

LEVERAGING ARTIFICIAL INTELLIGENCE AGENTS TO DRIVE CUSTOMER
EXPERIENCE IN THE REALM OF AI AGENTS IN THE RETAIL INDUSTRY IN
INDIA

by

Sonia Jeetendar Thakurani

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Sonia Jeetendar Thakurani

APPROVED BY
Vasiliki Grougiou



Dissertation chair

RECEIVED/APPROVED BY:

Renee Goldstein Osmic

Admissions Director

DEDICATION

To my mother, while I chased my education and ambitions, you held my hand throughout.

To my husband, who never once stopped believing that this was possible, even on the days I gave up.

To my two little ones, you were small when my journey began. You are older now, and so am I. Thank you for letting me take time away from you to pursue something that you could not yet understand. One day you will.

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This research is sharper, more rigorous, and more honest because of their involvement.

ABSTRACT

LEVERAGING ARTIFICIAL INTELLIGENCE AGENTS TO DRIVE CUSTOMER EXPERIENCE IN THE REALM OF AI AGENTS IN THE RETAIL INDUSTRY IN INDIA

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India's retail industry faces a paradox: digital marketing tools are booming, yet the customer experience at the point of purchase in-store remains largely disconnected from them. Despite their wide distribution, digital coupons suffer from persistently low redemption rates: shoppers encounter them as buried emails or forgotten notifications rather than as the useful, valuable tools they are meant to be. The use of Artificial Intelligence beyond store-based information-dispensing tools or enhancements to the in-store shopping experience remains unexplored, especially in emerging markets. This research examined the factors driving the adoption of an AI agent that helps retrieve relevant coupons from their emails on demand at in-store checkout, thereby enhancing the in-store shopping experience for shoppers in India. It also studied whether such an agent could reshape shoppers' attitudes toward digital coupons as a category.

An extended Stimulus-Organism-Response framework served as the theoretical foundation, integrating constructs from the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Value-Based Adoption Model (VAM). A mixed-methods exploratory sequential design was used. Qualitative interviews with shoppers were conducted first to extract contextual and attitudinal themes, followed by a structured online quantitative study of urban Indian shoppers.

Findings indicated that 'Attitude toward AI' and 'Social Influence' were the strongest predictors of adoption intention, followed by perceived ease of use, perceived usefulness, and risk perception, suggesting that AI adoption in the Indian retail context is shaped less

by functional utility and more by value-based and relational evaluations. Unlike established studies, the demographic analysis revealed that AI exposure variables, such as occupation, have a greater impact on behavioral intention towards artificial intelligence agents than socioeconomic variables. Additionally, the findings indicate that AI agent adoption is a value-exchange negotiation in which shoppers weigh perceived benefit against perceived risk. More importantly, a significant spillover effect established that AI agents serve as ‘perception accelerators’ and ‘category rehabilitators’ for the underlying tasks or tools they assist with.

For retailers, marketers, and AI product designers operating in emerging markets like India, these results recommend a design centered on the trustworthiness of the agent and security of handling their data, socially anchored marketing strategies, and the use of AI agents as instruments of perceptual change towards the underlying tools and tasks they support.

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CHAPTER 1:

INTRODUCTION

1.1 Introduction

The field of Artificial Intelligence has advanced from an abstract concept to an omnipresent technology. It is reforming sectors through increased speed, scalability, adaptability, decision-making skills, and customization (Wilson & Daugherty, 2018). It is relevant in media, finance, manufacturing, logistics, and healthcare (Nti et al., 2021; Yang et al., 2021; Nimmagadda, 2022; Askin et al., 2023; Erafy, 2023). Today, it is embedded in people's day-to-day activities, including facial recognition systems in banks, personalized social media news feeds, and efficient traffic management systems (Wilson & Daugherty, 2018).

