeopathy/Yunani/Small Medicine Shops also represent a sizeable portion (13%), which could reflect a specific need or trend in technology adoption within these sectors.

4.2 SEM MEASUREMENT MODEL

The methodology of Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to evaluate the sub-constructs for internal consistency, convergent validity, and discriminant validity. This was conducted to assess the internal consistency, convergent validity, and discriminant validity of the sub-constructs. This study seeks to clarify the technological landscape in this sector by examining the relationships among constructs including attitude, hedonic motivation, perceived risk, effort expectancy, facilitating conditions, habit, performance expectancy, price value, and social influence, as well as their effects on adoption intention and perceived benefits. The Structural Equation Modelling (SEM) diagram illustrates a clear measurement model, showcasing the links between observable variables and their corresponding latent constructs within the study framework. Thus, the measurement model lays the groundwork for further structural analysis by offering a clear and succinct mapping of the observed variables onto their corresponding latent constructs. The integrity of the suggested theoretical linkages to be examined in the SEM framework and the validity of the constructs are guaranteed by this delineation. This model's goal is to accomplish the main objectives that the study established. The "Measurement Model" and the "Structural Model" are the two models identified in the PLS-SEM literature. The Measurement Model, sometimes called Confirmatory Factor Analysis (CFA), analyses the constructs' validity and reliability.

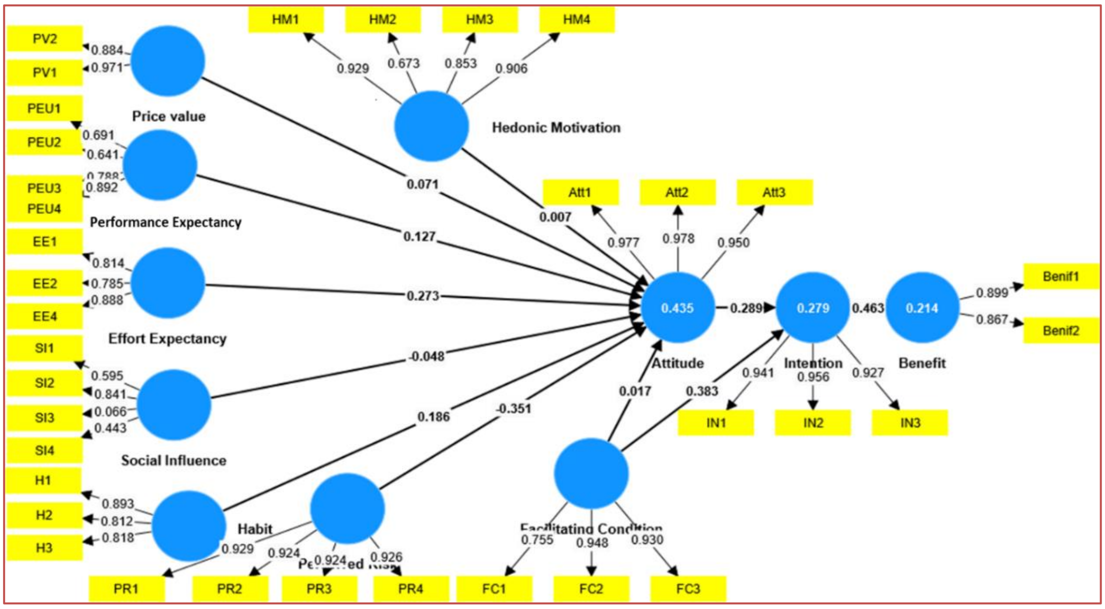

Figure 4.1: PLS-SEM: Model of Observed variables

Table 4.2: Constructs and Item descriptions of UTAUT-2 factors

First-order construct code	Item code	Item
Price Value (PV)	*PV1*	The financial burden of adopting the technology is warranted by the prospective advantages it provides.
	PV2	Embracing technology presents prospects for cost reduction through enhanced operational efficiency, diminished expenditures, or augmented revenue potential.
Performance expectancy (PEU)	*PEU1*	Integrating technology into business will enhance my ability to service consumers effectively.
	PEU2	Technology has augmented the likelihood of accomplishing objectives.
	PEU3	The utilisation of technology has streamlined job processes and tasks.
	PEU4	Technology facilitated the expedited completion of tasks.
Effort Expectancy (EE)	*EE1*	Utilising the technology post-adoption is straightforward.
	EE2	Technological solutions pertinent to the retail sector are user-friendly.
	EE4	Utilising the technology would conserve time and effort relative to the existing approaches.

First-order construct code	Item code	Item
Social Influence (SI)	*SI1*	Influential people believe that this should be implemented in the retail sector.
	SI2	Influenced by the endorsements of esteemed individuals while evaluating technology adoption
	SI3	If other retailers within social circles embrace technology, it is more probable that they will adopt it in the retail sector.
	SI4	The perspectives and views of peers and colleagues influence retailers' decisions to employ technology in the retail sector.
Habit (H)	*H1*	The utilisation of technology in the retail sector has become customary for retailers.
	H2	Envisioning retail business operations devoid of technology is challenging.
	H3	Retailers adopt technology instinctively, without conscious assessment, when executing business operations.
Perceived Risk (PR)	*PR1*	Implementing technological advances into business operations is highly advantageous.
	PR2	The advent of technology has enhanced the possibility of achieving goals.
	PR3	The adoption of technology has streamlined job processes and tasks.
	PR4	Technology enabled me to achieve tasks more efficiently.
Hedonic Motivation (HM)	*HM1*	The utilisation of technology amplifies the happiness and satisfaction derived from engaging in commercial tasks.
	HM2	Implementing technological advances enhances the dynamism and enjoyment of business operations.
	HM3	Implementing technological advances offers a sense of freshness and creativity to retail business methods.
	HM4	Adopting technology provides me with a sense of satisfaction and fulfilment in the retail business endeavours

First-order construct code	Item code	Item
Facilitating Condition	*FC1*	The necessary technological infrastructure (e.g., internet connectivity, hardware) is readily available and accessible to support the adoption of new technologies by the Retail Business
	FC2	Retailers have access to the necessary resources (financial, human, and technical) to adopt and effectively utilize the technology
	FC3	Retailers possess the requisite expertise to embrace and utilise the technology.
Attitude (Att)	*Att1*	Using technology in Retailer Business would greatly enhance their productivity and efficiency
	Att2	Retailers believe that adopting technology in their business would improve their overall performance and effectiveness
	Att3	Using technology in their business would lead to a competitive advantage and help retailers to stay ahead in the market
Behavioural Intention (IN)	*IN1*	Retailers see their self extensively using technology as part of their everyday business operations
	IN2	Retailers plan to make consistent efforts to incorporate technology into their business practices
	IN3	Retailers are willing to allocate resources and invest in the necessary technology in their business
Benefits of Adoption (Beni)	*Benif1*	Retailers' business experienced more footfall after adopting retail technology
	Benif2	Technology adoption has provided competitive advantage in the market

Source: *Created by the researcher*

4.3 MEASUREMENT MODEL

Partial Least Squares Structural Equation Modelling (PLS), a more sophisticated statistical method than multiple linear regression, was used to analyse the data. Partial Least Squares Structural Equation Modelling (PLS) improves result dependability, mitigates specification errors, and rectifies structural deficiencies. Moreover, Partial Least Squares Structural Equation Modelling (PLS) may assess many relationships concurrently and furnish a comprehensive model fit assessment (Fornell & Larcker, 1981). The model was evaluated in this study using Partial Least Squares Structural Equation Modelling (PLS-SEM). The model was measured using the SmartPLS 4.0 program. This method uses a reflective model to quantify first-order variables, which are indicators of constructs (Schumacker & Lomax, 2016). The outer loadings of each variable were examined, requiring a standard loading value of at least 0.70. According to Hair et al (2011), the model did not include indicators whose outer loadings were less than 0.60. In the event that additional indicators within the same construct show higher loadings, loadings between 0.50 and 0.70 are typically considered acceptable (Nitzl et al, 2017). On the associated latent variables, the majority of the indicator loading values were more than 0.70. Internal consistency dependability was assessed using "Cronbach's alpha, the rho_A value, and Composite Reliability (CR) indices." Cronbach's alpha gauges the dependability of internal consistency, with the lowest bound being composite reliability (Nitzl et al, 2017). Greater reliability is indicated by higher composite reliability values (Hair et al, 2014). It became apparent that the majority of the indicator loading values on the associated latent variables were more than 0.70. Cronbach's alpha, Composite dependability (CR) indices, and the rho_A value were used to assess internal consistency dependability. A higher degree of reliability has been demonstrated by higher composite reliability values (Hair et al, 2014). Afthanorhan (2013) proposed an acceptable alpha value of 0.70 and a composite reliability of 0.70 or higher to attain internal consistency.

4.3.1 UTAUT-2: INTERNAL CONSISTENCY OF MEASUREMENT MODEL

Evaluating the strength of the UTAUT-2 framework necessitates a careful examination of the internal consistency within the measurement model. This assessment entails analysing the dependability and authenticity of different constructs to confirm that they effectively embody the foundational theoretical concepts. We can evaluate the consistency and reliability of the items that measure each construct by using metrics such as "Cronbach's alpha, rho_A, composite reliability, and average variance extracted (AVE)". This study validates UTAUT-2 model constructions and pinpoints areas for improvement to enhance prediction accuracy and structural integrity (Ahmed et al, 2017).

Table 4.3: Measurement Model with UTAUT-2 factors

Construct	**Items**	**Loadings**	**Cronbach's Alpha**	**rho_A**	**Composite Reliability**	**Average Variance Extracted (AVE)**
Attitude (Att)	Att1	0.977	0.967	0.968	0.978	0.937
	Att2	0.978				
	Att3	0.950				
Benefits of Adoption (Benif)	Benif1	0.899	0.719	0.727	0.876	0.780
	Benif2	0.867				
Effort Expectancy (EE)	EE1	0.814	0.774	0.790	0.869	0.689
	EE2	0.785				
	EE4	0.888				
Facilitating Condition	FC1	0.755	0.857	0.917	0.912	0.778
	FC2	0.948				
	FC3	0.930				
Habit (H)	H1	0.893	0.813	0.955	0.879	0.709
	H2	0.812				
	H3	0.818				
Hedonic Motivation (HM)	HM1	0.929	0.906	0.819	0.909	0.716
	HM2	0.673				
	HM3	0.853				
	HM4	0.906				
	IN1	0.941	0.936	0.937	0.959	0.886
	IN2	0.956				

Construct	Items	Loadings	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Behavioural Intention (IN)	IN3	0.927				
Performance expectancy (PEU)	PEU1	0.691	0.778	0.849	0.843	0.577
	PEU2	0.641				
	PEU3	0.788				
	PEU4	0.892				
Perceived Risk (PR)	PR1	0.929	0.944	0.953	0.960	0.857
	PR2	0.924				
	PR3	0.924				
	PR4	0.926				
Price Value (PV)	PV1	0.971	0.856	0.824	0.926	0.862
	PV2	0.884				
Social Influence (SI)	SI1	0.595	0.870	0.864	0.902	0.516
	SI2	0.841				
	SI3	0.066				
	SI4	0.443				

Source: *Created by researcher from analysis*

The table laid out above offers a comprehensive overview of the measurement model for constructs derived from the UTAUT-2 framework, evaluating several parameters including "loadings, Cronbach's alpha, rho_A, composite reliability, and average variance extracted (AVE)". Attitude (Att): Items associated with Attitude (Att1, Att2, Att3) exhibit strong loadings, indicating a robust relationship with the Attitude construct. Strong reliability is indicated by internal consistency measurements, including "Cronbach's Alpha, rho_A, and Composite Reliability, exceeding the acceptable threshold." The high Average Variance Extracted (AVE) score of 0.937 signifies robust convergent validity. The Benefits of Adoption (Benif) construct, represented by items Benif1 and Benif2, demonstrates significant loadings, signifying a strong correlation. The AVE value (0.780) is above 0.50, indicating acceptable convergent validity. Effort Expectancy (EE): Items related to Effort Expectancy (EE1, EE2, EE4) exhibit notable loadings, indicating a strong association with Effort Expectancy. Internal consistency measures suggest satisfactory reliability, with acceptable convergent validity indicated by the AVE value (0.689). Facilitating Condition: Items associated with Facilitating Condition (FC1, FC2, FC3) demonstrate strong loadings, suggesting a robust relationship with Facilitating Condition. Internal consistency measures indicate good reliability, with a strong convergent validity indicated by the AVE value (0.778). Habit (H): Items linked to Habit (H1, H2, H3) show substantial loadings, indicating a strong association with the Habit construct. Internal consistency measures suggest good reliability, with acceptable convergent validity suggested by the AVE value (0.709). Hedonic Motivation (HM): Items associated with Hedonic Motivation (HM1, HM3, HM4) exhibit notable loadings, indicating a strong association with Hedonic Motivation. Internal consistency measures suggest satisfactory reliability, with acceptable convergent validity indicated by the AVE value (0.716). Behavioural Intention (IN): Items related to Behavioural Intention (IN1, IN2, IN3) demonstrate high loadings, indicating a strong association with Behavioural Intention. Internal consistency measures suggest good reliability, with strong convergent validity indicated by the AVE value (0.886). Performance expectancy (PEU): Items associated with Performance expectancy (PEU1, PEU3, PEU4) exhibit notable loadings, indicating a strong association with Performance expectancy. Internal consistency measures suggest satisfactory reliability, with acceptable convergent validity indicated by the AVE value (0.577). Perceived Risk (PR): Items linked to Perceived Risk (PR1, PR2, PR3, PR4) show substantial loadings, indicating a strong association with Perceived Risk. Internal consistency measures suggest good reliability, with strong convergent validity indicated by the AVE value (0.857). Price Value (PV): Items associated with Price Value (PV1, PV2) demonstrate high loadings, indicating a strong association with Price Value. Internal consistency measures suggest satisfactory reliability, with strong convergent validity indicated by the AVE value (0.862). Social Influence (SI): Item SI1 exhibits a notable loading, indicating a moderate association with Social Influence. Internal consistency measures suggest acceptable reliability, with weaker convergent validity indicated by the AVE value (0.516). Overall, the UTAUT-2 factors demonstrate associations with their respective constructs, indicating reliability and convergent validity.

4.3.1.1 INTERNAL CONSISTENCY

The constructions' internal consistency was evaluated using Cronbach's alpha values, which fall between 0.72 to 0.97. Reliability is considered adequate when the Cronbach's alpha value is at least 0.72. Since composite dependability is crucial for internal consistency, it was also assessed (Saini et al, 2022). The composite reliability values exceeded the 0.7 threshold value and ranged from 0.72 to 0.97 (Gefen et al, 2000). These results are operational and meet the intended benchmarks. The requirement for rho_A values is a minimum of 0.7, and all values in our investigation surpassed this barrier, signifying robust internal consistency (Hair et al, 2019).

4.3.1.2 CONVERGENT VALIDITY

Convergent validity is a vital concept in research methodology, indicating the degree to which two assessments of theoretically related constructs are actually associated. Convergent validity evaluates the correlation between different measures of the same construct. A strong correlation among these indicators indicates substantial convergent validity. A substantial correlation (typically surpassing 0.50) among diverse measurements indicates significant convergent validity, while a modest correlation suggests that the instruments may not be measuring the same construct. Convergent validity, which evaluates the extent to which markers of a certain construct share variance, was also examined. It assesses the efficacy with which the construct conveys the identical concept (Hair et al, 2019). The Average Variance Extracted (AVE) was computed as the average of the squared loadings of all indicators connected with the construct. To provide robust convergent validity, the Average Variance Extracted (AVE) must exceed 0.50 (Hair et al, 2014). The Average Variance Extracted (AVE) findings demonstrated the absence of convergent validity concerns among the constructs.

4.3.1.3 VARIANCE INFLATION FACTOR

The Variance Inflation Factor (VIF) is a critical tool in regression analysis for detecting and addressing multicollinearity, which occurs when predictor variables in a model exhibit a significant connection. The Variance Inflation Factor (VIF) quantifies the degree to which multicollinearity amplifies the variance of a regression coefficient. It is determined for each model predictor variable. By using VIF, analysts can effectively detect and mitigate multicollinearity, leading to more robust and reliable regression models. Identifies Multicollinearity: VIF helps in pinpointing which predictors are contributing to multicollinearity, allowing for targeted adjustments. Improves Model Reliability: By addressing multicollinearity, VIF ensures that the regression coefficients are reliable and interpretable. Enhances Predictive Power: Reducing multicollinearity can improve the model’s predictive accuracy by ensuring that each predictor variable contributes unique information.

Table 4.4: Testing for Multicollinearity using Variance Inflation Factor (VIF)

	VIF
Attitude -> Intention	1.051
Effort Expectancy -> Attitude	1.263
Facilitating Condition -> Attitude	1.582
Facilitating Condition -> Intention	1.051
Habit -> Attitude	1.484
Hedonic Motivation -> Attitude	1.582
Intention -> Benefits of Adoption	1.000
Performance expectancy -> Attitude	1.189
Perceived Risk -> Attitude	1.186
Price value -> Attitude	1.113
Social Influence -> Attitude	1.287

Source: *Created by researcher from analysis*

The table above presents a summary of the measurement model for constructs derived from the UTAUT-2 framework, evaluating the Variance Inflation Factor (VIF). The Variance Inflation Factor (VIF) values varied from 1.0 to 1.582, demonstrating acceptable levels of collinearity. Variance Inflation Factor (VIF) values must remain below 5 to prevent collinearity complications (Hair et al, 2014). All Variance Inflation Factor (VIF) values for the constructs were below 5, demonstrating the absence of any multicollinearity concerns.

4.3.1.4 DISCRIMINANT VALIDITY

Discriminant validity denotes the degree to which a construct is genuinely separate from other constructs, both in idea and in empirical measurement. Discriminant validity is essential in quantitative research for assessing the distinctiveness of constructs, particularly in confirmatory factor analysis (CFA) and structural equation modelling (SEM). Instead of just reflecting elements of other structures, it ensures that a latent variable embodies phenomena that are exclusive to itself. High discriminant validity signifies that a concept demonstrates greater variance with its own indicators than with any other construct within the model. Discriminant validity was established by the Heterotrait-Monotrait (HTMT) ratio, cross-loadings, and the Fornell-Larcker criterion. To ensure that a concept is free from discriminant validity concerns, its Average Variance Extracted (AVE) must surpass the squared correlations with other variables. Discriminant validity necessitates that the Average Variance Extracted (AVE) for each construct exceeds the squared correlations between that construct and other variables (Hair et al, 2019). The Fornell-Larcker criterion assesses the square root of the Average Variance Extracted (AVE) of a latent construct in relation to its correlations with other constructs in the model. AVE assesses the ratio of variance elucidated by a latent variable relative to the variance ascribed to measurement error. When a construct's Average Variance Extracted (AVE) square root is greater than its correlations with any other construct, the Fornell-Larcker criterion is satisfied.

Table 4.5: Discriminant Validity

Attitude	0.968										
Benefits of Adoption	0.260	0.883									
Effort Expectancy	0.467	0.179	0.830								
Facilitating Condition	0.220	0.438	0.063	0.882							
Habit	0.411	0.273	0.321	0.300	0.842						
Hedonic Motivation	0.217	0.306	0.062	0.473	0.466	0.846					
Intention	0.373	0.463	0.127	0.447	0.305	0.469	0.941				
Performance expectancy	0.190	0.415	0.015	0.398	0.113	0.169	0.293	0.759			
Perceived Risk	-0.513	-0.326	-0.313	-0.156	-0.277	-0.183	-0.321	-0.058	0.925		
Price value	0.152	-0.011	0.214	0.082	0.045	-0.050	0.053	0.037	-0.044	0.929	
Social Influence	-0.228	-0.221	-0.120	-0.336	-0.286	-0.345	-0.320	-0.145	0.224	0.155	0.562

The model demonstrated discriminant validity, as the correlations were smaller than the square roots of the AVEs for the components. between the constructs. The square root of AVE values, manually calculated and indicated diagonally in the table, exceed the latent variables in each row and column. These results demonstrate no discriminant validity concerns.

4.4 HETEROTRAIT-MONOTRATIT (HTMT) RATIO

In Structural Equation Modelling (SEM), the Heterotrait-Monotrait (HTMT) Ratio measures discriminant validity between model constructs. Discriminant validity measures how well theoretically different conceptions are differentiated in practice. HTMT ratios were introduced as alternatives to the Fornell-Larcker criterion and cross-loadings, which have been criticised for failing to discover discriminant validity concerns. HTMT assumes that monotrait correlations are higher than heterotrait correlations. HTMT is often used to evaluate SEM measurement models, especially PLS-SEM and CB-SEM. Thus, the HTMT ratio analyses the average correlations between heterotrait indicators and monotrait indicators. In the exploration of construct relationships within the research model, the Heterotrait-Monotrait (HTMT) ratio emerges as a critical metric. This statistical tool delivers information about the model's discriminant validity, illuminating the degree of divergence between constructs. We may better grasp the uniqueness of each construct and the measurement model's overall robustness by looking at the HTMT ratios (Grosova, 2022).

Table 4.6: HTMT analysis of UTAUT-2 factors

UTAUT-2 Factors	Attitude	Benef of Adop	Effort Expect	Facilit Condi	Habit	Hedo Motiv	Inten	Perf Expectancy	Perceiv Risk	Price value	Soc Infl
Attitude											
Benefits of Adoption	0.309										
Effort Expectancy	0.534	0.245									
Facilitating Condition	0.237	0.544	0.112								
Habit	0.413	0.407	0.351	0.389							
Hedonic Motivation	0.157	0.343	0.230	0.472	0.512						
Intention	0.391	0.562	0.156	0.482	0.392	0.479					
Performance expectancy	0.196	0.604	0.152	0.486	0.188	0.258	0.330				
Perceived Risk	0.531	0.402	0.358	0.173	0.308	0.142	0.347	0.118			
Price value	0.152	0.097	0.236	0.109	0.077	0.138	0.069	0.200	0.074		
Social Influence	0.099	0.235	0.185	0.309	0.205	0.344	0.265	0.234	0.131	0.361	

Source: *Created by researcher from analysis*

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The discriminant validity of the model was evaluated using the "Heterotrait-Monotrait (HTMT)" ratio in the table above. The use of the HTMT ratio improves the accuracy of model testing, particularly in intricate research designs, and constitutes a substantial breakthrough in the evaluation of discriminant validity, particularly in SEM techniques. According to established criteria, an HTMT value below 0.85 or 0.90 indicates sufficient discriminant validity. Since none of the constructs have an HTMT value more than 0.85, the results clearly demonstrate that discriminant validity is suitable (Hair et al, 2019). The HTMT ratios demonstrate that the constructs in the UTAUT-2 model possess strong discriminant validity. A minor fraction of HTMT values reach the conservative threshold of 0.9, while the majority are considerably lower. This indicates that the measurement model is robust and that the constructs are distinct from each other

4.5 STRUCTURAL MODEL

By drawing a path diagram, a Structural Model, also known as Path Analysis, seeks to determine the causal links between variables, representing the connections between latent variables within the model. This process involves several phases. The initial phase involves defining the model; the subsequent step guarantees the model's identifiability, indicating that each parameter possesses a unique solution. Upon identification, the model may be estimated, and its appropriateness for the data can be evaluated by analysing the model's fit (Sarstedt, et al., 2020). This process persists until an effective model is found. Thus, the model's parameters test internal causal theories (Hair et al, 2019). Initially, the model predicts whether technology adoption will impact unorganized retailers. Secondly, it examines how the sub-constructs of Technology Adoption influence the sub-constructs of Unorganized Retailers' business performance.

The structural model tested the predictability hypothesis for these sub-constructs on Unorganised Retailers. A combination of route coefficient, coefficient of determination, and predictive relevance evaluates data model fit.

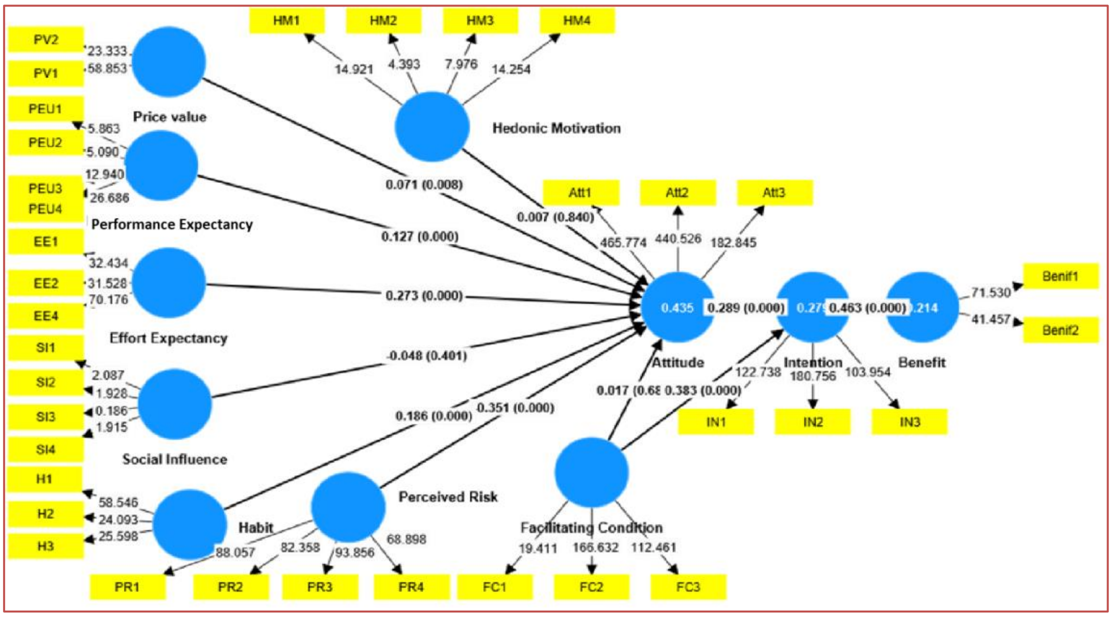

Figure: 4.2 Structural Model

4.5.1 RESULT OF PATH MODEL

The intricate dynamics of technology adoption among unorganised retailers in Kolkata are depicted in the Path Model study (Hanif, 2022).

Table 4.7: Path model with UTAUT 2 factors

	Original sample (O)	Sample Mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Attitude -> Intention	0.289	0.29	0.035	8.146	0.000
Effort Expectancy -> Attitude	0.273	0.27	0.035	7.708	0.000
Facilitating Condition -> Attitude	0.017	0.02	0.041	0.406	0.685
Facilitating Condition -> Intention	0.383	0.38	0.042	9.220	0.000
Habit -> Attitude	0.186	0.18	0.036	5.214	0.000

	Original sample (O)	Sample Mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Hedonic Motivation -> Attitude	0.007	0.02	0.036	0.202	0.840
Intention -> Benefits of Adoption	0.463	0.46	0.043	10.713	0.000
Performance expectancy -> Attitude	0.127	0.13	0.036	3.519	0.000
Perceived Risk -> Attitude	-0.351	-0.35	0.043	8.201	0.000
Price value -> Attitude	0.071	0.07	0.027	2.671	0.008
Social Influence -> Attitude	-0.048	-0.02	0.057	0.840	0.401

Source: *Created by researcher from analysis*

A route model with UTAUT 2 elements is illustrated in the table above, demonstrating construct relationships and statistical data. Attitude -> Intention: A retailer's intent to embrace technology is significantly influenced by their attitude, as evidenced by the strong and significant positive association between attitude and intention to implement technology (T statistic = 8.146, P value = 0.000). Effort Expectancy -> Attitude: An additional significant positive correlation is shown between effort expectancy and attitude (T statistic = 7.708, P value = 0.000), demonstrating that retailers' attitudes towards adoption are positively impacted when they believe technology is user-friendly. Facilitating Condition -> Attitude and Facilitating Condition -> Intention: Facilitating conditions have significant beneficial effects on intention (T statistic = 9.220, P value = 0.000), but they have very little impact on attitude (P value = 0.685). Therefore, it appears that the presence of infrastructure and sufficient resources increases the intention to use technology. Habit -> Attitude: According to this significant association (T statistic = 5.214, P value = 0.000), attitudes regarding the adoption of technology are positively influenced by habitual tendencies to use it. Hedonic Motivation -> Attitude:

There is no significant correlation between the two (P value = 0.840), indicating that merchants' attitudes on the use of technology are not strongly predicted by hedonic motivation. desire -> Benefits of Adoption: The desire to adopt technology is a powerful predictor of perceiving the benefits of adoption, as evidenced by the very strong positive association with the greatest T statistic of 10.713 and a P value of 0.000. Performance Expectancy -> Attitude: This positive correlation (T statistic = 3.519, P value = 0.000) indicates that people are more likely to be in favour of adopting technology if they believe it to be user-friendly. Perceived Risk -> Attitude: The negative relationship (T statistic = -8.201, P value = 0.000) suggests that perceived risks associated with technology negatively affect the attitude towards its adoption. Price value -> Attitude: A significant positive relationship (T statistic = 2.671, P value = 0.008) implies that cost-benefit considerations are important in shaping a positive attitude towards technology adoption. Social Influence -> Attitude: This relationship is insignificant (P value = 0.401), indicating that social factors do not significantly influence the attitude towards technology adoption in this context. All things considered; the route model research offers several important insights into the variables affecting unorganised shops' use of technology. First of all, attitudes and beliefs towards technology have a significant impact on the intention to utilise it. Effort expectancy, also known as performance expectancy, has a beneficial effect on attitudes towards adoption. while attitudes are negatively impacted by perceived risks related to the deployment of technology. Additionally, habitual tendencies towards technology usage positively influence attitudes, indicating the importance of past behaviours in shaping current attitudes. Facilitating environments like resources and infrastructure boost retailers' technology adoption intentions. This shows that supportive systems and suitable surroundings might boost technology adoption. The data also shows that retailers' intentions strongly predict technology adoption advantages. However, hedonic motivation and social influence had no significant effects on attitudes towards technology adoption, suggesting that these factors may not influence decisions made by unorganised retailers to adopt technology. In summary, the results highlight the significance of tackling perceptions, enabling conditions, and intentions to enhance technology adoption among unorganised retailers, while also acknowledging the subtle impacts of elements like perceived risk and price value on attitudes towards adoption. The analysis of path coefficients provides significant insights into the relationships among variables in the structural model, clarifying the magnitude and direction of their influence.

Table 4.8: Path coefficient: R_2 and Q_2 value

	R-square	R-square adjusted	Q^2predict
Attitude	0.435	0.429	0.415
Benefits of Adoption	0.214	0.213	0.178
Intention	0.279	0.277	0.260

Source: *Created by the researcher from analysis*

This table demonstrates the Adjusted R-square, Q^2 predict and R-square (R^2) and values for the constructs of attitude, benefits of adoption, and intention as part of the path model analysis (Anggraini, 2019). Attitude: The exogenous components included in the model may explain for approximately 43.5% of the variability in attitude, according to the R-square value of 0.435. The adjusted R-square value of 0.429 indicates a little change to account for the number of predictors in the model. The Q2 predict value of 0.415 indicates that the model can predict attitude with a reasonable degree of accuracy. Benefits of Adoption: According to the R-square value of 0.214, the exogenous factors in the model can explain around 21.4% of the variation in the benefits of adoption. The modified R-square value remains consistent at 0.213, indicating a moderate level of predictive potential for the benefits of adoption construct as suggested by the Q^2 predict value of 0.178. Intention: The exogenous components included in the model can account for about 27.9% of the variation in intention, according to the R-square value of 0.279. A minor adjustment for the number of predictors is indicated by the corrected R-square value of 0.277. The Q2 predict score of 0.260 demonstrates that the intention construct has a significant amount of predictive power. All things considered, the route coefficient analysis provides insightful information on how the variables in the structural model relate to one another. A good fit is indicated by the model's ability to explain a significant amount of the variance in the endogenous constructs, as indicated by R-square values ranging from 0.214 to 0.435. Taking into account the amount of predictors included, the corrected R-square values further validate the model's robustness. The Q^2 predictive values, spanning from 0.178 to 0.415, imply that the model possesses predictive relevance, demonstrating its capacity to effectively foresee outcomes beyond the sample data. In conclusion, these results demonstrate that the path model adequately explains the variance in attitude, advantages of adoption, and intention components, indicating that the model possesses strong explanatory and predictive capacities for these constructs.

4.6 SPSS ANALYSIS

4.6.1 ADOPTION OF TECHNOLOGY METHOD BY RETAILERS

The adoption of technology by retailers is a critical factor in modern commerce. With a plethora of options available, from mobile payments to inventory management systems, technology integration enhances operations and boosts competitiveness.

Table 4.9: Stages of technology adoption

	Frequency	**Percent**
Innovator	17	2
Early Adopter	18	3
Early Majority	30	4
Late Majority	172	25
Laggard	461	66
Total	**698**	**100**

The analysis demonstrates that a significant majority of respondents (66%) fall into the Laggards category, suggesting that a large segment of the unorganised retail sector has not yet actively adopted technological innovations. After Laggards, the Late Majority adopters form a significant portion, accounting for 25% of the respondents. This group typically adopts technology after it has been proven and widely accepted. Early Majority adopters comprise 4% of respondents, suggesting a growing but still relatively small proportion of retailers embracing technology in its earlier stages of adoption. Early Adopters and Innovators represent the smallest segments, comprising 3% and 2% of respondents, respectively.

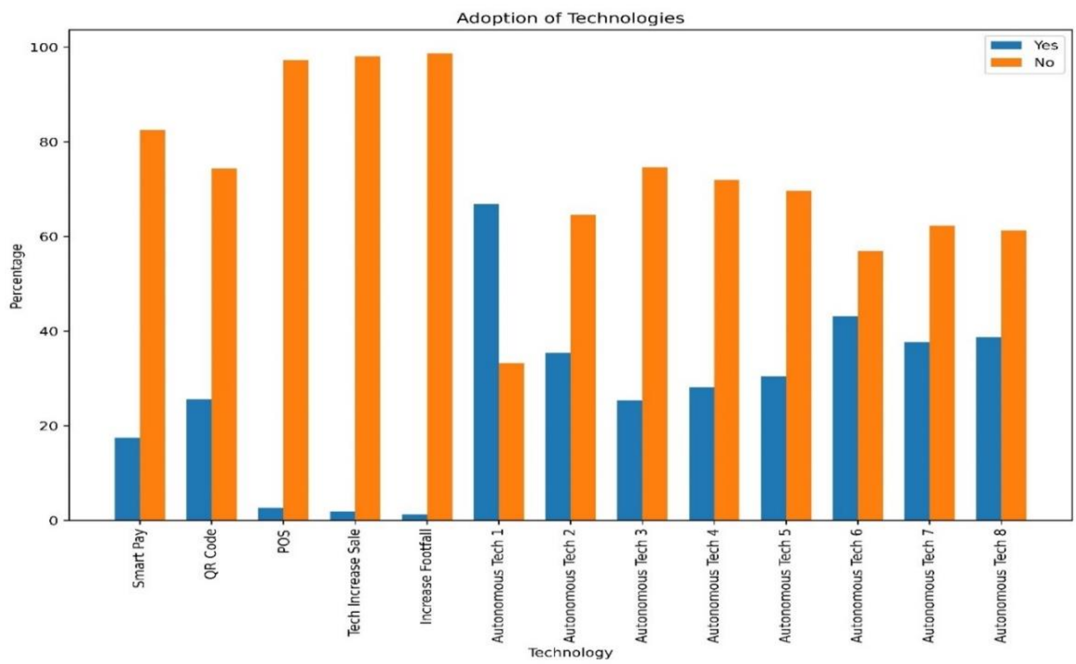

Figure 4.3: Methods of Technology Adoption

Table 4.10: Simple Percentages for methods and technology

		Count	Column N %
Digital Wallets, RTGS, NEFT	No	576	83%
	Yes	122	17%
QR_Codes	No	519	74%
	Yes	179	26%
POS (Debit / Credit Cards)	No	679	97%
	Yes	19	3%
Technology Increased Sales	No	685	98%
	Yes	13	2%
Technology Increased Footfall	No	689	99%
	Yes	9	1%
Inventory Management Software	No	232	33%
	Yes	466	67%
Customer Relationship Management	No	451	65%
	Yes	247	35%
E- Commerce Technologies	No	521	75%
	Yes	177	25%
Digital Marketing Tools	No	502	72%
	Yes	196	28%
POS Machines (for credit or debit cards)	No	486	70%
	Yes	212	30%
Billing Software	No	397	57%
	Yes	301	43%
Accounting Software (like Tally etc)	No	435	62%
	Yes	263	38%
QR Codes or UPI	No	428	61%
	Yes	270	39%

The table above shows that 83% of respondents do not use smart pay, while 17% do. This suggests moderate adoption but still indicates a massive portion of the sector not utilizing this payment method. QR code usage is slightly higher, with 26% of respondents using it compared to 74% who do not. The adoption of POS systems is low, with only 3% of respondents using them, while 97% do not. A vast majority (98%) of respondents do not perceive technology to significantly increase sales, with only 2%

indicating a positive impact. Similarly, the majority (99%) do not believe technology increases foot traffic, with only 1% acknowledged a positive impact. Across various automated technologies, adoption varies but leans towards non-adoption.