In the retail industry, AI helps create hyper-personalized customer engagement and enables new retailers to disrupt traditional business models (Almahairah et al., 2022). Despite AI's growing influence in everyday lives and industries, retailers and shoppers have not adopted artificial intelligence technologies equally (Tangi et al., 2023). The retail scene has experienced considerable operational transformations in recent history. This rapid pace of change continues to be driven by increasingly demanding customers and shorter product/trend life cycles (Begley et al., 2018). AI has seen significant adoption in retail, yet its integration into different parts of a customer journey remains in its early stages. Retailers lack clarity on strategies and opportunities for integrating AI, particularly among offline retailers. The complexity increases due to concerns about Return on Investment(ROI), security, and other considerations (Almahairah et al., 2022; Chhabra et al., 2024). Retailers are increasingly leveraging AI applications for practical purposes such as product recommendations and shopper behavior monitoring (Lee et al., 2018). AI is also helping drive customer experiences via personalized interactions and AI assistants (Tula et al., 2024). Innovations such as data engineering and machine learning have helped the retail sector close the experience gap by providing tools such as AI-enhanced checkout processes, sentiment analysis, Internet of Things (IoT)-driven consumption monitoring, and content delivery systems (Babatunde et al., 2024; Deloitte, 2016). In the online retail space in particular, these technologies have enabled the delivery of personalized

experiences in real time (Babatunde et al., 2024). There is a shift from fixed personalization to just-in-time relevance, in which artificial intelligence tools serve as real-time decision aids (Lopes et al., 2024). The success of these tools depends not merely on their technical availability but on how users perceive their adoption based on “perceived benefits, ease, and trust”. Importantly, there is a value-exchange negotiation in which value is contingent on consumer trust, effort, and relevance (Tangi et al., 2023).

In the current era of rapid digital change, characterized by the unprecedented pace at which innovative technologies are announced daily, the integration of AI into a brand’s marketing strategy represents a fundamental shift in how brands approach targeting, understanding, and engaging with their customers (Cogoljević et al., 2024). The customer is at the core of hyper-segmentation. Hyper-segmentation is the practice of treating each customer as a segment and involves understanding their preferences, motivations, requirements, and buying patterns. The concept of segmentation enables companies to offer highly personalized products/services; this is known as hyper-personalization (Florido-Benítez, 2024). There have been developments in marketing techniques that have become very popular due to technological advancements; the use of hyper-personalization in marketing has grown by 357% since 2021 (Saksena, 2024). With this increased interest in personalizing marketing strategies, the way companies interact with customers and the marketing tools they use have changed significantly. An example of this is the emergence of personalized digital coupons as a key approach (Venkatesan & Farris, 2012).

Innovations in digital technology have led to the creation and increased adoption of digital coupons, a core element that companies use to create unique customer experiences in their marketing plans. Digital coupons are electronic codes or vouchers, sent via email or text message, that offer incentives for customers to purchase or use certain products or services (Akman & Turkmen, 2021). Unlike traditional coupons, digital coupons use personalized approaches to transform the marketing process (Pandey et al., 2024). The promotional campaign is expected to eventually help customers make decisions, thereby impacting total sales. Digital coupons remain an important marketing strategy, especially when targeting Gen Z, who already surpass millennials as the world’s most populous generation (Wandhe, 2024). Brands spend a significant amount of money on personalization and targeted digital

coupons and offers, but coupon redemption in itself needs addressing. Of all coupons issued in 2023, only 0.87% were redeemed in the US. Coupon redemption in-store is a larger challenge, with only 35% of US shoppers redeeming coupons during in-store visits (Capital One Shopping Research, 2025). The challenges of redemption may be mitigated by designing processes that make the redemption experiences easier and hassle-free (Nayal & Pandey, 2020).

Digital channels have grown significantly; however, in-store environments remain more complex, particularly as brick-and-mortar stores undergo rapid change in the wake of the digital surge. COVID-19 accelerated the adoption of e-commerce, and since then, traditional brick-and-mortar shopping has undergone a significant transformation (Ogunbukola, 2025). In light of the growing importance of the digital environment, retailers are now adopting diverse business models, including e-commerce sites, rapid delivery systems, and optimized business processes, while keeping their physical stores open (Dang, 2023). Furthermore, new technologies are being used, such as mobile payments, social networking, and digital coupons (Piotrowicz & Cuthbertson, 2014). Consequently, customers' shopping habits are evolving toward cross-device and cross-channel experiences (Huang, 2010). The current market environment indicates a greater likelihood of activities occurring across various devices. The availability of multiple devices has played an important role in shaping customers' purchase decisions (Gupta et al., 2024). The combination of multiple devices has led to what is known as "showrooming". Showrooming involves customers browsing for items in physical stores and buying them online. This trend has led to significant interruption in the retail sector following the onset of the COVID-19 pandemic, resulting in the closure of several stores.