Table: 4-11 Descriptive Statistics for technology adoption

	Mean	Std. Deviation
Cost	2.75	1.425
Awareness	2.65	1.310
Technical Complexity	2.78	1.381
Lack of Resources	2.41	1.529
No Perceived Benefit	2.36	1.160
Data Security Concerns	1.69	.671

The table shows that the mean adoption scores for the first five dimensions range from approximately 2.36 to 2.78. This suggests a moderate level of adoption across these dimensions. The standard deviations indicate some variability in adoption levels, with dimensions like Cost and Lack of Resources have higher standard deviations compared to others. Data Security Concerns exhibit a lower mean adoption score of 1.69, indicating a significantly lower level of adoption for this dimension. The standard deviation for Data Security Concerns is low (.671), suggesting less variability in adoption levels compared to other dimensions.

Table 4.12: Descriptive Statistics for UTAUT-2 factors

	Mean	Std. Deviation
Performance expectancy	2.09	0.697
Price Value	2.49	0.871
Social Influence	2.47	0.844
Habit	1.52	0.680
Perceived Risk	4.53	0.872
Facilitating Condition	1.70	0.914
Hedonic Motivation	1.99	0.840
Attitude	2.26	1.456
Intention	1.76	1.027
Benefits	1.47	0.639
Effort Expectancy	1.62	0.715

The table demonstrates that the mean score of 2.094 implies that respondents view technology as moderately easy to use, while the low standard deviation of 0.697 reflects a reasonable level of agreement among the respondents. The mean scores for both factors are closely aligned at 2.49 and 2.47, reflecting moderate perceptions of value and social influence in the context of technology adoption. Additionally, there is moderate variability in the responses, as indicated by standard deviations of 0.871 and 0.844. With a mean score of 1.52, habit has a lower perception among respondents, indicating that habitual usage may not be a significant driver of technology adoption within the sector. The mean score of 4.53 demonstrates that perceived risk is a significant fret among respondents, while the low standard deviation of 0.872 implies a strong consensus on this issue. Facilitating Condition, Hedonic Motivation, Attitude, Intention, Benefits, and Effort Expectancy factors have mean scores ranging from 1.47 to 2.26, indicating varied perceptions and attitudes towards technology adoption, with moderate to low consistency in responses (as reflected by the standard deviations).

4.7: INDEPENDENT SAMPLE T-TEST

The T-Value signifies the computed difference expressed in terms of standard error units. A larger t-value signifies a more substantial difference between the groups, while a larger absolute t-value denotes a more significant difference between the groups in relation to the variability within them. The probability that the observed disparity occurred by chance is indicated by the P-Value. The difference is considered statistically significant if the p-value is less than the selected significance level, which is typically 0.05. Reject the null hypothesis if the p-value is below to the significance threshold (e.g., 0.05). This signifies that the disparities between the groups are statistically significant. If the p-value exceeds the significance level, do not reject the null hypothesis. This indicates that there is no statistically significant disparity between the groups. An Independent Sample T-Test was performed to ascertain whether there is a disparity in opinions regarding the sub-constructs of UTAUT2 based on gender.

Table 4.13: Difference of opinion on the Sub-Constructs of UTAUT2 based on Gender

		N	Mean	S. D	t-value	Sig
Performance expectancy	Male	581	2.14	0.708	4.804	0.000
	Female	117	1.85	0.580		
Price Value	Male	581	2.54	0.895	3.776	0.000
	Female	117	2.26	0.694		
Social Influence	Male	581	2.50	0.853	2.534	0.012
	Female	117	2.29	0.778		
Habit	Male	581	1.47	0.668	-4.343	0.000
	Female	117	1.77	0.684		
Perceived Risk	Male	581	4.56	0.841	2.407	0.016
	Female	117	4.35	0.997		
Facilitating Condition	Male	581	1.71	0.934	.600	0.549
	Female	117	1.66	0.806		
Hedonic Motivation	Male	581	1.96	0.850	-1.839	0.066
	Female	117	2.12	0.775		
Attitude	Male	581	2.25	1.463	-.332	0.740
	Female	117	2.30	1.421		
Intention	Male	581	1.76	1.033	-.377	0.706
	Female	117	1.79	1.000		
Benefits	Male	581	1.48	0.651	1.041	0.299
	Female	117	1.41	0.577		
Effort Expectancy	Male	581	1.60	0.696	-1.439	0.151
	Female	117	1.70	0.800		

Hypothesis for t-test

No significant disparity in opinion regarding technology adoption attributes exists among respondents depending on gender.

Interpretation

Performance expectancy: Male Mean = 2.14, Female Mean = 1.85, t-value = 4.804, p-value = 0.000. The p-value being below 0.05 demonstrates a statistically significant difference between females and males regarding the "Performance expectancy" sub-construct. Men have greater performance expectancy than women. Price Value: Male Mean = 2.54, Female Mean = 2.26, t-value = 3.776, p-value = 0.000. The significant p-value denotes a noteworthy disparity in perceived value according to gender. Males perceive higher value than females in technology adoption. Social Influence: Male Mean = 2.50, Female Mean = 2.29, t-value = 2.534, p-value = 0.012. The fact that the p-value is less than 0.05 demonstrates that there is significant variation in social influence, with males experiencing a greater degree of effect from social variables than females. Habit: Male Mean = 1.47, Female Mean = 1.77, t-value = -4.343, p-value = 0.000. A significant difference exists here as well, but females show a higher mean, indicating that females are more habituated to certain aspects of technology usage compared to males. Perceived Risk: Male Mean = 4.56, Female Mean = 4.35, t-value = 2.407, p-value = 0.016. When compared to females, males report somewhat greater levels of perceived risk. This difference in perceived risk is statistically significant. Males report slightly higher levels of perceived danger. Facilitating Condition: Male Mean = 1.71, Female Mean = 1.66, t-value = 0.600, p-value = 0.549. The p-value exceeds 0.05, demonstrating that there is no significant difference in facilitating conditions based on gender. Hedonic Motivation: Male Mean = 1.96, Female Mean = 2.12, t-value = -1.839, p-value = 0.066. Although females have a slightly higher mean in hedonic motivation, the p-value is greater than 0.05, indicating no significant difference between males and females. Attitude: Male Mean = 2.25, Female Mean = 2.30, t-value = -0.332, p-value = 0.740. No discernible variation in attitude towards technology adoption based on gender (p-value > 0.05). Intention: Male Mean = 1.76, Female Mean = 1.79, t-value = -0.377, p-value = 0.706. No discernible variation in intention to adopt technology based on gender. Benefits: Male Mean = 1.48, Female Mean = 1.41, t-value = 1.041, p-value = 0.299. No discernible difference depending on gender in perceived benefits (p-value > 0.05). Effort Expectancy: Male Mean = 1.60, Female Mean = 1.70, t-value = -1.439, p-value = 0.151. No significant gender disparity exists in effort expectations. The t-test hypothesis supports the null hypothesis for these variables, indicating that sub-constructs such as Facilitating Condition, Hedonic Motivation, Attitude, Intention, Benefits, and Effort Expectancy did not exhibit significant differences.

4.8: ANALYSIS OF VARIANCE (ANOVA)

ANOVA has been used to analyse the opinions of respondents based on occupation, experience, education, and income, in relation to the UTAUT-2 sub-constructs.

Table 4.14: Difference of opinion based on the Sub-Constructs of UTAUT2 Type of Business

		N	Mean	Std. Deviation	F	Sig.
Performance expectancy	Grocery / Kirana	219	2.38	.701	34.500	.000
	Medicine / Ayurveda / Homeopathy / Yunani	103	2.02	.577		
	Footwear	119	1.87	.489		
	Readymade Garments	139	1.99	.512		
	Handicrafts & Artisan	48	1.26	.468		
	Electronics	54	2.68	.911		

		N	Mean	Std. Deviation	F	Sig.
	Other Manufacturing	16	1.89	.223		
	Total	698	2.09	.697		
Price Value	Grocery / Kirana	219	2.41	.712	8.133	.000
	Medicine / Ayurveda / Homeopathy / Yunani	103	2.19	.852		
	Footwear	119	2.59	.860		
	Readymade Garments	139	2.48	.854		
	Handicrafts & Artisan	48	2.53	1.374		
	Electronics	54	3.13	.702		
	Other Manufacturing	16	2.72	.632		
	Total	698	2.49	.871		
Social Influence	Grocery / Kirana	219	2.47	.901	2.712	.013
	Medicine / Ayurveda / Homeopathy / Yunani	103	2.47	.665		
	Footwear	119	2.42	.809		
	Readymade Garments	139	2.33	.836		
	Handicrafts & Artisan	48	2.51	.660		
	Electronics	54	2.72	1.008		
	Other Manufacturing	16	3.02	.989		
	Total	698	2.47	.844		
Habit	Grocery / Kirana	219	1.43	.683	7.726	.000
	Medicine / Ayurveda /	103	1.42	.657		

		N	Mean	Std. Deviation	F	Sig.
	Homeopathy / Yunani					
	Footwear	119	1.52	.500		
	Readymade Garments	139	1.77	.726		
	Handicrafts & Artisan	48	1.27	.518		
	Electronics	54	1.79	.867		
	Other Manufacturing	16	1.15	.271		
	Total	698	1.52	.680		
Perceived Risk	Grocery / Kirana	219	4.54	.890	2.733	.012
	Medicine / Ayurveda / Homeopathy / Yunani	103	4.68	.805		
	Footwear	119	4.41	.960		
	Readymade Garments	139	4.51	.894		
	Handicrafts & Artisan	48	4.75	.438		
	Electronics	54	4.24	.965		
	Other Manufacturing	16	4.83	.313		
	Total	698	4.53	.872		
Facilitating Condition	Grocery / Kirana	219	1.77	.753	4.387	.000
	Medicine / Ayurveda / Homeopathy / Yunani	103	1.59	1.056		
	Footwear	119	1.61	.714		
	Readymade Garments	139	1.71	.997		
	Handicrafts & Artisan	48	1.39	.748		

		N	Mean	Std. Deviation	F	Sig.
	Electronics	54	2.17	1.33		
	Other Manufacturing	16	1.40	.611		
	Total	698	1.70	.914		
Hedonic Motivation	Grocery / Kirana	219	1.79	.688	9.372	.000
	Medicine / Ayurveda / Homeopathy / Yunani	103	2.16	.826		
	Footwear	119	1.88	.680		
	Readymade Garments	139	2.09	.854		
	Handicrafts & Artisan	48	2.18	.701		
	Electronics	54	2.46	1.365		
	Other Manufacturing	16	1.27	.559		
	Total	698	1.99	.840		
Attitude	Grocery / Kirana	219	2.29	1.32	5.913	.000
	Medicine / Ayurveda / Homeopathy / Yunani	103	2.04	1.536		
	Footwear	119	2.40	1.577		
	Readymade Garments	139	2.35	1.482		
	Handicrafts & Artisan	48	1.49	1.067		
	Electronics	54	2.95	1.587		
	Other Manufacturing	16	1.50	.272		
	Total	698	2.26	1.456		
Intention	Grocery / Kirana	219	1.79	.854	6.628	.000

		N	Mean	Std. Deviation	F	Sig.
	Medicine / Ayurveda / Homeopathy / Yunani	103	1.61	1.005		
	Footwear	119	1.65	.945		
	Readymade Garments	139	1.86	1.071		
	Handicrafts & Artisan	48	1.38	.894		
	Electronics	54	2.43	1.545		
	Other Manufacturing	16	1.27	.547		
	Total	698	1.76	1.0266		
Benefits	Grocery / Kirana	219	1.60	.559	9.276	.000
	Medicine / Ayurveda / Homeopathy / Yunani	103	1.27	.5182		
	Footwear	119	1.45	.537		
	Readymade Garments	139	1.36	.584		
	Handicrafts & Artisan	48	1.24	.601		
	Electronics	54	1.87	1.125		
	Other Manufacturing	16	1.28	.446		
	Total	698	1.47	.639		
Effort Expectancy	Grocery / Kirana	219	1.63	.703	9.482	.000
	Medicine / Ayurveda / Homeopathy / Yunani	103	1.36	.546		
	Footwear	119	1.73	.590		
	Readymade Garments	139	1.60	.712		

		N	Mean	Std. Deviation	F	Sig.
	Handicrafts & Artisan	48	1.33	.724		
	Electronics	54	2.14	1.007		
	Other Manufacturing	16	1.56	.315		
	Total	698	1.62	.715		

Hypothesis for ANOVA

Based on business type, respondents' opinions on technology adoption attributes do not significantly differ from one another.

Interpretation

Performance expectancy: F-value: 34.500, Sig: .000: The p-value (Sig) is less than 0.05, demonstrating a notable variation in Performance expectancy across different types of businesses. Specifically, businesses like Electronics have the highest mean (2.68), while Handicrafts & Artisan has the lowest (1.26), demonstrating variability in ease of technology adoption. Price Value: F-value: 8.133, Sig: .000: The price values of the various businesses vary significantly. The highest mean score is for Electronics (3.13), indicating that respondents in this category perceive greater value from technology, compared to other sectors like Medicine or Footwear. Social Influence: F-value: 2.712, Sig: .013: The p-value indicates a moderate difference in social influence even if it is marginally over the typical limits for strong significance. Other Manufacturing (mean 3.02) has higher social influence compared to other sectors. Habit: F-value: 7.726, Sig: .000: The p-value indicates significant differences in habitual use of technology across sectors. Respondents from the Electronics sector (mean 1.79) seem more habitual in their technology use compared to others like Handicrafts or Other Manufacturing.

Perceived Risk: F-value: 2.733, Sig: .012: There is a notable difference in perceived risk between sectors. Other Manufacturing (mean 4.83) and Handicrafts (mean 4.75) exhibit higher levels of risk perception, whereas Electronics shows lower perceived risk (4.24). Facilitating Condition: F-value: 4.387, Sig: .000: The p-value suggests significant differences across sectors. Electronics (mean 2.17) respondents find better facilitating conditions for adopting technology, while Handicrafts (1.39) report the least favourable conditions. Hedonic Motivation: F-value: 9.372, Sig: .000: This significant result indicates that respondents in the Electronics sector (mean 2.46) are more motivated by pleasure in technology use compared to other sectors such as Grocery/Kirana or Other Manufacturing. Attitude: F-value: 5.913, Sig: .000: There is a significant difference in attitude toward technology adoption. Respondents in Electronics (mean 2.95) have the most positive attitudes, whereas sectors like Handicrafts (1.49) exhibit less favourable attitudes. Intention: F-value: 6.628, Sig: .000: Significant differences are observed in the intention to adopt technology. Electronics (mean 2.43) has a higher intent to adopt technology, while Handicrafts (mean 1.38) has lower intention. Benefits: F-value: 9.276, Sig: .000: There is a significant difference in perceived benefits. Respondents from Electronics (mean 1.87) perceive more benefits, whereas those from Medicine and Handicrafts report lower benefit perceptions. Effort Expectancy: F-value: 9.482, Sig: .000: This significant value indicates differences in effort expectancy. Respondents from Electronics (mean 2.14) expect higher effort to adopt technology compared to other sectors like Medicine or Footwear.

Homogeneous Subsets

Performance expectancy

Type_Product		**N**	**Subset for alpha = 0.05**		
			1	**2**	**3**
Tukey HSD[a,b]	Handicrafts & Artisan	48	1.2552		
	Footwear	119		1.8739	
	Other Manufacturing	16		1.8906	
	Readymade Garments	139		1.9874	
	Medicine / Ayurveda / Homeopathy / Yunani	103		2.0170	
	Grocery / Kirana	219			2.3756
	Electronics	54			2.6759
	Sig.		1.000	.894	.153

Group means in homogenous subsets are provided.

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes.. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed.

Price Value

Type_Product		**N**	**Subset for alpha = 0.05**		
			1	**2**	**3**
Tukey HSD[a,b]	Medicine / Ayurveda / Homeopathy / Yunani	103	2.1893		
	Grocery / Kirana	219	2.4110	2.4110	
	Readymade Garments	139	2.4820	2.4820	
	Handicrafts & Artisan	48	2.5313	2.5313	
	Footwear	119	2.5882	2.5882	
	Other Manufacturing	16		2.7188	2.7188
	Electronics	54			3.1296
	Sig.		.186	.496	.158

Group means in homogenous subsets are provided.

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes.. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed.

Social Influence

Type_Product		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	Readymade Garments	139	2.3273	
	Footwear	119	2.4181	
	Medicine / Ayurveda / Homeopathy / Yunani	103	2.4660	
	Grocery / Kirana	219	2.4669	
	Handicrafts & Artisan	48	2.5104	
	Electronics	54	2.7222	2.7222
	Other Manufacturing	16		3.0156
	Sig.		.188	.545

Group means in homogenous subsets are provided.

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes.. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed.

Habit

Type_Product		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	Other Manufacturing	16	1.1458	
	Handicrafts & Artisan	48	1.2708	
	Medicine / Ayurveda / Homeopathy / Yunani	103	1.4239	1.4239
	Grocery / Kirana	219	1.4338	1.4338
	Footwear	119	1.5210	1.5210
	Readymade Garments	139		1.7674
	Electronics	54		1.7901
	Sig.		.054	.066

Group means in homogenous subsets are provided.

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed.

Perceived Risk

Type_Product		**N**	**Subset for alpha = 0.05**	
			1	**2**
Tukey HSD[a,b]	Electronics	54	4.2407	
	Footwear	119	4.4097	4.4097
	Readymade Garments	139	4.5090	4.5090
	Grocery / Kirana	219	4.5377	4.5377
	Medicine / Ayurveda / Homeopathy / Yunani	103	4.6772	4.6772
	Handicrafts & Artisan	48		4.7500
	Other Manufacturing	16		4.8281
	Sig.		.128	.164

Group means in homogenous subsets are provided.

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed.

Facilitating Conditions

Type_Product		**N**	**Subset for alpha = 0.05**	
			1	**2**
Tukey HSD[a,b]	Handicrafts & Artisan	48	1.3889	
	Other Manufacturing	16	1.3958	
	Medicine / Ayurveda / Homeopathy / Yunani	103	1.5922	
	Footwear	119	1.6106	
	Readymade Garments	139	1.7098	1.7098
	Grocery / Kirana	219	1.7671	1.7671
	Electronics	54		2.1728
	Sig.		.316	.113

Group means in homogenous subsets are provided.

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed.

Hedonic Motivation

Type_Product		N	Subset for alpha = 0.05		
			1	2	3
Tukey HSD[a,b]	Other Manufacturing	16	1.2656		
	Grocery / Kirana	219		1.7854	
	Footwear	119		1.8803	
	Readymade Garments	139		2.0935	2.0935
	Medicine / Ayurveda / Homeopathy / Yunani	103		2.1578	2.1578
	Handicrafts & Artisan	48		2.1823	2.1823
	Electronics	54			2.4583
	Sig.		1.000	.153	.237

Group means in homogenous subsets are provided.

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed..

Attitude

Type_Product		N	Subset for alpha = 0.05		
			1	2	3
Tukey HSD[a,b]	Handicrafts & Artisan	48	1.4931		
	Other Manufacturing	16	1.5000		
	Medicine / Ayurveda / Homeopathy / Yunani	103	2.0356	2.0356	
	Grocery / Kirana	219	2.2892	2.2892	2.2892
	Readymade Garments	139		2.3477	2.3477
	Footwear	119		2.4034	2.4034
	Electronics	54			2.9506
	Sig.		.062	.838	.204

Group means in homogenous subsets are provided.

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed.levels

Intention

Type_Product		**N**	**Subset for alpha = 0.05**		
			1	**2**	**3**
Tukey HSD[a,b]	Other Manufacturing	16	1.2708		
	Handicrafts & Artisan	48	1.3819	1.3819	
	Medicine / Ayurveda / Homeopathy / Yunani	103	1.6052	1.6052	
	Footwear	119	1.6527	1.6527	
	Grocery / Kirana	219	1.7915	1.7915	
	Readymade Garments	139		1.8561	1.8561
	Electronics	54			2.4259
	Sig.		.106	.184	.054

Group means in homogenous subsets are provided.

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed.

Benefits

Type_Product		**N**	**Subset for alpha = 0.05**		
			1	**2**	**3**
Tukey HSD[a,b]	Handicrafts & Artisan	48	1.2396		
	Medicine / Ayurveda / Homeopathy / Yunani	103	1.2718	1.2718	
	Other Manufacturing	16	1.2813	1.2813	
	Readymade Garments	139	1.3561	1.3561	
	Footwear	119	1.4538	1.4538	
	Grocery / Kirana	219		1.5982	1.5982
	Electronics	54			1.8704
	Sig.		.557	.094	.260

Group means in homogenous subsets are provided..

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed..

Effort Expectancy

Type_Product		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	Handicrafts & Artisan	48	1.3333	
	Medicine / Ayurveda / Homeopathy / Yunani	103	1.3592	
	Other Manufacturing	16	1.5625	
	Readymade Garments	139	1.5995	
	Grocery / Kirana	219	1.6271	
	Footwear	119	1.7255	
	Electronics	54		2.1420
	Sig.		.054	1.000

Group means in homogenous subsets are provided..

a. Uses Harmonic Mean Sample Size = 53.141.

b. Uneven group sizes. The harmonic mean of the group sizes is applied. The levels of Type I error are not confirmed.

Benefits

Age		N	Subset for alpha = 0.05			
			1	2	3	4
Tukey HSD[a,b]	More than 55 Years	177	1.15			
	45 to 55 Years	189		1.47		
	35 to 45 years	182		1.52	1.52	
	5- 35 years	104			1.73	1.73
	Less than 25	46				1.87
	Sig.		1.00	0.98	0.08	0.46

Effort Expectancy

Age		N	Subset for alpha = 0.05		
			1	2	3
Tukey HSD[a,b]	More than 55 Years	177	1.27		
	45 to 55 Years	189		1.58	
	35 to 45 years	182		1.66	
	Less than 25	46			1.99
	5- 35 years	104			2.04
	Sig.		1.00	0.92	0.99

Interpretation

Performance expectancy: The ANOVA results reveal significant differences in the Performance expectancy across different occupations ($F = 34.500$, $p < .001$). Notably, those in the Handicrafts & Artisan sector reported the lowest mean score (1.2552), indicating they find technology least easy to use. Conversely, individuals in Electronics reported the highest mean score (2.6759), suggesting they find technology most user-friendly. The Grocery/Kirana sector also reported relatively high Performance expectancy (2.3756), while Footwear and Readymade Garments sectors had intermediate scores. Perceived Value: The perceived value of technology also varies significantly by occupation ($F = 8.133$, $p < .001$). Electronics professionals value technology the most (3.1296), while Medicine/Ayurveda/Homeopathy/Yunani professionals value it the least (2.1893). Grocery/Kirana sector (2.4110) and Footwear (2.5882) show moderate value perceptions. Social Influence: Social influence on technology adoption differs by occupation ($F = 2.712$, $p = .013$). The Electronics sector shows the highest influence (2.7222), followed by Other Manufacturing (3.0156), suggesting that social factors are more significant in these domains. In contrast, Readymade Garments and Footwear sectors report lower social influence. Habit: Differences in habit related to technology usage are significant ($F = 7.726$, $p < .001$). Handicrafts & Artisan and Other Manufacturing sectors exhibit lower habitual technology use scores, suggesting less frequent engagement with technology. The Electronics sector shows the highest habit score (1.7901), reflecting a stronger routine use of technology. Perceived Risk: Perceived risk also varies significantly ($F = 2.733$, $p = .012$). The handicrafts & Artisan sector has the highest perceived risk (4.7500), while Electronics professionals perceive the lowest risk (4.2407), indicating greater confidence in technology in this field. Facilitating Condition: Facilitating conditions impacting technology adoption vary ($F = 4.387$, $p < .001$). Electronics professionals report the highest mean (2.1728), suggesting better support and resources. In contrast, Handicrafts & Artisan and Other Manufacturing sectors report lower mean scores, indicating less supportive conditions. Hedonic Motivation: Hedonic motivation, or the delight derived from utilising modern technology use, varies ($F = 9.372$, $p < .001$). The electronics sector scores highest (2.4583), indicating more enjoyment, while Handicrafts & Artisan scores lowest (2.1823), suggesting less pleasure from technology use. Attitude: Attitudes towards technology also show significant variation ($F = 5.913$, $p < .001$). Electronics professionals have the highest attitude score (2.9506), reflecting a more positive attitude. The Handicrafts & Artisan sector has the lowest score (1.4931), indicating less favorable attitudes. Intention: Intention to use technology shows significant differences ($F = 6.628$, $p < .001$). The Electronics sector reports the highest intention score (2.4259), while Handicrafts & Artisan shows the lowest (1.3819), indicating varying levels of future technology adoption intent. Benefits: Perceived benefits from technology usage differ significantly ($F = 9.276$, $p < .001$). The electronics sector has the highest perceived benefits score (1.8704), whereas Handicrafts & Artisan has the lowest (1.2396). Effort Expectancy: Effort expectancy also varies significantly ($F = 9.482$, $p < .001$). The electronics sector reports the highest mean score (2.1420), indicating higher expectations of effort in using technology, while Handicrafts & Artisan reports the lowest (1.3333).

Table 4.15: ANOVA results based on education

		N	Mean	S.D.	F	Sig.
Performance expectancy	Uneducated	202	1.85	0.675	17.943	.000
	Primary School	265	2.18	0.677		
	High School	153	2.07	0.619		
	Graduate	74	2.43	0.659		
	Others	4	3.63	1.181		
	Total	698	2.09	0.697		
Perceived Value	Uneducated	202	2.50	1.064	12.943	.000
	Primary School	265	2.34	0.726		
	High School	153	2.43	0.809		
	Graduate	74	3.06	0.561		
	Others	4	3.75	0.866		
	Total	698	2.49	0.871		
Social Influence	Uneducated	202	2.33	0.745	4.833	.001
	Primary School	265	2.45	0.835		
	High School	153	2.51	0.876		
	Graduate	74	2.76	0.980		
	Others	4	3.31	0.125		
	Total	698	2.47	0.844		
Habit	Uneducated	202	1.44	0.611	3.384	.009
	Primary School	265	1.54	0.641		
	High School	153	1.55	0.758		
	Graduate	74	1.58	0.778		
	Others	4	2.58	0.419		
	Total	698	1.52	0.680		
Perceived Risk	Uneducated	202	4.61	0.822	1.367	.244
	Primary School	265	4.56	0.785		
	High School	153	4.40	0.994		
	Graduate	74	4.48	1.017		
	Others	4	4.63	0.750		
	Total	698	4.53	0.872		
Facilitating Condition	Uneducated	202	1.66	0.935	6.707	.000
	Primary School	265	1.67	0.747		
	High School	153	1.64	0.963		

		N	Mean	S.D.	F	Sig.
	Graduate	74	1.96	1.140		
	Others	4	3.67	0.667		
	Total	698	1.70	0.914		
Hedonic Motivation	Uneducated	202	2.13	0.781	8.656	.000
	Primary School	265	1.91	0.671		
	High School	153	2.00	0.937		
	Graduate	74	1.74	1.110		
	Others	4	3.81	1.028		
	Total	698	1.99	0.840		
Attitude	Uneducated	202	1.96	1.255	4.903	.001
	Primary School	265	2.32	1.433		
	High School	153	2.34	1.613		
	Graduate	74	2.58	1.534		
	Others	4	4.08	1.833		
	Total	698	2.26	1.456		
Intention	Uneducated	202	1.78	1.050	3.379	.009
	Primary School	265	1.70	0.780		
	High School	153	1.76	1.186		
	Graduate	74	1.86	1.289		
	Others	4	3.50	1.036		
	Total	698	1.76	1.027		
Benefits	Uneducated	202	1.42	0.520	.624	.646
	Primary School	265	1.49	0.508		
	High School	153	1.49	0.841		
	Graduate	74	1.45	0.824		
	Others	4	1.75	1.190		
	Total	698	1.47	0.639		
Effort Expectancy	Uneducated	202	1.46	0.632	5.415	.000
	Primary School	265	1.62	0.674		
	High School	153	1.71	0.800		
	Graduate	74	1.85	0.802		
	Others	4	1.33	0.667		
	Total	698	1.62	0.715		

Performance expectancy

Edu		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	Uneducated	202	1.8502	
	High School	153	2.0719	
	Primary School	265	2.1774	
	Graduate	74	2.4324	
	Others	4		3.6250
	Sig.		.068	1.000

Perceived Value

Edu		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	Primary School	265	2.3434	
	High School	153	2.4314	
	Uneducated	202	2.5050	
	Graduate	74	3.0608	3.0608
	Others	4		3.7500
	Sig.		.081	.103

Social Influence

Edu		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	Uneducated	202	2.3280	
	Primary School	265	2.4509	
	High School	153	2.5098	
	Graduate	74	2.7601	2.7601
	Others	4		3.3125
	Sig.		.530	.276

Habit

Edu		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	Uneducated	202	1.4439	
	Primary School	265	1.5371	
	High School	153	1.5490	
	Graduate	74	1.5811	
	Others	4		2.5833
	Sig.		.974	1.000

Facilitating Condition

Edu		**N**	**Subset for alpha = 0.05**	
			1	**2**
Tukey HSD[a,b]	High School	153	1.6427	
	Uneducated	202	1.6551	
	Primary School	265	1.6654	
	Graduate	74	1.9595	
	Others	4		3.6667
	Sig.		.829	1.000

Hedonic Motivation

Edu		**N**	**Subset for alpha = 0.05**	
			1	**2**
Tukey HSD[a,b]	Graduate	74	1.7399	
	Primary School	265	1.9094	
	High School	153	2.0016	
	Uneducated	202	2.1262	
	Others	4		3.8125
	Sig.		.623	1.000

Attitude

Edu		**N**	**Subset for alpha = 0.05**	
			1	**2**
Tukey HSD[a,b]	Uneducated	202	1.9637	
	Primary School	265	2.3245	
	High School	153	2.3442	
	Graduate	74	2.5766	
	Others	4		4.0833
	Sig.		.707	1.000

Intention

Edu		**N**	**Subset for alpha = 0.05**	
			1	**2**
Tukey HSD[a,b]	Primary School	265	1.6956	
	High School	153	1.7582	
	Uneducated	202	1.7822	
	Graduate	74	1.8604	
	Others	4		3.5000
	Sig.		.989	1.000

Effort Expectancy

Edu		**N**	**Subset for alpha = 0.05**
			1
Tukey HSD[a,b]	Others	4	1.3333
	Uneducated	202	1.4604
	Primary School	265	1.6189
	High School	153	1.7146
	Graduate	74	1.8514
	Sig.		.182

Interpretation

Performance expectancy: Significant differences are observed in Performance expectancy across education levels ($F = 17.943$, $p < .001$). Those with Graduate education report the highest mean score (2.43), suggesting they find technology easier to use, whereas Uneducated individuals report the lowest mean (1.85). Perceived Value: Perceived value of technology also varies significantly ($F = 12.943$, $p < .001$). Graduate individuals perceive the highest value (3.06), while Uneducated individuals perceive the lowest value (2.50). Social Influence: Social influence varies by education level ($F = 4.833$, $p = .001$). Graduate individuals report the highest influence (2.76), while Uneducated individuals report the lowest (2.33). Habit: Habit-related scores vary ($F = 3.384$, $p = .009$). Uneducated individuals have the lowest habit score (1.44), while those with Graduate education have the highest (1.58). Perceived Risk: Perceived risk does not show significant variation by education level ($F = 1.367$, $p = .244$), suggesting that education level does not significantly impact the perception of risk associated with technology. Facilitating Condition: Significant differences are noted in facilitating conditions ($F = 6.707$, $p < .001$). Graduate individuals report the highest support (1.96), while Uneducated individuals report lower support (1.66). Hedonic Motivation:

Hedonic motivation differs by education level (F = 8.656, p < .001). Graduate individuals report the lowest motivation (1.74), while Uneducated individuals report the highest (2.13). Attitude: Attitudes towards technology vary significantly (F = 4.903, p = .001). Graduate individuals report the highest attitude score (2.58), while Uneducated individuals report the lowest (1.96). Intention: Intention to use technology also shows significant differences (F = 3.379, p = .009). Graduate individuals have the highest intention score (1.86), while Uneducated individuals have the lowest (1.78). Benefits: Perceived benefits do not show significant differences across education levels (F = 0.624, p = .646), indicating that education level does not significantly impact the perception of benefits from technology. Effort Expectancy: Significant differences are found in effort expectancy (F = 5.415, p < .001). Graduate individuals expect the most effort (1.85), while Uneducated individuals expect the least (1.46).

Table 4.16: ANOVA results based on Income

		N	**Mean**	**Std. Deviation**
Performance expectancy	<25000	432	2.05	0.766
	25000 to 49999	123	2.21	0.603
	50000 to 74999	122	2.05	0.370
	75000 to 99999	19	2.51	0.766
	> 1 Lakh	2	4.00	0.707
	Total	698	2.09	0.697
Price Value	<25000	432	2.38	0.907
	25000 to 49999	123	2.46	0.774
	50000 to 74999	122	2.82	0.681
	75000 to 99999	19	3.03	0.935
	> 1 Lakh	2	4.00	0.000
	Total	698	2.49	0.871
Social Influence	<25000	432	2.21	0.624

		N	Mean	Std. Deviation
	25000 to 49999	123	2.50	0.897
	50000 to 74999	122	3.21	0.953
	75000 to 99999	19	3.14	0.914
	> 1 Lakh	2	3.25	0.000
	Total	698	2.47	0.844
Habit	<25000	432	1.58	0.698
	25000 to 49999	123	1.69	0.666
	50000 to 74999	122	1.18	0.476
	75000 to 99999	19	1.40	0.733
	> 1 Lakh	2	2.33	0.471
	Total	698	1.52	0.680
Perceived Risk	<25000	432	4.48	0.887
	25000 to 49999	123	4.39	0.972
	50000 to 74999	122	4.79	0.702
	75000 to 99999	19	4.93	0.233
	> 1 Lakh	2	5.00	0.000
	Total	698	4.53	0.872
Facilitating Condition	<25000	432	1.73	0.879
	25000 to 49999	123	1.81	0.982
	50000 to 74999	122	1.45	0.860
	75000 to 99999	19	1.74	1.098
	> 1 Lakh	2	4.00	0.000
	Total	698	1.70	0.914
Hedonic Motivation	<25000	432	2.13	0.733
	25000 to 49999	123	2.10	0.989
	50000 to 74999	122	1.32	0.597
	75000 to 99999	19	1.93	1.067
	> 1 Lakh	2	4.38	0.884
	Total	698	1.99	0.840
Attitude	<25000	432	2.35	1.448
	25000 to 49999	123	2.50	1.545
	50000 to 74999	122	1.76	1.272

		N	Mean	Std. Deviation
	75000 to 99999	19	1.79	1.344
	> 1 Lakh	2	3.17	2.593
	Total	698	2.26	1.456
Intention	<25000	432	1.87	1.032
	25000 to 49999	123	1.84	1.067
	50000 to 74999	122	1.31	0.811
	75000 to 99999	19	1.56	0.882
	> 1 Lakh	2	4.00	1.414
	Total	698	1.76	1.027
Benefits	<25000	432	1.54	0.646
	25000 to 49999	123	1.58	0.733
	50000 to 74999	122	1.16	0.407
	75000 to 99999	19	1.18	0.342
	> 1 Lakh	2	1.00	0.000
	Total	698	1.47	0.639
Effort Expectancy	<25000	432	1.63	0.736
	25000 to 49999	123	1.79	0.746
	50000 to 74999	122	1.45	0.547
	75000 to 99999	19	1.39	0.739
	> 1 Lakh	2	1.00	0.000
	Total	698	1.62	0.715

Performance expectancy

Inc		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	<25000	432	2.0469	
	50000 to 74999	122	2.0492	
	25000 to 49999	123	2.2134	
	75000 to 99999	19	2.5132	
	> 1 Lakh	2		4.0000
	Sig.		.612	1.000

Price Value

Inc		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	<25000	432	2.3796	
	25000 to 49999	123	2.4634	
	50000 to 74999	122	2.8197	
	75000 to 99999	19	3.0263	3.0263
	> 1 Lakh	2		4.0000
	Sig.		.502	.117

Social Influence

Inc		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	<25000	432	2.2124	
	25000 to 49999	123	2.5000	2.5000
	75000 to 99999	19	3.1447	3.1447
	50000 to 74999	122		3.2111
	> 1 Lakh	2		3.2500
	Sig.		.072	.226

Habit

Inc		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	50000 to 74999	122	1.1776	
	75000 to 99999	19	1.4035	
	<25000	432	1.5764	1.5764
	25000 to 49999	123	1.6856	1.6856
	> 1 Lakh	2		2.3333
	Sig.		.490	.116

Perceived Risk

Inc		N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	25000 to 49999	123	4.3862
	<25000	432	4.4769
	50000 to 74999	122	4.7869
	75000 to 99999	19	4.9342
	> 1 Lakh	2	5.0000
	Sig.		.570

Facilitating Condition

Inc		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	50000 to 74999	122	1.4508	
	<25000	432	1.7276	
	75000 to 99999	19	1.7368	
	25000 to 49999	123	1.8076	
	> 1 Lakh	2		4.0000
	Sig.		.922	1.000

Hedonic Motivation

Inc		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	50000 to 74999	122	1.3217	
	75000 to 99999	19	1.9342	
	25000 to 49999	123	2.0976	
	<25000	432	2.1319	
	> 1 Lakh	2		4.3750
	Sig.		.185	1.000