On the other hand, webrooming, or reverse showrooming, occurs when customers browse items online before making purchases in physical stores (Gupta et al., 2024). The decline in sales at physical stores post-COVID has affected reverse showrooming. Retail stores can, in fact, increase sales, loyalty, and customer experience by adopting digital practices, including personalized experiences (Prashanthi & Valliyammai, 2024). For AI in in-store experiences, Augmented Reality (AR) has emerged as a disruptive tool to enhance customer experiences. In brick-and-mortar stores, AR-enabled tactile simulations impact

the experience and, in turn, sales (Grewal et al., 2020). Given the limitations of package size and in-store information space, AR has the opportunity to become the tactile solution that allows brands to engage with customers and deliver information as needed about the product, nutrition, etc (Wolniak et al., 2024). Yet, beyond product information, purchase decisions are also strongly shaped by promotional incentives.

In-store promotions, such as coupons, significantly increase the planned purchase size, in turn increasing sales per shopping event (Heilman et al., 2002). In their research, the authors argue that the value of purchases made after such in-store coupons exceeds the value of the coupon gains. This effect is attributed to the psychological benefits the customer perceives from experiencing immediate, unforeseen gains. Such savings not only increase the proportion of planned spending the customer walks in with, but it also has a positive impact on the customer's mood. However, there are several issues with consumers' access to digital coupons. The ease with which these coupons can be used significantly affects their impact on the purchasing process, especially among Gen Z customers (Pandey et al., 2024). Limitations on the use of such coupons significantly affect their ability to influence not only the shopping experience but also the purchasing process and overall sales. Hybrid shopping makes it even more important to provide a smooth transition between digital and physical aspects. But there is a lack of studies exploring how AI can help with this gap.

A significant amount of academic work has been pursued in studying technology like AI and AR for in-store experiences and checkout experiences to nudge a customer's purchase decision; however, there is limited academic work that studies the use of AI to make a customer's digital coupons available in real-time during an in-store shopping event to nudge them into a conversion. With insights from this research, brands can ensure customers have better experiences and realize the benefits by integrating digital and in-store experiences. In fact, this offers competitive advantages for brands/retailers (Khan et al., 2022). Using the help of AI, retailers can enhance customer experience and increase conversions during in-store visits (Abbas, 2024).

In India, technology adoption often carries a social dimension, where the use of technology can improve social perceptions and increase the end product's consumption value (Aaradhi & Chakraborty, 2024). Conversely, in developing countries like India, social push can drive technology adoption. For example, in the edtech space, a nudge from parents or peers can motivate students to consider adopting an edtech platform. (Dinh et al., 2025). In India's retail industry, the growth of e-commerce has had a profound impact. The Indian e-commerce industry has expanded at an exceptional pace due to factors such as growing disposable income and rising technology adoption. For a value-conscious market like India, the ease and accessibility of e-commerce have changed the retail landscape (Haque et al., 2024). Among Indian consumers, especially Gen Z, purchase intentions are shaped by their attitudes towards digital coupons (Pandey et al., 2024). This shows the influential role digital coupons, such as those received via email, play in driving sales conversions. Nevertheless, despite this change in the landscape, Indian customers are more likely to shop in-store than US customers (Mendelson et al., 2015). Chauhan (2025) argues that an average Indian consumer's need for purchase visibility, trust issues with online platforms, collectivist family-based decision-making, and emotional attachment to sensory shopping experiences all reinforce a cultural preference for in-store retail. With the advent of omnichannel marketing strategies being adopted by brands, the need for brick-and-mortar stores to engage with customers has increased multi-fold (Shukla & Vyas, 2019).

Existing research has made significant contributions to the body of knowledge on personalized digital marketing and the use of artificial intelligence for personalization (Huang & Rust, 2021; 2022; Gao & Liu, 2023; Ziakis & Vlachopoulou, 2023; Jain & Kumar, 2024). But, there remains a lack of research on the use of artificial intelligence to assist consumer decision-making at the point of purchase during in-store shopping by retrieving relevant promotional offers.