Attitude

Inc		N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	50000 to 74999	122	1.7623
	75000 to 99999	19	1.7895
	<25000	432	2.3511
	25000 to 49999	123	2.4986
	> 1 Lakh	2	3.1667
	Sig.		.246

Intention

Inc		N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	50000 to 74999	122	1.3087	
	75000 to 99999	19	1.5614	
	25000 to 49999	123	1.8374	
	<25000	432	1.8673	
	> 1 Lakh	2		4.0000
	Sig.		.770	1.000

Benefits

Inc		N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	> 1 Lakh	2	1.0000
	50000 to 74999	122	1.1557
	75000 to 99999	19	1.1842
	<25000	432	1.5370
	25000 to 49999	123	1.5772
	Sig.		.295

Effort Expectancy

Inc		N	Subset for alpha = 0.05
			1
Tukey HSD[a,b]	> 1 Lakh	2	1.0000
	75000 to 99999	19	1.3860
	50000 to 74999	122	1.4536
	<25000	432	1.6273
	25000 to 49999	123	1.7886
	Sig.		.137

Interpretation

Performance expectancy: The Performance expectancy of technology varies significantly across different income brackets ($F = 12.589$, $p < .001$). Individuals with the greatest earnings (>1 Lakh) record the optimal performance standards (Mean = 4.00), showing a preference for technology due to its user-friendly nature. This contrasts with those in lower income brackets, especially those earning between ₹25,000 and ₹49,999 (Mean = 2.21) and below ₹25,000 (Mean = 2.05), who find technology less user-friendly. The results of Tukey's HSD post hoc test reveal significant differences between the highest income bracket and the lower income brackets. Price Value: Price value also shows significant differences ($F = 9.639$, $p < .001$). Higher income groups, particularly those earning between ₹75,000 and ₹99,999 (Mean = 3.03) and above ₹1 Lakh (Mean = 4.00), perceive greater value in technology compared to lower income groups. This indicates that higher-income individuals find technology more beneficial. Significant disparities between the top and lower income categories are revealed by Tukey's HSD post hoc test. Social Influence: Social influence on technology adoption varies ($F = 15.084$, $p < .001$). Individuals with an income between ₹50,000 and ₹74,999 (Mean = 3.21) and those earning between ₹75,000 and ₹99,999 (Mean = 3.14) report higher social influence, suggesting that social factors have a greater impact on these income groups. Tukey's HSD test shows significant differences between the highest and lower income brackets. Habit: Habitual use of technology varies significantly ($F = 15.982$, $p < .001$). Higher-income individuals, especially those earning above ₹1 Lakh (Mean = 2.33) and those earning between ₹75,000 and ₹99,999 (Mean = 1.40), show higher habitual use compared to lower income groups. Tukey's HSD test highlights significant differences between higher and lower income brackets. Perceived Risk: Perceived risk does not show significant variation across income levels ($F = 1.783$, $p = .130$). However, individuals earning above ₹1 Lakh perceive the highest risk (Mean = 5.00), while those in the ₹25,000 to ₹49,999 bracket perceive slightly lower risk (Mean = 4.39). This suggests that higher-income individuals might be more cautious about technology. Facilitating Conditions: Facilitating conditions affecting technology adoption differ significantly ($F = 7.636$, p

$< .001$). Higher-income individuals, particularly those earning above ₹1 Lakh (Mean = 4.00) and those earning between ₹50,000 and ₹74,999 (Mean = 1.45), report better facilitating conditions compared to lower-income groups. Tukey's HSD test shows significant differences between the highest and lower income groups. Hedonic Motivation: Hedonic motivation, or the delight of technology use, varies ($F = 23.964$, $p < .001$). Those with an income above ₹1 Lakh report the highest hedonic motivation (Mean = 4.38), while those earning between ₹50,000 and ₹74,999 report the lowest (Mean = 1.32). Tukey's HSD test confirms significant differences between higher and lower income brackets. Attitude: Attitudes towards technology show significant differences ($F = 10.485$, $p < .001$). Higher-income individuals, particularly those earning above ₹1 Lakh (Mean = 3.17), have a more positive attitude towards technology compared to those in lower income brackets. Tukey's HSD test reveals significant differences between the highest and lower income groups. Intention: Intention to use technology varies ($F = 17.478$, $p < .001$). Individuals earning above ₹1 Lakh report the highest intention (Mean = 4.00), while those in lower income brackets, especially those earning between ₹50,000 and ₹74,999 (Mean = 1.31), report lower intention. Tukey's HSD test shows significant differences between the highest and lower income brackets. Benefits: Perceived benefits from technology show significant differences ($F = 12.594$, $p < .001$). Individuals with an income above ₹1 Lakh perceive the highest benefits (Mean = 1.00), while those earning between ₹50,000 and ₹74,999 report the lowest (Mean = 1.16). Tukey's HSD test confirms significant differences between the highest and lower income groups. Effort Expectancy: Effort expectancy, or the apparent effort necessary for adopting technology, varies significantly ($F = 11.931$, $p < .001$). Higher-income individuals, particularly those earning above ₹1 Lakh (Mean = 1.00) and those earning between ₹50,000 and ₹74,999 (Mean = 1.45), perceive less effort compared to lower-income groups. Tukey's HSD test reveals significant differences between higher and lower income brackets. In summary, higher income individuals generally perceive technology as more valuable, easier to use, and associated with greater benefits and enjoyment. They also show higher habitual use, more positive attitudes, and greater intention to use technology. Lower-income individuals, in contrast, tend to find technology less user-friendly, perceive higher risks, and experience lower facilitating conditions and hedonic motivation.

Table 4.17: Hypotheses Test Results

Main Hypotheses	**Accept/Reject Hypothesis**
H1: Performance expectancy has a significant effect on the attitude of unorganized retailers.	Accepted
H2: Perceived risk has a significant effect on the attitude of unorganized retailers.	Accepted
H3: Effort expectancy has a significant effect on the attitude of unorganized retailers	Accepted
H4: Social influence has a significant effect on the attitude of unorganized retailers.	Rejected
H5: Facilitating Conditions has a significant effect on the attitude of unorganized retailers.	Rejected
H6: Hedonic motivation has a significant effect on the attitude of unorganized retailers.	Rejected
H7: Price value has a significant effect on the attitude of unorganized retailers.	Accepted
H8: Habit has a significant effect on the attitude of unorganized retailers.	Accepted
H9: Attitude has a significant effect on the intention of adopting technology by unorganized retailers.	Accepted
H10: Behavioural Intention has a significant effect on the benefits of adopting technology by unorganized retailers.	Accepted

4.9 CHAPTER SUMMARY

The chapter provides a comprehensive analysis of the factors affecting unorganised retail stores' adoption of technology. The research study confirms that enabling factors, effort expectation, performance expectancy, and price value significantly impact technology adoption, with all related hypotheses being supported. Habit and behavioural intention are strong predictors of adoption, highlighting the crucial significance of consistent usage and the goal to change. In contrast, the impact of social influence and hedonic incentive was deemed to be negligible, resulting in the rejection of the corresponding hypotheses. Demographic factors such as experience, age, and gender significantly impact adoption rates, underscoring the need of considering these elements. In conclusion, outcomes demonstrate that improving the accessibility, usability, and perceived advantages of resources, alongside demographic factors, can facilitate technology adoption in disorganised retail stores.

CHAPTER 5

Results, Discussion and Conclusion

CHAPTER 5

RESULTS, DISCUSSION AND CONCLUSION

The research aims to elucidate the determinants impacting technology adoption among unorganised retailers in Kolkata, West Bengal. The present research applies the UTAUT2 framework to evaluate the influence of hedonic motivation, performance expectancy, facilitating conditions, social influence, effort expectancy, habit, and price value on technology adoption among unorganised retailers across diverse product categories, including groceries, pharmaceuticals, footwear, ready-made garments, handicrafts, and electronics. This research intends to understand consumer attitudes towards technology in unorganised retail, assess how shop format and product category affect technology adoption, and look into the benefits for retailers. This study involves stratified sampling, with a sample size of 698 respondents, and incorporates data analysis tools such as SPSS and PLS SEM to extract insights from primary data sources. This research highlights the need for tailored strategies to overcome the challenges faced by people from low-income backgrounds and suggests doable actions to increase technology adoption across various demographic groups.

5.1 RESULTS AND DISCUSSION

5.1.1 GENDER: Examination of gender distribution indicated a notable imbalance, with males constituting 83% of the respondents (n=581) in contrast to females at merely 17% (n=117). The researcher observed that there were more males than females in the unorganised retail markets. The under-representation of women in the organised retail markets indicate cultural or socio-economic obstacles that may restrict their involvement in unorganised retail operations. However, there were representations from both the genders which makes the study free from gender bias.

5.1.2 AGE: Age distribution of responses reveals a predominance of middle-aged adults within the retail industry. The predominant age group consisted of those aged 45 to 55 years, representing 27% (n=189) of the respondents, closely followed by the 35 to 45 age group at 26% (n=182). The youngest population, aged 18 to 25, comprised merely 7% (n=46) of the sample. The majority of respondents, being over 35, likely possessed substantial expertise and consistency in unorganised trading, potentially enhancing their engagement with technology adoption. The participants in this study were mature and capable of providing relevant responses during the primary data collection phase. Furthermore, the study is devoid of age bias, as all age groups were adequately represented.

5.1.3 EDUCATION QUALIFICATION: Respondents' educational background reveals a significant tendency towards reduced degrees of formal schooling. The largest proportion of respondents (38%, n=265) indicated they had completed only primary education, whilst 22% (n=153) possessed a high school diploma. Only 11% (n=74) of the respondents possessed undergraduate degrees, while a tiny 1% (n=4) held postgraduate qualifications. The predominance of retailers with basic school education may influence their proficiency with disruptive technological systems, hence hindering their capacity to adapt new technologies efficiently. This educational context highlights the necessity of developing accessible training programs that cater to persons with diverse educational backgrounds to promote technology integration. From the above, we note that most of the respondents did not reach the under-graduate level and therefore may not be aware of the technological disruptions in the retail sector.

Nonetheless, the research is free from education bias considering all educational classifications were represented.

5.1.4 INCOME: Income analysis reveals that a substantial majority of respondents (62%, n=432) earned below 25,000 INR, categorising them as possibly price-sensitive individuals. This financial constraint may impede their ability to invest in innovative technologies. A minority of respondents belonged to the salary ranges of 25,000 to 49,999 INR (18%, n=123) and 50,000 to 74,999 INR (18%, n=122). Merely 3% (n=19) earned between 75,000 and 99,999 INR, whereas a trivial 0.3% (n=2) earned more than 100,000 INR. The researcher observed that due to low income, the financial ability to invest in latest technologies may be adversely impacted and therefore technology adoption may not be a priority for the low-income group of retailers. Nonetheless, this research is free from income bias because all income classifications were represented.

5.1.5 TYPE OF BUSINESS: The business types operated by respondents indicate the sectors most involved in the unorganised retail market. Grocery/Kirana stores constituted the predominant section at 31% (n=219), succeeded by Readymade Garments at 20% (n=139) and Footwear at 17% (n=119). Furthermore, Ayurveda, Homoeopathy, Yunani, and Small Medicine Shops comprised 13% (n=94), while other industries, like Electronics (8%, n=54) and Handicrafts & Artisan (7%, n=48), were also included. This diversity of business types reflects varying levels of technological engagement driven by market dynamics and sector-specific requirements. All business groups were represented, hence there is no business group bias in the research.

5.1.6 PLS-SEM ANALYSIS OF CONSTRUCTS: The examination of the constructs via Partial Least Squares Structural Equation Modelling (PLS-SEM) indicated that the majority of indicator loading values surpassed the suggested threshold of 0.70, showing robust associations between the constructs and their corresponding items. Internal consistency reliability was established, as evidenced by Cronbach's alpha, rho-A, and Composite Reliability (CR) values surpassing the acceptable level of 0.70, indicating dependable constructs for evaluating technology adoption in the retail sector. The outer loadings for all components were assessed, leading to the exclusion of indicators with loadings below 0.60, hence enhancing the model's robustness. The results underscored the importance of Price Value, Social Influence, Performance expectancy, Facilitating Conditions as critical determinants affecting Behavioural Intention and the Advantages of Adoption.

5.1.7 T-TEST ANALYSIS: An Independent Sample T-Test was performed to evaluate gender-based differences in attitudes concerning the sub-constructs of the UTAUT2 model. The study indicated multiple statistically significant disparities: males exhibited a greater Performance expectancy (Mean = 2.14, p-value = 0.000) and perceived value (Mean = 2.54, p-value = 0.000) in comparison to females (Mean = 1.85 and 2.26, respectively). Furthermore, social influence was much greater for males (Mean = 2.50, p-value = 0.012) compared to females (Mean = 2.29). Females had a higher mean for habit (Male Mean = 1.47, Female Mean = 1.77, p-value = 0.000), suggesting greater habituation to specific facets of technology usage. Males exhibited a marginally elevated perceived risk (Mean = 4.56, p-value = 0.016) in comparison to females (Mean = 4.35). No significant differences were observed for facilitating conditions (p = 0.549), hedonic motivation (p = 0.066), attitude (p = 0.740), intention (p = 0.706), benefits (p = 0.299), and effort expectancy (p = 0.151), thereby corroborating the null hypothesis for these variables. The study found with male dominance in unorganized retail markets, suggesting that probably cultural and socio-economic barriers limit women's participation in this sector. However, there were representations from both the genders which makes the study free from gender bias.

5.1.8 ANOVA ANALYSIS: An Analysis of Variance (ANOVA) was applied to assess the differences in opinions among respondents based on occupation, experience, education, and income about the sub-constructs of UTAUT-2.

Intention to Benefits of Adoption: The results indicated a strong intention to adopt technology, suggesting that high adoption intentions are positively correlated with increased technology adoption rates. This relationship probably implies that when the intention to adopt technology is strong, actual technology adoption may be significantly more.

Improved Facilitating Conditions to Intention: The results indicate that in situations where facilitating conditions were optimized and exemplary, there was a significant increase in the intention to adopt technology. This probably indicates that favourable conditions could significantly impact the incentive for adopting technology.

Perceived Risk to Attitude: The results indicate that lower perceived risks might have a significant relationship with higher attitudes towards technology adoption. This probably indicates that the lower the perception towards risks, the stronger the desire for technology adoption.

The F-value for Performance expectancy was 34.500 (Sig: .000), indicating that respondents from the Electronics sector exhibited the greatest mean (2.68), whereas Handicrafts & Artisan reported the lowest mean (1.26). Electronics achieved the greatest mean perceived value of 3.13, yielding an F-value of 8.133 (Significance: .000). Social influence exhibited a moderate variance (F-value: 2.712, Sig: .013), with Other Manufacturing reporting a mean of 3.02. The habitual usage of technology exhibited considerable variation (F-value: 7.726, Sig: .000), with Electronics (mean 1.79) demonstrating greater habitual engagement than Handicrafts. Perceived risk exhibited significant variations (F-value: 2.733, Sig: .012), with Other Manufacturing (mean 4.83) and Handicrafts (mean 4.75) reflecting elevated risk perceptions. Moreover, favourable conditions (F-value: 4.387, Sig: .000) were more advantageous for Electronics (mean 2.17) compared to Handicrafts (mean 1.39). Hedonic motivation (F-value: 9.372, Sig: .000) was most pronounced in the Electronics sector (mean 2.46), whereas attitude (F-value: 5.913, Sig: .000) was most favourable in Electronics (mean 2.95) in comparison to Handicrafts (mean 1.49). The intention to acquire technology (F-value: 6.628, Sig: .000) was greater in Electronics (mean 2.43) compared to Handicrafts (mean 1.38). Ultimately, perceived benefits (F-value: 9.276, Sig: .000) were more pronounced in Electronics (mean 1.87) relative to other sectors, while effort expectancy (F-value: 9.482, Sig: .000) similarly shown elevated expectations in Electronics (mean 2.14) compared to sectors such as Medicine or Footwear.

5.1.9 SUB-CONSTRUCTS OF ADOPTION OF TECHNOLOGY

5.1.9.1 The integration of technology across many sectors, especially in retail, is shaped by multiple factors defined in UTAUT-2 Theory. This section examines the literature on the sub-constructs pertinent to technology adoption, emphasising their interactions and effects on behavioural intentions and usage.

5.1.9.2 PRICE VALUE (PV) is a critical construct that reflects the cognitive assessment of the costs versus the benefits of adopting technology. Research demonstrates that PV1 (the expense of technology adoption is warranted by its prospective advantages) and PV2 (technology adoption presents opportunities for cost reduction through enhanced operational efficiency and augmented revenue) significantly influence retailers' decisions to adopt technology. Studies have shown that when retailers perceive that the benefits outweigh the costs, their likelihood of adoption increases. For instance, Oyetade et al. (2024) highlight that cost-saving opportunities linked to technology adoption can lead to improved operational efficiency, making a compelling case for the integration of technology in retail operations.

5.1.9.3 PERFORMANCE EXPECTANCY (PEU) denotes the extent to which people regard their utilisation of technology as seamless. The components PEU1 to PEU4 exemplify the diverse facets of this design, highlighting the efficacy and streamlining of labour processes via technology. Research indicates that elevated levels of performance anticipation result in enhanced adoption rates. For example, Ghnaimeh (2024) found that when users feel confident that technology can simplify tasks and help achieve goals efficiently, their intention to adopt technology rises significantly. This aligns with Venkatesh et al. (2012), who saw simplicity of use as a pivotal factor in the UTAUT2 framework.

5.1.9.4 EFFORT EXPECTANCY (EE) refers to a technology's perceived convenience following adoption. The items EE1, EE2, and EE4 assess users' perceptions of how simple technology is to use. Higher effort expectations have been found to positively connect with both user happiness and technology adoption willingness. The simplicity of use of technology, as demonstrated in EE4 (using technology would reduce time and effort compared to conventional methods), is particularly significant in the retail context. As noted by Son Nguyen (2024), Behaviour intentions are directly influenced by diminishing the perceived effort necessary for applying innovative technologies.

5.1.9.5 SOCIAL INFLUENCE (SI) assesses the extent to which respondents perceive that their significant others believe they should embrace a new technology. Items SI1 to SI4 illustrate the influence of social networks and peer recommendations on adoption decisions. Research demonstrates that social impact is essential in technology adoption, since retailers often want validation from their peers. Esawe (2022) found that social circles and the opinions of trusted colleagues significantly impact retailers' decisions to adopt new technologies, reinforcing the importance of a supportive community in the adoption process.

5.1.9.6 HABIT (H) refers to how extensively users' daily routines have been impacted by technology use. The items H1 through H3 demonstrate how habitual usage can influence technology adoption. Research indicates that as technology becomes habitual, the likelihood of continued use increases. For example, Ghnaimeh (2024) indicates that habit is a key factor in maintaining technology use over time, as retailers who adopt technology into their everyday activities frequently find it difficult to envision their operations without it.