This research aimed to address the research gap by examining the drivers of adoption of an AI agent for personalized shopping experiences in India, specifically one that retrieves relevant digital coupons from users' emails during in-store purchase checkouts. Foundational technology adoption theories, such as TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003), remain central to explaining technology adoption. Still, emerging

evidence highlights the importance of additional factors - including risk and value -in understanding the adoption of AI-driven personalization. Although digital coupons are largely used for promotions, their widespread consumer disregard highlights an opportunity to leverage artificial intelligence to deliver timely, relevant digital coupons. Thus, this research aimed to bridge the gap in the literature regarding the use of artificial intelligence for personalization at the point of purchase.

The problem presented above is analyzed through two different but related lenses of research inquiry:

First, the research examined baseline attitudes and demographics related to customers' adoption of AI agents when shopping in-store in India, with a specific focus on a concept of an AI agent that helps retrieve relevant digital coupons stored in shoppers' email inboxes at checkout. Using existing technology adoption models, the paper evaluated the effects of constructs such as attitudes towards AI technology, demographics, usefulness, ease of use, social influence, risks, and perceived value on behavioral intention to adopt the innovation.

Second, this part of the research focused on determining whether the adoption of an AI agent affected shoppers' attitudes towards digital coupons received via email as a whole or as a category, thereby functioning as an attitude-accelerator. By providing access to digital coupons at the right time, the research studied if the AI agent improved the perceived role of digital coupons in shoppers' shopping experience.

To sum it up, this research sought to understand the factors that influence digitally literate consumers in India to adopt an AI agent that presents shoppers with relevant coupons at the time of purchase, thereby solving the coupon redemption problem. In addition, this research paper analyzed the effect of exposure to such technology on shoppers' attitudes towards digital coupons as a whole, highlighting the role of AI agents as an *attitude-accelerator*.

To lay the foundation for the research, it is important to understand the core challenges that drove this research. The next section investigates the research problem in depth,

highlighting the issues faced by brands and customers globally with a special focus on India, and underscoring the need for further study in this area.

1.2 Statement of the problem

There is substantial academic work demonstrating AI's ability to transform personalization and marketing practices (Huang & Rust, 2021; 2022; Gao & Liu, 2023; Ziakis & Vlachopoulou, 2023; Jain & Kumar, 2024). Nonetheless, the effectiveness of these strategies hinges on their ability to influence a customer's purchase decision at the moment of truth- the moment of purchase. Brands invest significant effort and money in personalizing coupons, digital coupons being the most accessible and easiest instruments at their disposal (Liu et al., 2022). Conversely, their practical impact on a customer's purchase decision depends on their availability and ease of access. From the consumer's point of view, participation in these coupons is based on an implicit evaluation of whether the cost of searching for the coupon and the attention it draws during the shopping process is justified by the magnitude of the benefit derived (Liu et al., 2022).

According to YouGov (2017), a substantial share of consumers reported purchasing items they did not need simply because they had a coupon. This statistic highlights the importance of digital coupons in influencing customer behavior. It is a fact that digital coupons and offers positively impact customer loyalty and purchase decisions, given the multitude of offers. But, targeted marketing emails are often treated as spam and end up lying unutilized in customers' mailboxes (Kanich et al., 2009). The effectiveness of coupons as a tool for retention and conversions is amplified when they are available in real time during in-store (Mimoso, 2018). Despite this, the adoption of technology to deliver personalized, real-time experiences during shopping, especially in-store, remains limited.

One of the main benefits of digital coupons is that they enable the creation of personalized experiences, which are an essential building block of one-to-one marketing. Still, such marketing strategies are mainly implemented before or after shopping experiences (Klabjan & Pei, 2011). Timing plays a major role in coupon redemption (Lee & Choeh, 2021). In that regard, making coupons available in real time is an important aspect of the

brand's digital marketing. However, technical issues may impede the integration of online communications with in-store experiences. Offline coupon redemption is largely customer-initiated (Oliver & Shor, 2003). But an overwhelming amount of digital promotion can lead to them being treated as spam (Dickinger & Kleijnen, 2008). Which means, shoppers are not aware that they have those coupons. Information and knowledge play a significant role in shaping the purchase decision-making process, influencing customer behavior in various distinct ways (Kang et al., 2020). Customers not being aware of the coupons they receive in emails leads to low coupon redemption. Customers utilize a range of methods in their decision-making process (Kokila & Sampathlakshmi, 2022).

This research is set in India, where the foregoing friction is both more acute and consequential. In fact, India is one of the fastest-growing retail markets in the world, estimated at \$1.06 trillion by 2024 and \$1.93 trillion by 2030, accounting for more than 10 percent of the country's GDP and 9 percent of its employment (Deloitte and FICCI, 2025). What makes the Indian scenario distinct lies in its structure: the dominant nature of the physical form of retail, wherein conventional forms of retail stores occupy about 93% of the market in 2024, and organized retail making up less than a fifth, dispersed amongst nearly twelve million Kirana stores and local stores (Deloitte and FICCI, 2025; IBEF, 2025). This makes it quite unlike scenarios in which couponing studies have taken place before, where the key point in time for a digital coupon would be in-store, when context-based recall is minimal.

At the same time, Indian consumers report being highly comfortable performing digital transactions at the point of sale. The UPI has been handling about 20 billion transactions, with a total value of approximately ₹25 lakh crore in one month of 2025, representing about 84% of the nation's total retail digital payments in volume (NPCI, 2025). It means that the barrier to an AI-based coupon system is unlikely to be digital unfamiliarity at the point of sale, but rather problems of lack of awareness, lack of trust, and a lack of a contextual layer that would bring to consumers ' attention the coupons they had before. The possibility is even more clearly articulated by demographic characteristics: Gen Z will account for about 43% of total consumption in India in 2025 (Deloitte and FICCI, 2025).

Against this backdrop, modern customers are tech-savvy and accustomed to digital purchases that have built-in loyalty programs and coupons. Hence, customers are expected to default to online purchases where effort expectancy is low (Gupta et al., 2024). With current coupon strategies, while digital coupons are delivered, many customers still default to in-store purchases. If coupons are not easily accessible or available in real time during the in-store journey, customers are likely to default to online channels where effort expectancy is lower. The use of AI to drive personalized experiences or one-to-one marketing in real time is currently limited to AI agents answering product-related questions (Söderlund et al., 2022). This research introduced the concept of an AI Agent that, when linked to a customer's emails, retrieves all coupons and vouchers a customer has received as part of personalized digital marketing messages from brands. The agent categorizes and delivers these vouchers/coupons in real time at the moment of purchase to help drive customers' decision-making. This research aimed to understand the impact on customers' adoption and use of such an AI agent, as well as the opportunity to improve coupon redemption rates for brands.

Despite the increasing prevalence of AI technologies in retail settings, little empirical research has examined the successful adoption of these technologies for omnichannel retailing. Current research shows that AI technology can provide customers with a more pleasant experience by making it easier to visualize products and navigate them (Hoyer et al., 2022; Vashishth et al., 2024). The application of AI to enhance these processes has already been demonstrated; however, it is also important to study how AI can enable a smooth transition from offline to online shopping (Flame, 2024). This gap is especially pronounced in India: with it being one of the leading markets for digital coupons (Global Growth Insights, 2024). Despite this, there is limited research that examines the redemption of digital coupons in the Indian context. Additionally, in the Indian context, the involvement of AI incites mistrust among a large section of the population (Patil, 2025). Notably, AI-mediated commerce is no longer hypothetical in this market - NPCI, in pilot with industry partners, has begun trying out agentic and conversational payment journeys on UPI (NPCI, 2025) - which renders the question of B2C or shopper adoption both timely and under-explored.

Research has shown a gap between willingness to use coupons and actual coupon use (Abhishek & Mathen, 2014). Yet, there is limited academic work investigating the reasons for the gap. Significant research has been conducted on technology-enabled personalization in the digital messaging space, yet a gap remains in driving such personalization in in-store experiences. As retail research increasingly emphasizes integrated omnichannel experiences, it is crucial to recognize that customer preferences, demands, and conduct can differ across different channels. It is important to explore customer attitudes toward personalization, especially digital coupons. Frequent exposure to personalized content during online shopping leads customers to anticipate similar levels of personalization during their in-store visits (Szocs et al., 2023). More than 50% of customers' in-store purchases are unplanned (Inman & Winer, 1998). In-store coupons and offers have a greater impact on impulsive buying behavior compared to store atmosphere and scents (Kiran et al., 2012). Many retailers continue to use a hybrid "bricks-and-clicks" strategy, which complicates the implementation of effective personalization in both physical stores and online. This dual approach causes challenges in delivering a consistent and tailored customer experience across different channels, as the integration of personalized content and services must be managed across both in-store and digital platforms.