5.1.9.7 PERCEIVED RISK (PR) addresses the apprehensions users may have about adopting new technologies. Items PR1 through PR4 assess various dimensions of perceived risk. Research shows that higher levels of perceived risk can deter users from adopting technology. This is particularly relevant in retail contexts, where uncertainties surrounding technology performance and potential disruptions can lead to hesitancy. Oyetade et al. (2024) point out that addressing perceived risks through clear communication and support can enhance technology adoption rates.

5.1.9.8 HEDONIC MOTIVATION (HM) shows how much people find utilising technology to be fun. The pleasure and contentment that come from embracing new technology are encapsulated in items HM1 through HM4. Venkatesh et al. (2012) assert that a key component of the UTAUT2 model that impacts people's willingness to embrace technology is hedonic motivation. Retailers are more willing to use technology when they find it exciting and rewarding, according to research, as evidenced by the findings of Son Nguyen (2024).

5.1.9.9 FACILITATING CONDITIONS (FC) encompass the resources and support available to users for technology adoption. Items FC1 through FC3 reflect the necessary technological infrastructure, access to resources, and expertise required for successful adoption. Studies indicate that adequate facilitating conditions significantly enhance the likelihood of technology adoption. Esawe (2022) emphasizes the importance of these conditions in enabling retailers to embrace and utilize technology effectively.

5.1.9.10 ATTITUDE (ATT) pertains to the overall perception of technology's usefulness in retail. Items Att1 through Att3 highlight the positive impacts of technology on productivity, performance, and competitive advantage. Research shows that positive attitudes towards technology are crucial for fostering adoption. For instance, Oyetade et al. (2024) found that retailers with a favourable attitude towards technology are more likely to incorporate it into their operations.

5.1.9.11 BEHAVIOURAL INTENTION (IN) represents the likelihood of users intending to adopt technology. Items IN1 through IN3 demonstrate retailers' commitment to incorporating technology into their practices. Research indicates that strong behavioural intentions correlate with actual technology usage. Ghnaimeh (2024) notes that when retailers envision themselves using technology extensively, their likelihood of adoption increases.

5.1.9.12 THE BENEFITS OF ADOPTION (BENI) assess the tangible outcomes of technology integration. Items Benif1 and Benif2 highlight increased footfall and competitive advantages gained through technology adoption. Perceived benefits have a beneficial impact on decisions to adopt technology, according to multiple research studies. As highlighted by Venkatesh et al. (2012), acknowledging the positive effects of adoption of disruptive technologies is critical for promoting its uptake.

Consequently, the aforementioned constructions offer a thorough framework for interpreting the sub-constructs which impact technology adoption in retail. The interplay of Price Value, Social Influence, Performance expectancy, Habit, Effort Expectancy, Perceived Risk, Hedonic Motivation, Facilitating Conditions, Attitude, Behavioural Intention, and Benefits of Adoption highlights the complexity of technology adoption. Research indicates that addressing these constructs holistically can facilitate better understanding and implementation of technology in retail environments, ultimately leading to enhanced operational efficiencies and competitive advantages.

5.1.10 THE LINK BETWEEN DEMOGRAPHIC FACTORS AND THE ADOPTION OF TECHNOLOGY

The investigation investigates the variations in perspectives concerning the sub-constructs of the UTAUT2 model, differentiated by gender and product categories.

5.1.10.1 GENDER: Males reported a mean score of 2.14 for Performance expectancy, greatly surpassing the mean score of 1.85 given by females. The observed difference was statistically significant (t-value = 4.804, $p < 0.001$), implying that men are more adept at using technical tools than women. In terms of Perceived Value, males exhibited a higher mean score (mean = 2.54) than females (mean = 2.26), with a t-value of 3.776

($p < 0.001$), indicating that male respondents perceive the advantages of technology more favourably than females. Regarding Social Influence, males achieved an average score of 2.50, but females attained an average of 2.29, with a t-value of 2.534 ($p = 0.012$). This suggests that males recognise a greater impact from their social networks on technology adoption. In contrast, females had higher mean scores in the Habit construct (1.77) than males (1.47), with a t-value of -4.343 ($p < 0.001$), indicating that females may possess more entrenched habits regarding technology use than males. Regarding Perceived Risk, guys exhibited a mean score of 4.56, statistically surpassing females' score of 4.35 (t-value = 2.407, $p = 0.016$), demonstrating that men were more conscious of potential risks associated with modern technology. The notions of Facilitating Condition, Hedonic Motivation, Attitude, and Intention exhibited no significant gender differences, suggesting that both groups perceive these features equally. The mean scores for Facilitating Condition were 1.71 for males and 1.66 for females ($p = 0.549$), but for Hedonic Motivation, males scored 1.96 and females scored 2.12 ($p = 0.066$), indicating no significant gender disparity in these domains.

5.1.10.2 PRODUCT CATEGORIES: The analysis additionally examines the variations in perceptions among product categories, employing a one-way ANOVA methodology. The data for Performance expectancy revealed a significant difference among the different product kinds ($F = 34.500$, $p < 0.001$). Participants engaged in Electronics recorded the highest mean score (2.68), suggesting this category is regarded as the most user-friendly, whilst those active in Handicrafts & Artisan items obtained the lowest mean score (1.26), underscoring the difficulties they encounter in technology adoption. A notable difference in Perceived Value was recorded ($F = 8.133$, $p < 0.001$), with Electronics achieving a mean score of 3.13, in contrast to

Medicine/Ayurveda/Homeopathy/Yunani, which attained a mean score of 2.19. This indicates that those in the electronics sector attribute higher importance to technology compared to those in healthcare-related industries. The Social Influence construct exhibited notable variation ($F = 2.712$, $p = 0.013$), with Electronics participants reporting a mean of 2.72, in contrast to the lower mean scores of Readymade Garments (2.33) and Footwear (2.42). The Habit construct demonstrated significant disparities ($F = 7.726$, $p < 0.001$), with Other Manufacturing recording the lowest score (1.15) and Grocery/Kirana stores achieving a somewhat higher score (1.43). The examination of Perceived Risk revealed notable disparities among product categories ($F= 2.733$, $p = 0.012$), with respondents in Medicine/Ayurveda/Homeopathy/Yunani exhibiting the highest mean (4.68), signifying a heightened perception of risk relative to the Electronics category (4.24).

5.1.10.3 INCOME: The results demonstrate that income levels substantially influence perceptions of technological adoption. To evaluate how different socioeconomic classes perceived UTAUT2 constructs, a one-way ANOVA was conducted. The findings for Performance expectancy indicate a substantial disparity among income categories ($F = 21.500$, $p < 0.001$). Individuals in the highest income level reported a mean score of 2.87, suggesting they find technology considerably easier to use. Conversely, those from lower income categories exhibited much lower mean scores, with the lowest income group averaging 1.49. This indicates that persons with lesser incomes may encounter greater obstacles and difficulties in utilising technology, which can impede its general adoption and utilisation. The study indicated substantial variations in the construct of Perceived Value ($F = 10.423$, $p < 0.001$). The high-income group indicated a mean score of 3.47, reflecting a robust view of value in technology utilisation. The lower-income groups exhibited markedly lower mean scores, underscoring their restricted access to technology and its advantages. This gap indicates that wealth level directly affects individuals' perception of the value obtained from technology, with higher-income individuals more inclined to benefit from its advantages. Social influence shown notable heterogeneity across income levels ($F = 3.891$, $p = 0.002$). The highest income group recorded a mean score of 2.86, whilst lower-income groups had diminished scores, with the lowest income group scoring 1.99. This indicates that persons from higher income groups receive more robust social support and encouragement to use technology, thereby facilitating their greater ease and willingness to engage with it. The findings for Habit revealed significant differences ($F = 5.562$, $p < 0.001$), with respondents of higher income demonstrating more entrenched technology usage habits (mean = 2.13) than those of lower income (mean = 1.24). This data underscores that those with elevated income levels may be more adept at incorporating technology into their daily activities, resulting in increased usage. The concept of Perceived Risk shown notable disparities among income categories ($F = 4.264$, $p = 0.004$). Respondents with lower incomes indicated a greater perception of risk related to technology (mean = 4.78) than those in higher income categories (mean = 4.21). The increased sense of risk among lower-income individuals may further deter their engagement with technology, perpetuating a cycle of exclusion from digital progress.

5.1.10.4 EDUCATION DIFFERENCES: The investigation underscores the influence of educational achievement on attitudes of technology. To assess the variations in the UTAUT2 constructs across different educational levels, a one-way ANOVA was used. The results for Performance expectancy revealed a significant difference ($F = 14.223$,

$p < 0.001$). Individuals possessing postgraduate degrees had the highest mean score (2.83), suggesting they perceive technology as more user-friendly. Conversely, individuals with solely basic school exhibited a markedly lower mean score (1.58), signifying that educational background profoundly affects views of ease of use. The findings indicated substantial differences in Perceived Value between educational groups ($F = 9.722$, $p < 0.001$). Postgraduate respondents achieved a mean score of 3.56, in contrast to lower results from less educated cohorts, such as 2.17 for individuals with only primary education. This contrast underscores that elevated education levels are associated with a more positive impression of technology's benefits, validating the notion that education enhances comprehension and enjoyment of technical capabilities. The concept of Social Influence demonstrated notable differences ($F = 2.682$, $p = 0.008$). Individuals with higher education (mean = 2.79) indicated a greater influence from their social networks on technology adoption than those with lower education (mean = 2.23 for primary education). This indicates that educated individuals may possess more substantial social relationships and networks that promote technology utilisation. Individuals possessing postgraduate degree exhibited more entrenched technology usage patterns (mean = 2.45) compared to those with primary education (mean = 1.35). This suggests that educational background significantly influences individuals' technological behaviours. The study of Perceived Risk revealed significant variations among educational groups ($F = 3.771$, $p = 0.015$). persons with lower education levels indicated a higher mean score for perceived danger (mean = 4.63) compared to those with higher education (mean = 4.15), indicating that less educated persons may experience greater apprehension towards technology due to insufficient familiarity or comprehension.

5.1.10.5 TECHNOLOGICAL ADOPTION ACROSS DEMOGRAPHICS:

The analysis reveals how demographic characteristics, especially gender and product categories, affect views of technological adoption. Men typically exhibit a more positive perspective on the UTAUT2 components, indicating a necessity for customised interventions to address the varying perceptions between genders. These insights enhance the overarching discussion on technology adoption, emphasising the intricacies of human issues within the digital realm. The findings underscore notable disparities in perceptions of technological adoption correlated with income and educational attainment. Individuals with higher incomes generally see technology as more user-friendly, beneficial, and encounter less risks, hence promoting increased adoption. In contrast, those with lesser incomes encounter greater hurdles and an increased feeling of danger, which may impede technology utilisation. Educational achievement additionally affects impressions, as persons with advanced degrees claim enhanced usability and value in technology. These findings emphasise the necessity of addressing differences in technology adoption driven by poverty and education, indicating that customised measures are required to improve technological engagement among lower-income and less-educated groups. Comprehending these relationships can guide policy and practice to foster equal access to technology and its advantages, ultimately resulting in a more inclusive digital environment.

5.2 IMPLICATIONS OF THE STUDY

The study's conclusions have significant ramifications for comprehending the many factors influencing technology adoption in the unorganised retail industry. The study shows that while industries like grocery/kirana and handicrafts continue to be resistant or accept technology more slowly, industries like electronics and ready-made clothing have adopted technology more quickly, mostly because of the obvious advantages of technology. This post-COVID trend underscores the need for tailored digital solutions for different sectors. Despite increased interest in digital tools, the adoption is often superficial or focused only on essential technologies, like UPI payments, with little integration into broader business operations. Addressing this requires focusing on training and awareness programs that can demonstrate the broader applications of digital tools, from inventory management to customer relationship management. These implications span across institutional, theoretical, and practical realms.

This research makes significant contributions to the understanding of unorganized retailers' technological adoption patterns in Kolkata, emphasizing six key categories: grocery/kirana, medicine (Ayurveda, homeopathy, Yunani), footwear, ready-made garments, handicrafts/artisans, and electronics. The study's contributions are manifold and warrant reiteration with clarity and emphasis:

Table 5.1: Key Implications and Contributions

Sr.	Key Observation	Summary
1	**Sector-Specific Insights into Technology Adoption**	The research systematically analysed the technological lag in unorganized retail sectors, offering granular insights into the barriers specific to each category. This sectoral focus bridges a critical gap in existing literature, which often treats unorganized retailers as a homogeneous group, ignoring intra-sectoral variations.
2	**Geographical Relevance**	By focusing on Kolkata, a city with a vibrant yet underrepresented retail ecosystem, the study not only adds a regional perspective but also highlights the socio-economic and cultural factors that influence technology adoption in urban unorganized markets.
3	**Innovative Use of Stratified Sampling**	The adoption of a stratified sampling method allowed for robust representation across diverse retailer groups. This methodological rigor ensures that the findings are comprehensive and reflective of the nuanced dynamics within the unorganized retail ecosystem.

Sr.	Key Observation	Summary
4	**Pilot Study Refinements**	The pilot study's findings significantly refined the research instrument, ensuring reliability, validity, and relevance. The emphasis on resolving inconsistencies and aligning variables with real-world contexts exemplifies the study's commitment to methodological excellence.
5	**Actionable Insights for Policy and Practice**	This research offers practitioners and policymakers insight into practical issues. By identifying barriers such as low awareness, infrastructure gaps, and resistance to change, the study lays a foundation for targeted interventions to promote technology adoption.
6	**Contribution to Literature on Technology Adoption**	The study extends theoretical frameworks on technology acceptance and usability by contextualizing them within the unorganized retail space. This contextualization enriches existing models and sets a precedent for future research in similar markets.
7	**Empirical Evidence Supporting Change**	Through reliability testing and carefully structured data collection, the study offers robust empirical evidence on the factors inhibiting technology adoption. These findings are instrumental in shaping strategies for technological inclusion in unorganized retail.

This research serves to illuminate the intersection of unorganized retail and technology adoption in Kolkata. It not only advances academic understanding but also provides a practical roadmap for improving the technological landscape of small, unstructured retailers. The study's contributions resonate beyond academia, offering tangible benefits for retailers, technology providers, and policymakers alike. This research substantially enhances the knowledge of technology adoption in unorganised retail by addressing a significant gap in the literature, especially within the setting of Kolkata. It is unique in several ways, combining a detailed examination of sector-specific technology adoption patterns with a focus on a geographical area that has been relatively underexplored in existing studies.

Table 5.2: Unique study and Understanding Research Gaps

Sr.	Key Parameters Observed	Summary
1	**Contextualizing Technology Adoption in Unorganized Retail**	Unorganized retail in India, particularly in Kolkata, is a vast yet understudied area. Previous research on technology adoption in retail often focuses on larger, more structured retail operations or overlooks regional nuances (Kumar & Ramesh, 2018; Mehta et al., 2020). This study provides much-needed empirical insights into the technology adoption barriers faced by small, unorganized retailers in Kolkata, considering the socio-economic and infrastructural challenges specific to the city. It also highlights how cultural factors, and regional disparities affect technological uptake, offering a more nuanced understanding of the issue (Jha & Singh, 2019).
2	**Focus on Sector-Specific Barriers**	The study's categorization of unorganized retailers into six distinct sectors—grocery/kirana, medicine, footwear, ready-made garments, handicrafts, and electronics— facilitates an in-depth understanding of the obstacles encountered by each industry in the use of technology. This approach is distinct from generalized studies on small retailers, offering tailored insights into how different types of businesses react to technological changes. This sector-specific analysis significantly strengthens the literature on technology adoption in small and medium-sized firms (SMEs), which has frequently been overly generalised to address the distinct requirements of various business types (López et al., 2020).
3	**Technological Acceptance in Kolkata's Unorganized Retail**	The study addresses the significant gap in research concerning low-tech adoption in unorganized retail, particularly in Kolkata, where retail practices are still deeply rooted in traditional methods (Chakraborty & Das, 2019). The current research highlights the impact of social variables, perceived utility, and the technological landscape on retailers' use of technology. The study employs a synthesis of theoretical frameworks, including the TAM, and empirical analysis, to provide an extensive understanding of how external factors

Sr.	Key Parameters Observed	Summary
		such as infrastructure, education, and awareness influence technology adoption in Kolkata's small retail sector.
4	**Contributions to Technology Adoption Theory**	This research enhances the academic discourse on technology adoption by utilising known frameworks, including the TAM and the UTAUT, in addition to contextual awareness. The research not only improves on current theories but also offers fresh perspectives on how these models might be used to smaller, non-formal business sectors by customising them to the unique circumstances of unorganised retail (Davis, 1989; Venkatesh et al., 2003).
5	**Practical Implications for Policymakers and Retailers**	The results offer insightful guidance for legislators seeking to advance digital inclusion as well as technological firms hoping to enhance unorganised retailers' use of digital technologies. The research provides implementable strategies to close the technological divide by identifying major challenges like ignorance, resistance to change, and a lack of digital infrastructure. It is particularly valuable for local government bodies, NGOs, and tech firms seeking to design targeted interventions for the small retail sector in Kolkata and similar urban settings (Kumar & Kumar, 2019).
6	**Strategic Policy Interventions**	The study highlights the critical role of technology training programs, infrastructure development, and awareness campaigns tailored to Kolkata's unorganized retailers. These findings support existing calls for a more inclusive digital economy, where small businesses are not left behind due to infrastructural or educational gaps (Mehta et al., 2020). It positions the research as a foundational step toward formulating policies that can better equip unorganized retailers to embrace technological innovations, thus enhancing their competitiveness and resilience in a digital economy.

In conclusion, along with offering a roadmap for useful, practical interventions that can aid in closing the technological divide in Kolkata's small retail market, The theoretical understanding of technology adoption in the unorganised retail sector is further enhanced by this research. This research sets itself apart by focussing on a specific field and sector., offering focused and useful insights that advance both research and practice.

By addressing the unique barriers faced by these retailers, this study lays the groundwork for future research and technological solutions that can drive sustainable growth in the unorganized retail sector.