Consequently, achieving the appropriate levels of personalization in each context remains a significant difficulty for retailers employing this strategy (Lindecrantz et al., 2020). There have been studies indicating the efficacy of targeted coupons in driving redemption (Gong et al., 2024). Nonetheless, there is limited research on AI tools that make it easy to retrieve these coupons in a context-specific manner and in real time during in-store purchases. With the proliferation of digital marketing, many brands are veering towards distributing coupons via digital channels like email, creating an inundation of such emails and resulting in a spam-like situation for customers (Dickinger & Kleijnen, 2008). Beyond a low redemption rate, this suggests that consumers might become hesitant towards digital coupons, regarding them as clutter rather than as something valuable (Dickinger & Kleijnen, 2008). Studies indicate that a positive experience with a tool can translate into attitudes towards the tasks it performs and the objects it handles (Qin et al., 2025). But

limited research has examined AI tools that help customers cut through the chaos and use coupons.

Taken together, these aims locate the research within an Indian coupon-redemption context that, while increasingly studied, remains narrowly understood. Recent studies have sought to understand how Indian customers interact with digital and mobile coupons and have identified coupon proneness, perceived coupon value, search intention, perceived convenience, and perceived privacy risks as crucial to the coupon redemption process (Nayal and Pandey, 2020a; Nayal et al., 2021). In addition, they have applied a technology acceptance model to explore how Generation Z customers adopt mobile and digital coupons in India (Pandey et al., 2024). Kolar (2024) demonstrates that perceived risks affect the use of AI technologies, but little has been written on extending the UTAUT model to include perceived value. Value negotiations highlight the importance of value exchanges, which rely heavily on information sharing. However, all these works identify themselves as being in an early phase of development and call for deeper research regarding the adoption of coupons and agents by Indian shoppers (Nayal and Pandey, 2020b). None of the works have considered an AI agent as a tool to improve customer experience through relevant coupon redemption at in-store checkout, and none have considered how this agent can affect customer attitudes towards digital coupons as a whole. This research attempts to fill this research gap.

1.3 Purpose of Research

The purpose of this research is to examine how shoppers in India evaluate and adopt an AI agent during an in-store purchase experience, using relevant digital coupon retrieval as the setting. This single purpose unfolds across two connected dimensions of adoption. First, the research explores the factors that influence shoppers' behavioral intention to use such an AI agent, particularly in an in-store retail environment where digital support is more limited than in online shopping (Cuni-Mertz & Jung, 2021). The second explores whether adopting such an AI agent could also influence shoppers' broader attitudes towards digital coupons. Examined together, these dimensions allow the research to develop a contextually

grounded understanding of how AI agents can shape shopper attitudes, intentions, and decision-making within physical store environments in India.

1.4 Significance of the Study

The research addresses an existing gap in the academic discourse on the role of artificial intelligence in retailing and on consumer adoption of emerging technological tools by focusing on a specific decision-making scenario that remains underexplored in both academic and practical frameworks. Despite the abundance of academic research on the application of AI in e-commerce and the influence of in-store technologies on the customer experience, little attention has been paid to consumer evaluations of and adoption of AI in in-store scenarios (Rizwana et al., 2024). This situation is especially true for India: whereas shopper's use of coupons in-store has started being explored and their proneness, perceived value and privacy risks identified as crucial factors for coupons' redemption (Nayal and Pandey, 2020a; Nayal, Pandey, and Paul, 2021), with the recent addition of Generation Z shoppers and using the technology acceptance model (Pandey et al., 2024), none of the research done has focused on the AI agent performing the task of retrieving and applying coupons.

This study has two main contributions. The first contribution comes from exploring the determinants that may influence consumers' behavioral intentions to use an AI agent in physical stores, where digital support for decision-making during purchases is less available than online (Cuni-Mertz & Jung, 2021). Personalized marketing is closer to the point of decision in Online shopping than in an in-store environment. In an in-store purchase, the shopper usually has less digital assistance available at their fingertips than in online environments. If brands extend the same digital personalization into physical environments, shoppers may view it as an intrusion (Cuni-Mertz & Jung, 2021). Thus, along with perceived usefulness and ease of use, adoption of the technology may depend on the balance between the perceived benefits and costs associated with its use - namely, privacy, trust, and the willingness to share personal email data (Kim, Chan, & Gupta, 2007). By treating these costs as part of the adoption calculus rather than as a separate

concern, the research offers a more complete account of what may drive, and what may deter, the uptake of AI agents at the shelf.

The second, and more novel, contribution concerns whether adopting such an agent could in turn reshape shoppers' broader attitudes towards digital coupons. Digital coupons are widely distributed yet frequently dismissed as spam and left unredeemed. This research contributes to the study of whether the adoption of AI agents that mediate concerns about coupon retrieval might spill over into attitudes towards the category itself (Qin et al., 2025). This research foregrounds the possibility that an AI agent, by surfacing relevant coupons at the right moment, may not only be adopted but also rehabilitate shoppers' regard for the very instrument it delivers. This attitude-spillover effect marks the research's principal theoretical departure from existing adoption work, which tends to treat the tool and the task it supports as separate.

This research proposed a digital mock-up of an AI agent capable of detecting and displaying contextually relevant coupons that match the consumer's purchase context. Theoretically, this research extends the TAM and UTAUT frameworks by incorporating context-specific factors drawn from the Indian in-store setting and connects them to value-based reasoning about perceived benefit and cost. Its practical implications follow from these findings. By conceptualizing a digital mock-up of an AI agent that reads a shopper's purchase context and retrieves coupons by relevance, the research points to ways two persistent frictions in digital couponing, i.e., the timeliness of a coupon's value and the cognitive burden of locating it amid digital clutter, might be eased. If shoppers adopt such an agent, brands may, in turn, find opportunities to deliver coupons more promptly and reduce messaging overload, with potential downstream benefits for engagement, loyalty, and conversion. The research thereby offers a foundation for future inquiry into AI technologies that may enable a more seamless merging of digital and physical shopping experiences in India.

1.5 Research Questions

The literature review identified gaps in integrating established AI adoption models with AI agents for real-time in-store purchase experiences, particularly in emerging markets such as India. Existing theoretical models, including the Technology Acceptance Model (TAM) (Davis, 1987) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Chao, 2019), do explain technology adoption in broad digital settings. But their applicability to AI-agentic retail interactions, specifically in enabling real-time coupon retrieval and influencing immediate purchase behavior, remains insufficiently examined. Resolving this gap required an empirical investigation of the behavioral mechanisms that influence consumers' readiness to adopt and use AI agents during in-store shopping. Behavioral intention was selected as the primary dependent variable because prior research has shown it to be a reliable predictor of actual technology use (Davis, 1987), particularly in situations where real-time usage may not be immediately observable.

1.6 Research Aim

This research is aimed at examining how shoppers in India evaluate and adopt an AI agent for contextual digital coupon retrieval during in-store purchases, and whether such adoption may, in turn, reshape their attitudes towards digital coupons.

The importance of this aim lies in addressing a gap that the existing technology adoption and retail promotion literature has not sufficiently bridged. While studies of artificial intelligence in retail have primarily centered on e-commerce and efficiency gains, the in-store moment - where the bulk of impulse buying takes place (Inman and Winer, 1998) and digital assistance is minimal- remains relatively under-researched (Rizwana et al., 2024). In pursuing this research objective, the thesis will seek to expand well-known theories of adoption into an area for which they were not initially developed - i.e., to explore how the adoption of an AI agent could affect consumers' attitudes towards digital coupons offered by the agent (Qin et al., 2025). The importance of this research objective, therefore, lies in two things: first, the expansion of consumer-adoption theory in technology in an underexplored physical retail environment and AI agent adoption setting; second,

understanding the impact of AI agents to increase couponing engagement in the most in-store-dominated major retail market in the world (Deloitte and FICCI, 2025).