5.2.1 INSTITUTIONAL IMPLICATIONS

The findings of this research have significant institutional ramifications for a number of important stakeholders, such as financial institutions, trade associations, and legislators. These findings highlight the urgent need for proactive government action to alleviate the unorganised retail sector's below-optimal rates of technology use. From a policy standpoint, the findings suggest that legislators should formulate targeted initiatives to promote technology adoption among lower-income retailers. Such strategies could involve the implementation of financial support programs, such as subsidies, grants, and low-interest loan schemes, to mitigate the financial barriers faced by these small-scale enterprises. Additionally, regulatory bodies should consider developing policies that foster digital literacy and facilitate the seamless integration of technology within retail operations. For several key parties, including lawmakers, trade associations, and financial institutions, the research's outcomes have significant institutional repercussions. These results underline how urgently the government must take aggressive measures to reduce the below-optimal rates of technology use in the unorganised retail sector.would empower unorganized merchants to overcome the cognitive and logistical challenges associated with technological adoption. The pivotal role of industry associations in driving technology uptake also emerges as a key institutional implication. These organizations are uniquely positioned to organize workshops, training sessions, and awareness campaigns aimed at educating unorganized retailers about the operational and competitive advantages of embracing digital technologies. By establishing platforms that facilitate knowledge exchange and networking, industry associations can assist merchants in comprehending and navigating the complexities of technological implementation. Furthermore, the research highlights the importance of financial institutions in catalysing technology adoption among unorganized retailers. Banks and microfinance organisations ought to create specialised financial services and solutions to meet the unique requirements of this industry. This could involve offering specialised financing options to make technology purchases possible and offering advising services to help merchants deal with the complexities of technology implementation. Such programs would support the larger goal of advancing financial inclusion in addition to improving the operating capacities of unorganised retailers.

Collectively, the research findings underscore the multifaceted nature of the institutional interventions required to address the gap in the unorganised retail sector's adoption of technology. By aligning the efforts of policymakers, industry associations, and financial institutions, a comprehensive approach can be established to empower small-scale retailers, improve their competitive positioning, and foster sustainable economic development. The insights found could be utilised by policymakers to create targeted regulations that encourage lower-income retailers to adopt technology. An example of potential strategies involves the implementation of financial support programs, including subsidies, grants, and low-interest loans, with the objective of mitigating the financial obstacles encountered by these shops. Furthermore, the report posits that regulatory entities ought to contemplate the development of rules that foster digital literacy and facilitate the integration of technology inside retail operations. It is imperative to acknowledge the significant role that industry associations play. Organizations have the capacity to arrange workshops, training sessions, and awareness campaigns with the specific objective of teaching unorganized merchants regarding the advantages of embracing technology and its potential to augment their company operations. By creating a platform that promotes networking and knowledge sharing, organisations like these can help retailers understand and overcome the challenges that come with embracing technology. On the other hand, financial institutions are able to establish customised financial services and products that meet the unique needs of the unorganised retail industry. One such strategy is for banks and microfinance organisations to offer tailored financing options to make technology acquisitions easier. Additionally, these institutions might offer advisory services to assist shops in effectively managing the intricacies associated with technology deployment. These initiatives would not only provide assistance to shops in enhancing their operational processes but also make a significant contribution towards the overarching objective of promoting financial inclusion.

5.2.2 THEORETICAL IMPLICATIONS

The current research contributes to the existing theoretical framework by improving our comprehension of technology adoption in the unorganised retail sector, especially in emerging economies. This approach develops on popular frameworks like the TAM and the UTAUT by taking into account the particular problems and advantages faced by unorganised merchants Venkatesh et al (2012) created a technology adoption paradigm in their work known as the UTAUT. A recent study emphasised the factors affecting retailers' acceptance of mobile payments (Wijaya et al, 2024). Multiple elements influencing mobile payments include facilitating conditions, performance expectancy, social influence, effort expectancy, perceived security, habit, privacy, and intentions, as delineated by the UTAUT model (Ariffin e. a., 2020). Clarifying users' intentions regarding the usage of an information system and their interaction with it is the goal of the UTAUT-2 framework. The theory comprises four fundamental constructs: 1) Performance expectancy, 2) Effort expectancy, 3) Social influence, and 4) Facilitating conditions. (Chang, 2012). The theory was developed by combining the ideas of eight previously used models that explained how people used information systems: the theory of reasoned action, technology acceptance model, motivational model, theory of planned behaviour, a combined theory of planned behaviour/technology acceptance model, model of personal computer use, diffusion of innovations theory, and social cognitive theory. The examination of determinants Utilising the UTAUT-2 paradigm, it was discovered that the first three are direct indicators of usage intention and behaviour impacting technology adoption in Kolkata's unorganised retail sector, while the fourth directly impacts user activity. All principal elements of the framework—performance expectancy, effort expectancy, social influence, enabling conditions, hedonic motivation, price value, and perceived risk—were found to have a substantial impact on the behavioural intention of retailers to employ technology. The results support the hypotheses that performance expectancy positively affects business operations and behavioural intention, particularly with the use of QR codes and smartphones. Similarly, social influence and enabling conditions were confirmed as key factors in adoption decisions, with merchants influenced by their peers and the availability of supportive infrastructure. The study also highlights how crucial it is to take into account the perceived risks and issues that lower-income shops face, such as worries about security and the amount of labour needed. Even though these factors have a big impact on how people adopt technology, conventional models usually don't take them into account enough. This research creates a more thorough theoretical framework for comprehending technology adoption in the unorganised retail sector by identifying and examining these gaps. The research findings substantially enhance the understanding of technology adoption, particularly within unorganised retail, by utilising the UTAUT2. UTAUT2 is a significant paradigm for analysing the determinants of technology acceptance in consumer-oriented settings, and its theoretical implications are evident in the results of this study. By integrating UTAUT2's constructs with the specific realities of Kolkata's unorganized retail sector, this research refines the model and extends its applicability to a new, underexplored domain.

Performance Expectancy

According to UTAUT2, performance expectancy measures how much a person believes using technology will help them perform better (Venkatesh et al., 2012). This study found that unorganized retailers in Kolkata had mixed perceptions of technology's utility, especially in the grocery/kirana and electronics sectors. Retailers in the electronics category were more likely to recognize the benefits of technology for streamlining operations, improving inventory management, and reaching a larger customer base. However, grocery/kirana retailers, who typically rely on traditional cash transactions, exhibited scepticism toward the perceived advantages of adopting digital payment systems (Mehta et al., 2020). These findings highlight the vital importance for additional sector-specific interventions that accentuate the tangible benefits of technology, a nuance inadequately represented by the UTAUT2 model. This aligns with prior research demonstrating that performance expectancy is crucial in the adoption of technology by small business owners (Venkatesh et al., 2003; Sadiq et al., 2020). However, the study reveals that performance expectancy is not universally strong across all unorganized retail sectors, suggesting the need to incorporate sector-specific considerations into future models of technology acceptance.

Effort Expectancy

Effort expectation within the UTAUT2 paradigm pertains to the use of technology and its perceived intricacy (Venkatesh et al., 2012). The results of this research demonstrate the complexity of digital tools and payment methods significantly hindered numerous small shops, especially in industries such as handicrafts and Ayurveda medicine, where technology infrastructure is deficient. Despite the ostensibly simple nature of mobile wallets and UPI payments, some shops had challenges in using digital interfaces and comprehending the technology's complete functionalities. These findings align with prior research indicating that small business owners in developing economies often struggle with the technical aspects of new systems (Mehta et al., 2020; López et al., 2020).

This research emphasises that the effort expectancy construct should be broadened to encompass the wider context of digital literacy, which is relatively inadequately reflected in the original UTAUT2 model. Retailers with lower educational backgrounds were more likely to view digital tools as cumbersome and overwhelming, a finding echoed by prior studies (Sadiq et al., 2020). Thus, a more comprehensive understanding of effort expectancy should consider the skills gap that limits the adoption of technology among unorganized retailers.

Social Influence

Another essential element of UTAUT2 is the role of social influence, or the extent to which people believe that significant others think they ought to adopt a technology (Venkatesh et al., 2012). The present research established social impact as a critical factor in technology adoption, especially in areas where peer pressure or community links are significant. Retailers who observed successful technology adoption among their peers, particularly in the ready-made clothing and footwear industries, were more inclined to contemplate the adoption of analogous technologies.

This research corroborates the UTAUT2 model's claim that social influence significantly impacts conduct (Venkatesh et al., 2012), but the research also reveals how social networks in Kolkata's unorganized retail sector are more tightly knit than expected. In these close-knit networks, influence extends beyond just family and friends to include local traders' associations and informal business groups. The study suggests that future iterations of UTAUT2 should account for community-based influence in local economies, which plays a much more significant role than formalized social influence mechanisms in larger markets (Mehta et al., 2020; Kumar & Kumar, 2019).

Facilitating Conditions

Facilitating conditions, defined the resources and support available for technology adoption were critical in this research.. Retailers in Kolkata expressed a strong need for infrastructure support, including reliable internet connectivity and access to affordable digital devices. This aligns with previous research indicating that favourable conditions frequently provide a substantial obstacle to technology adoption in small enterprises, especially in areas with infrastructural deficiencies (Mehta et al., 2020).

The study also highlights how facilitating conditions are not only limited to physical infrastructure but also include external support networks. For instance, technical assistance from mobile payment providers and government initiatives designed to aid digital adoption in small businesses were found to enhance the likelihood of technology uptake. This observation extends UTAUT2 by suggesting that the concept of facilitating conditions could benefit from a more nuanced understanding of external support systems (Sadiq et al., 2020).

Hedonic Motivation and Price Value

Despite being part of the UTAUT2 model, price value (the perceived cost-benefit ratio of adopting technology) and hedonic motivation (the pleasure or enjoyment gained from using technology) did not appear to be significant factors in the adoption of technology in Kolkata's unorganised retail sector. This suggests that retailers are primarily driven by functional considerations (i.e., improving operational efficiency, enhancing customer reach) rather than by intrinsic enjoyment or cost-related concerns. This result works contrary to some previous research that highlight the part hedonic motivation plays in the adoption of retail technologies (Venkatesh et al., 2012; Sadiq et al., 2020). Therefore, this research casts doubt on the relevance of price value and hedonic incentive in the adoption of technology by small-scale businesses in developing nations with scarce resources. In conclusion, this study offers insightful information about how UTAUT2 might be applied to comprehend technology adoption in Kolkata's unorganised retail industry. While the UTAUT2 model offers a robust framework for examining key factors influencing technology acceptance, this study reveals that sector-specific, socio-economic, and infrastructure-related factors must be incorporated to fully understand technology adoption in smaller, resource-constrained retail environments.

The findings suggest that contextual refinements to UTAUT2 are needed, particularly in terms of sectoral specificity, digital literacy, and community-based social influence. UTAUT2 could be further evaluated and modified in future studies to better capture the intricacies of technology adoption in various retail scenarios.

5.2.3 PRACTICAL IMPLICATIONS

This research has important practical ramifications and provides crucial knowledge for important stakeholders, such as retail practitioners, marketing experts, and technology developers. This research underscores the pivotal role of technology developers in creating solutions that are not only accessible but also cost-effective, with a particular emphasis on addressing the unique needs of lower-income retailers.

For technology developers, the findings underscore the imperative to prioritize the development of user-friendly interfaces, deliver comprehensive customer support, and design scalable solutions capable of accommodating the growth and expansion of the retailer's business. By prioritizing these design considerations, technology developers can foster the adoption of their products and services among unorganized retailers, who may face limitations in terms of financial resources and technical proficiency when implementing robust systems.

The study's insights also hold significant implications for marketing practitioners. By using these information, marketers might develop more profound and successful communication strategies that connect to the concerns and motivations of unorganised retailers. By emphasizing the hedonic advantages of technology, such as its simplicity of use, inherent enjoyment, and potential commercial benefits, marketers can effectively appeal to the intrinsic drivers of technology adoption. Moreover, marketing campaigns can address prevalent concerns by providing transparent information and testimonials that effectively showcase the technology's benefits and safety, thereby mitigating perceived risks and effort expectancy.

From the perspective of retail practitioners, the research offers practical recommendations for merchants, including those operating in lower-income segments, on how to effectively address the challenges associated with technology adoption. Retailers can derive advantages by actively pursuing educational resources, engaging in training programs, and establishing support networks that facilitate the acquisition of essential skills and bolster their self-assurance in efficiently utilizing innovative technologies. Additionally, the study underscores the importance for retailers to undertake a comprehensive assessment of the prospective long-term benefits associated with the adoption of several disruptive technologies, which encompass enhanced operational efficiency, heightened customer satisfaction, and augmented profitability.

Furthermore, the research highlights the significance of fostering collaborative efforts among retailers, technology suppliers, and industry groups. Through such collaborative approaches, these diverse stakeholders can establish a more inclusive environment wherein the benefits of technology are made readily accessible to retailers of all financial backgrounds. The use of a collaborative framework has the potential to facilitate the creation of customized solutions that effectively address the unique requirements of unorganized retailers, thereby promoting a less unequal and technologically sophisticated retail industry.

The research's conclusions have important applications for a range of stakeholders, including legislators, business executives, tech companies, and professionals. The insights derived from studying technology adoption among unorganized retailers in Kolkata offer actionable recommendations that can be implemented to facilitate digital transformation in this critical segment of the retail sector. The following outlines the key practical implications of this research, which are grounded in its findings and have significant real-world applicability.

Policy Implications

This research highlights several barriers to technology adoption in the unorganized retail sector, including limited digital literacy, infrastructural challenges, and resistance to change. These insights are crucial for policymakers aiming to foster greater digital inclusion and economic empowerment. Key policy implications include:

> **Digital Literacy and Training Programs**: Policymakers should focus on developing targeted digital literacy initiatives tailored to the specific needs of small retailers. Training programs can be designed in collaboration with local universities, industry associations, and digital service providers to improve retailers' skills in using digital tools for payments, inventory management, and customer engagement (Mehta et al., 2020). By doing so, the government can help bridge the digital divide and promote economic growth in urban and rural areas.
>
> **Infrastructure Development**: The research identifies that poor internet connectivity and inadequate access to affordable devices are major obstacles to technology adoption. Policymakers should invest in improving the digital infrastructure in underserved areas, ensuring that unorganized retailers have reliable access to internet services and affordable mobile devices. Initiatives such

as subsidized internet packages for small businesses or partnerships with tech companies can make these technologies more accessible to unorganized retailers (Venkatesh et al., 2012).

Financial Support for Digital Transition: Given the financial constraints faced by small retailers, policymakers can introduce grants, or low-interest loans specifically designed to support the digital transformation of unorganized retail businesses. Programs such as the Digital India initiative can be further expanded to include targeted financial incentives for adopting digital payment systems (Singh & Mehta, 2019).

Industry Applications

The research's conclusions have an array of significant ramifications for business enterprises along with industry stakeholders, particularly those in the technology, payment services, and retail sectors:

Technology Providers and Payment Solutions: The study's results indicate that many unorganized retailers are hesitant to adopt digital technologies due to perceived complexity. This presents an opportunity for technology providers to develop simpler, more user-friendly solutions tailored to the needs of small retailers. For example, mobile wallets, QR codes, and point-of-sale systems that are easy to use, offer low transaction fees, and provide clear instructions can significantly increase adoption (Kumar & Kumar, 2019). Additionally, integrating technology solutions with existing local infrastructure will increase the likelihood of uptake.

E-commerce Platforms and Retail Ecosystems: The findings show that certain retail sectors, such as ready-made garments and electronics, are more open to adopting e-commerce platforms. Industry players in e-commerce should explore partnerships with unorganized retailers to provide easy entry points into digital selling channels. This collaboration can take the form of simple platforms that allow small businesses to list their products with minimal setup, fostering the rapid growth of e-commerce in markets that were previously underserved (Mehta et al., 2020).

Retail Associations and Trade Bodies: Retail communities have a significant impact on the choices made by small enterprises. The study's findings suggest that social influence has a major impact on small retail establishments' adoption of technology. Associations can be used to advocate for the beneficial effects of digital technology, schedule digital training sessions, and exchange best practices and knowledge. Additionally, industry associations can assist in establishing a cohesive voice that promotes government assistance and collaborations with tech firms (Venkatesh et al., 2012).

Technological Developments

This research has several implications for the development of digital technologies that cater to small, unorganized retailers:

Simplifying Technology: According to the research's conclusions, technology solutions must be made simpler and more suited to unorganised retail stores' requirements, as they may not have the necessary technical know-how. In order to make payment systems, inventory management, and customer engagement platforms accessible and simple to use, developers should concentrate on designing user-friendly interfaces (Sadiq et al., 2020).

Affordable Digital Tools: The research highlights the financial barriers that small retailers face when adopting technology. Consequently, there is a need for affordable, scalable digital tools that can be accessed by small retailers in Kolkata and other similar markets. Collaborations between technology firms and governments to offer subsidized tech packages could be instrumental in reducing the cost burden for retailers (Kumar & Kumar, 2019).

Mobile-First Solutions: Given the prevalence of mobile phone usage in India, especially among small retailers, mobile-first solutions can play a pivotal role in driving adoption. Mobile apps that facilitate payments, inventory tracking, and customer communication are highly effective for this target population (Singh & Mehta, 2019).

Professional Practice and Training

For professionals involved in consulting, training, and supporting small businesses, the findings from this research offer several practical applications:

Consultants and Trainers: Professionals working with small retailers should use the insights from this research to develop specialized training programs that address both technical and social factors affecting technology adoption. Tailored training can equip retailers with the skills they need to manage digital tools effectively, fostering confidence in technology use and ensuring successful integration into their business operations (Mehta et al., 2020).

Retail Consultants: Retail consultants can use the findings to help unorganized retailers identify the best digital tools for their business needs. This guidance should focus on simplicity, cost-effectiveness, and immediate business benefits to help businesses transition smoothly without overwhelming them (Sadiq et al., 2020).

Target Population: Who Will Benefit the Most

This research provides valuable insights for several key stakeholders:

Unorganized Retailers: The primary beneficiaries are the small, unorganized retailers in Kolkata and similar markets across India and developing countries. The findings will guide them in overcoming technology adoption barriers by showing the practical benefits of digital tools and providing a clearer path for integrating these solutions into their daily operations (Venkatesh et al., 2012).

Technology Providers and Innovators: Businesses that provide technology solutions will gain from these insights by creating more suitable tools that solve the particular difficulties small businesses experience, boosting user satisfaction and adoption (Mehta et al., 2020).

Policymakers and Government Bodies: These findings can be used by policymakers to create optimal regulations that support the widespread adoption of digital technology, especially in the unorganised retail sector, in order to foster digital inclusion and advancement in the economy (Singh & Mehta, 2019).

Academics and Researchers: The research's theoretical and empirical insights will serve as a basis for future studies on technology adoption in the unorganised retail industry, assisting in the creation of more sophisticated models of technology acceptance (López et al., 2020).

5.3 LIMITATIONS OF THE RESEARCH

There are various constraints inherent in the current research that have the potential to influence its conclusions.

i. The scope of this research was confined to the geography of Kolkata, where it was carried out. Similar research may likely be conducted in other Indian cities, particularly Bengaluru, Hyderabad, Mumbai, Delhi, and so on.

ii. The results of the study could potentially be impacted by many local economic, cultural, and infrastructural variables, hence constraining their generalizability to other contexts.

iii. Furthermore, future studies may include additional variables like potential future technical improvements or shifts in sociocultural settings, which may have implications for the long-term applicability of its findings.

iv. It's also crucial to remember that the scope of future research may include factors that go far beyond the UTAUT-2 framework, such as possible changes to laws pertaining to technology that could affect the long-term applicability of the findings of studies involving other models of technology adoption.

v. The findings may not be generalizable to other retail formats like Supermarkets, Chain Stores etc., that sell more comprehensive range of products. The research has been conducted in the Kolkata District and that too focussed on the unorganised retailers in Kolkata, and the findings may not represent the entire retail sector in the Eastern Part of India.

vi. Notwithstanding these limitations, the research being conducted might offer insightful information on the difficulties unorganised retailers encounter when using new technology and suggest solutions. Retailers, legislators, and other industry stakeholders may find the research's conclusions to be of significant help in making well-informed decisions regarding the adoption of technology and how it will affect the growth and economic success of the sector.

Despite the significant contributions of this research to understanding technology adoption among unorganized retailers in Kolkata, certain limitations should be acknowledged to contextualize the findings and highlight areas for future exploration.

- **Geographical Scope**:

  The study is limited to Kolkata's geographical boundaries, which, while representative of an urban unorganized retail landscape, may not capture the diversity of challenges faced by retailers in rural or semi-urban areas. The cultural, infrastructural, and economic conditions in Kolkata might limit, the research' applicability to other cities or areas with distinct socioeconomic dynamics.

- **Sectoral Focus**:

  While the six categories of unorganized retailers chosen for the study provide comprehensive insights, they do not encompass the entire spectrum of unorganized retail. Categories such as food vendors or hardware stores were excluded, which might have provided additional layers of understanding to the patterns of technology adoption.

- **Cross-Sectional Design**:

  Using a cross-sectional methodology, the study collects data at one particular moment in time. Because of this, it is unable to adequately account for the dynamic shifts in technology adoption patterns brought about by quickly changing market trends, governmental regulations, or technological breakthroughs. A longitudinal approach might offer deeper insights into the progression and sustainability of technology adoption.

- **Sample Size Constraints**:

  Although the stratified sampling approach ensured adequate representation across key retailer groups, the overall sample size may still limit the ability to generalize findings to the entire unorganized retail sector in Kolkata. This is particularly relevant for smaller subcategories, where sample sizes may not sufficiently reflect the diversity of challenges.

- **Focus on Retailer Perspectives**:

  The study primarily examines technology adoption from the retailers' perspective, potentially overlooking the influence of consumer preferences, competitive pressures, or supplier-driven incentives. A more comprehensive knowledge of the ecosystem impacting technology adoption may be possible by incorporating these other perspectives.

- **Technological Breadth**:

  The study evaluates a limited range of technological tools, such as digital payments and inventory management systems, without delving deeply into other transformative technologies like AI-based customer analytics or blockchain for supply chain transparency. Future research might broaden the focus to encompass cutting-edge disruptive technologies.

- **COVID-19 Context**:

  The pandemic has significantly influenced the technology adoption behaviours of businesses. While this provides a unique lens for the research, it also limits the ability to distinguish between temporary adaptations and long-term shifts.

The findings may reflect immediate responses to crisis conditions rather than sustainable behavioral changes.

By acknowledging these limitations, this study establishes the foundation for further studies that will fill up these gaps and elaborate on the discoveries made. A broader geographical focus, longitudinal design, and inclusion of additional technological and stakeholder perspectives would deepen the understanding of unorganized retailers' digital transformation journeys.

These afore-mentioned difficulties underscore the necessity for continuous research to tackle these limits and augment the correctness and pertinence of the study.

5.4 DIRECTIONS FOR FURTHER RESEARCH

There are many research opportunities in the field of technology adoption, particularly with regard to how cutting-edge technologies like blockchain, AI, and ML affect socioeconomically disadvantaged communities and marginalised population.

I. It is vital to comprehend the manner in which these technologies can be customized to accurately address the requirements of underprivileged populations.

II. Potential future research endeavours may prioritize the identification and resolution of obstacles pertaining to technology accessibility, financial viability, and digital literacy. By making sure that technological advancements benefit all demographic groups, the main goal of this research is to advance inclusion and equity.

III. Furthermore, evaluating the long-term effects of technology adoption on social justice and economic mobility is crucial. A more thorough grasp of the long-term effects of technology on income levels, job opportunities, and social inclusion can be obtained through extensive longitudinal studies.

IV. It is imperative for research to assess the efficacy of various training and support modalities, including a comparative analysis of online training, in-person training, peer support, and tailored programs.

V. A comprehensive analysis of legislative and regulatory effects, encompassing aspects such as data privacy and development incentives, would provide valuable insights for the formulation of fair and inclusive plans for technology access.

VI. Furthermore, gaining insight into cultural differences in technology utilization might contribute to the formulation of culturally appropriate and efficacious solutions that cater to varied communities.

5.5. CONCLUSIONS

In conclusion, this comprehensive research study offers profound insights into the multifaceted dynamics shaping technology adoption within the unorganized retail sector in Kolkata. By employing the robust UTAUT-2 theoretical framework, the researcher has systematically unpacked the complex interplay between socioeconomic status and the extent of technology integration, revealing a concerning pattern of disparities that merits urgent attention.

The results clearly show a significant connection between retailer income levels and their propensity to embrace and harness technological solutions. Higher-income merchants, buoyed by their positive perceptions of user-friendliness, discernible value propositions, and tangible operational benefits, have demonstrated a greater inclination to adopt and integrate technology into their business practices. Conversely, their lower-income counterparts face a daunting array of obstacles, ranging from perceived risks and difficulties in establishing effort expectancy, to a pervasive lack of adequate support mechanisms. This may culminate in a troubling technology adoption gap, where the unorganized retail sector's most vulnerable members are systematically excluded from the transformative potential of digital tools and applications.

The implications of these findings are profoundly significant, resonating across multiple institutional domains. Policymakers probably heed the urgent call to address this technological divide, crafting targeted interventions that empower lower-income retailers to overcome their adoption barriers. Such efforts may encompass tailored financial support programs, comprehensive digital literacy initiatives, and developing of technical solutions that are centred around users explicitly created to fulfil the specific needs and limitations of small-scale unorganised retailers. Simultaneously, industry associations must assume a pivotal role in organizing training, knowledge-sharing platforms, and awareness campaigns to equip unorganized retailers with the skills and confidence required to harness the full spectrum of technological capabilities. Only through such concerted, multifaceted efforts might ensure that the transformative promise of technological innovation is realized equitably, fostering a more inclusive and prosperous retail landscape for generations to come. It is incumbent upon policymakers, industry leaders, and technology providers to heed this call, collaborating in unprecedented ways to engineer a future where technology serves as an equalizer, empowering all unorganized retailers to thrive in an increasingly digital and dynamic marketplace.

Furthermore, the research underscores the critical importance of fostering collaborative ecosystems, wherein technology providers, financial institutions, and retail stakeholders converge to co-create inclusive, customized solutions. By aligning their efforts and resources, these diverse actors may establish a more level playing field, ensuring that the transformative power of technology is accessible to all merchants, irrespective of their socioeconomic standing. Through such coordinated, multi-stakeholder interventions, the technological divide may be bridged, empowering even the most marginalized retailers to enhance their operational efficiency, improve customer experiences, and ultimately, strengthen their competitive positioning within the evolving retail landscape. This research study, with its rigorous analytical approach and its profound practical implications, stands as a clarion call to action.

Ultimately, the successful integration of technology across the unorganized retail sector holds the promise of far-reaching economic and social implications. Beyond the immediate benefits to individual businesses, the equitable adoption of digital tools has the potential to catalyse broader systemic change, fostering a more inclusive and resilient retail ecosystem. As the unorganized sector embraces technological innovation, it may unlock new avenues for growth, productivity, and customer engagement – outcomes that transcend the boundaries of individual enterprises and contribute to the overall prosperity and competitiveness of the retail industry as a whole.

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APPENDICES

QUESTIONNAIRE USED FOR DATA COLLECTION

Dear Retailers

I am conducting a PhD research study on the retail market in Kolkata, and I would like to request your feedback through a survey. The survey will cover a range of topics related to retail, including purchasing habits, product preferences, and shopping experiences. Your feedback will be completely anonymous and will only be used for research purposes.

Participation in the survey is entirely voluntary, and it should take no longer than 10-15 minutes to complete. I would greatly appreciate your time and input, as it will provide valuable insights into the retail market in Kolkata.

Thank you in advance for your participation.

Sincerely,

Joydeep Mookerjee
PhD Scholar

Pin code					
Location					
Type of Product Sold	[ ] Grocery / Kirana [ ] Medicine / Ayurveda / Homeopathy / Yunani [ ] Footwear [ ] Readymade Garments [ ] Handicraft and Artisian [ ] Electronics [ ] Others				
Age	[ ] 18 to 25	[ ] 25 to 35	[ ] 35 to 45	[ ] 45 to 55	[ ] 55 & above
Gender	[ ] Male	[ ] Female	[ ] Others		
Education	[ ] Uneducated	[ ] Primary School	High School	[ ] Graduate	[ ] Post Graduate and above
Monthly Income	[ ] < 25,000	[ ] 25,000 to 49,999	[ ] 50,000 to 74,999	[ ] 75,000 to 99,999	[ ] > 1 Lakh
Do you use smartphones to make payments or receive payments?			Yes [ ]	No [ ]	
QR code reader / payment system			Yes [ ]	No [ ]	
POS machine for card swipe payment system			Yes [ ]	No [ ]	
Did technology adoption increase your sales?			Yes [ ]	No [ ]	
Did your customer footfall increase with technology adoption?			Yes [ ]	No [ ]	

Awareness and Usage

<table>
<tr><td>Please mention your awareness and the usage of the following in your business?</td><td>Never Heard</td><td>Heard but never used</td><td>Lack of resources to use</td><td>Would like to learn</td><td>I already use it</td></tr>
<tr><td>Computerised billing system</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Automatic accounting system</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>QR code payment system</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Credit/Debit card payment</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>UPI ID payments or UPI Apps</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>NEFT Payment from Banking</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>What type of Automatic technology you think is helpful for the Unorganized retail business process?</td><td colspan="5">[ ] Payment System (Digital Wallets/QR Code etc.,)
[ ] Inventory Management Software
[ ] Customer Relationship Management
[ ] E- Commerce Technologies
[ ] Digital Marketing Tools
[ ] AR/VR/IoT etc.,</td></tr>
<tr><td>What type of Automatic technology are used by you?</td><td colspan="5">[ ] Payment System (Digital Wallets/QR Code etc.,)
[ ] Inventory Management Software
[ ] Customer Relationship Management
[ ] E- Commerce Technologies
[ ] Digital Marketing Tools
[ ] AR/VR/IoT etc.,</td></tr>
</table>

SECTION A: TECHNOLOGY ADOPTION

Please indicate the current stage of technology adoption in your retail business:

[ ] **Innovator** (adopt new technologies, even if they are relatively untested or unfamiliar)
[ ] **Early Adopter** (adopt new technologies early on, before they become widely accepted in my sector)
[ ] **Early Majority** (adopt new technologies once I see positive results and feedback from others in my sector)
[ ] **Late Majority** (prefer to wait until new technologies are well-established before adopting them)
[ ] **Laggard** (resistant to adopting new technologies and prefer traditional methods)

Adoption of Technology	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
Performance Expectancy (PE)					
Adopting technology in business helps me to serve my customers better.					
With the help of technology, chances of achieving things have increased.					
Using the technology has simplified work processes and tasks					
Technology helped me to accomplish things more quickly.					
Perceived Risk (PR)					
The adoption of new technology in business involves a high level of financial risk.					
I am concerned about the potential cybersecurity risks associated with adopting new technology					
I am hesitant to adopt new technology due to the unknown risks involved.					
I perceive a risk of technological complexity and difficulties in using new technology in my business					
Effort Expectancy (EE)					
Using the technology after adopting is easy for me					

Adoption of Technology	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
Technology related to my business are easy to use					
Integrating the technology into my existing business operations would require significant effort and changes					
Using the technologies would save me time and effort compared to my current methods					
Social Influence (SI)					
People who are important to me think that I should adopt technology in my retail business					
I am influenced by the recommendations of people whose opinions I value when considering technology adoption					
If other retailers in my social circle adopt technology, I am more likely to adopt it as well					
The attitudes and opinions of my peers and colleagues have an impact on my decision to adopt technology in my retail business					
Facilitating Condition (FC)					
The necessary technological infrastructure (e.g., internet connectivity, hardware) is readily available and accessible to support the adoption of new technologies by our business					
I have access to the necessary resources (financial, human, and technical) to adopt and effectively utilize the technology.					
I have the knowledge necessary to adopt and use the technology					
Hedonic Motivation (HM)					
Using technology enhances my enjoyment and pleasure in conducting business activities					

Adoption of Technology	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Adopting technology makes my business operations more exciting and fun					
Adopting technology adds a sense of novelty and innovation to my business practices					
Adopting technology provides me with a sense of satisfaction and fulfilment in my business endeavours.					
Price Value (PV)					
The cost of adopting the technology is justified by the potential benefits it offers					
Adopting technology offers cost-saving opportunities in terms of operational efficiency, reduced expenses, or increased revenue potential					
The total cost of ownership, including maintenance, upgrades, and additional fees, is reasonable and aligns with the benefits received from the technology.					
Habit (H)					
Using technology in my business has become a habit for me					
I find it difficult to imagine my business operations without using technology					
I use technology automatically, without consciously thinking about it, when performing business tasks					
Attitude					
Using technology in my business would greatly enhance my productivity and efficiency					
I believe that adopting technology in my business would improve my					

Adoption of Technology	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
overall performance and effectiveness					
Using technology in my business would lead to a competitive advantage and help me stay ahead in the market					
Behavioural Intention (BI)					
I see myself regularly using technology as part of my everyday business operations.					
I plan to make consistent efforts to incorporate technology into my business practices					
I am willing to allocate resources and invest in the necessary technology in my business					
Benefits of Adoption					
My business experienced more footfall after adopting retail technology					
Technology adoption has provided competitive advantage in the market					
Technology adoption has positively impacted customer satisfaction levels					

PUBLICATIONS AND PRESENTATIONS BY THE SCHOLAR IN THE RESEARCH AREA

Publications:

Sr.	Title	Journal Name	Indexed	Volume and Issue no	Page Nos (from -to)	Month of Publication
1	A Review of The Impact of Disruptive Innovations on Markets and Business Performance of Players	International Journal of Grid and Distributed Computing	**Web of Science**	Vol. 14 No. 1 (2021)	605-630	May 2021
2	A Review of the Robotic Process Automation's Impact as a Disruptive Innovation in Accounting and Audit	Turkish Journal of Computer and Mathematics Education (*TURCOMAT*)	**Scopus**	Vol 12, Issue 12 (2021)	3675 - 3682	May 2021
3	Adoption of Technology and the Unorganized Retailers	Mathematical Statistician and Engineering Applications	**Scopus**	Vol 71, Issue 4 (2022)	12887 - 12903	February 2022
4	An Evolutionary Review of the Technology Adoption Models	Mathematical Statistician and Engineering Applications	**Scopus**	Vol 71, Issue 4 (2022)	12904 - 12923	March 2022
5	Technology Penetration & Adoption in An Unstructured Retail Market of Kolkata, India	Mathematical Statistician and Engineering Applications	**Scopus**	Vol 71, Issue 4 (2022)	12667 - 12679	May 2022
6	Exploring Consumer Behaviour and Technology Usage: Insights and Implications for Industry	Mathematical Statistician and Engineering Applications	**Scopus**	Vol 71, Issue 4 (2022)	12680 - 12697	June 2022
7	Measuring The Adoption of social media & Internet Technology for Retailing: An Analysis of Consumer Behaviour	Mathematical Statistician and Engineering Applications	**Scopus**	Vol 71, Issue 4 (2022)	12430 - 12450	July 2022
8	Statistical Measurements of Technology Adoption	Mathematical Statistician and Engineering Applications	**Scopus**	Vol 71, Issue 4 (2022)	7339 - 7353	August 2022

Sr.	Title	Journal Name	Indexed	Volume and Issue no	Page Nos (from -to)	Month of Publication
	Among Unstructured Retailers					
9	Statistical Tests for UTAUT-2 Model: An Analysis of Their Suitability for Technology Adoption in Unstructured Retailers	Mathematical Statistician and Engineering Applications	**Scopus**	Vol 71, Issue 4 (2022)	12451 - 12467	September 2022
10	Consumer Technology Acceptance in the Digital Age: Investigating the Influence of Age and Education	Mathematical Statistician and Engineering Applications	**Scopus**	Vol 71, Issue 4 (2022)	12924 - 12931	October 2022
11	Technology Uptake and Socio-demographic Factors: An Empirical Analysis of Unstructured Retailers and Consumers in Kolkata, West Bengal	Mathematical Statistician and Engineering Applications	**Scopus**	Vol 71, Issue 4 (2022)	12996 - 13008	December 2022
12	Impact of QR-Codes as a Disruptive Technology During the Covid-19 Contagion	International Journal on Recent and Innovation Trends in Computing and Communication	**Scopus**	Vol 10, Issue 1 (2022)	284 - 289	February 2023
13	A VOS-Viewer Bibliometric Analysis of UTAUT-2 Model of Technology Adoption	IJCERT PUBLICATIONS	**Peer Reviewed**	Vol 10, Issue 3 (2023)	113 - 127	March 2023
14	A Systematic review: disruptive innovation in non-branded retail markets	International Journal of Systematic Innovation	**Scopus**	Vol 7, No.6 (2023)	20-35	June 2023
15	Analysing Factors Influencing Technology Adoption by Unorganized Retailers Using UTAUT 2 Framework	International Journal of Innovations & Research Analysis (IJIRA)	**UGC**	Vol 4, No 3(2024)	141-147	September 2024

Presentations:

Sr.	Name of Conference	Date of Conference	Paper Title	Location	Arranged By
1	International Conference on Contemporary Issues in Business Management	March 5th and 6th, 2021	A REVIEW OF THE IMPACT OF DISRUPTIVE INNOVATIONS ON MARKETS AND BUSINESS PERFORMANCE OF PLAYERS	Sikkim, India	Sikkim Manipal Institute of Technology
2	2nd International Conference on Innovation on Engineering Sciences	March 27th and 28th, 2021	A REVIEW OF THE ROBOTIC PROCESS AUTOMATION'S IMPACT AS A DISRUPTIVE INNOVATION IN ACCOUNTING AND AUDIT	Coimbatore, India	International Research Journal on Advanced Science Hub
3	1st International Conference on Emerging Issues in Business and Technology (ICEiBT) 2021	June 24th and 26th, 2021	Impact of the Contagion on the Unorganized Retail Market	Kolkata, India	Brainware University