1.7 Research Objectives

The objectives of the research were:

- To examine the influence of consumers' pre-existing attitudes toward AI tools on their behavioral intention to use an AI agent for in-store coupon retrieval (Balakrishnan & Dwivedi, 2021).
- To investigate whether demographic characteristics - including age, gender, income, education, occupation, and digital literacy- produce significant differences in behavioral intention to use the AI agent (Venkatesh et al., 2003; Porter & Donthu, 2006).
- To identify and empirically test the drivers of AI agent adoption and their relative influence on behavioral intention during in-store (Davis, 1989; Kim et al., 2007).
- To assess whether exposure to the AI agent concept produces a spillover effect (Qin et al., 2025) on consumers' attitudes toward digital coupons

This study broke down the research problem into research questions to examine the attitudinal and contextual factors influencing the adoption of AI agents. It aimed to understand the impact of consumer attitudes towards AI in general in India. As part of the research, shoppers were exposed to the concept of an AI agent that can help retrieve relevant digital coupons from their emails at the point of decision-making during an in-store purchase. The research sought to understand the presence of baseline drivers of AI agent adoption, such as attitudes towards AI and demographic backgrounds.

The research further investigated the extent to which key adoption constructs- including perceived usefulness, perceived ease of use, social influence, perceived risk, and perceived value affect shoppers' behavior intentions to use AI agents for in-store coupon retrieval. It investigated the impact of an AI Agent on shoppers' attitudes towards digital coupons as a whole- using the coupon retrieval agent as an example, aiming to ascertain the attitude-

accelerating influence of AI agents- That is, whether AI-agents can improve shoppers' attitudes towards the tools, processes, or tasks it supports.

1.8 Research Questions

To do this, this research investigated the following questions:

Primary Question

What factors influence shoppers' adoption of an AI agent for in-store digital coupon retrieval in India, and does that adoption in turn influence their attitudes towards digital coupons?

Technology-adoption research has its roots in organizational and workplace settings - the technology acceptance model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) were developed and validated largely to explain employees' use of information systems at work. These have since been extended mostly to e-commerce and online channels (Rizwana et al., 2024).

The in-store decision moment in physical retail, where digital support is weakest, has received comparatively little attention, and India, in particular, remains underexplored. The study of shopper coupon-redemption behavior in India is in its nascent stages. It has also not been connected to AI-agent-led assistance at the point of purchase (Nayal and Pandey, 2020a; Nayal, Pandey, and Paul, 2021). The primary question speaks directly to these gaps. It also joins two strands the literature has kept apart - what drives adoption of a tool, and whether using that tool may, in turn, reshape attitudes towards the task it supports (Qin et al., 2025).

Sub-questions

The primary research question was broken into sub-questions to arrive at the answers

RQ1: How does a customer's attitude towards AI influence their intention to use an AI agent?

RQ2: What are the differences in behavioral intention when using AI agents across various demographic groups?

RQ3: What drives shoppers to accept and adopt an AI agent for in-store coupon retrieval?

RQ4: What is the significant impact of the AI agent on the shopper's attitude towards digital coupons in general?

To answer these questions, the research attempted to prove or disprove the following alternative hypotheses:

RQ1 is evaluated through H1 and RQ2 is evaluated through H2

H1:Attitude towards AI tools influences Behavior Intention to use the AI Agent for digital coupon retrieval

H2: Shopper demographics influence the behavioral intention to use the AI Agent for digital coupon retrieval.

RQ3 is evaluated through 5 hypotheses as follows:

H3: Usefulness of the AI agent for coupon redemption influences the behavioral intention to use the AI Agent for digital coupon retrieval

H4: Ease and intuitiveness of the AI agent influence the behavioral intention to use the AI Agent for digital coupon retrieval.

H5: Social influence on AI agent usage influences the behavioral intention to use the AI Agent for digital coupon retrieval.

H6: Risk Perception of AI Tool influences Behavior Intention to use the AI Agent for digital coupon retrieval.

H7: Value from the AI Tool influences Behavior Intention to use the AI Agent for digital coupon retrieval.

RQ4 is evaluated through H8.

H8: Attitude towards the AI agent positively influences the shopper's attitude towards the digital coupons as a whole

1.9 Limitations, Delimitations, and Assumptions

Limitations. Constraints beyond the researcher's control qualify the findings: a small purposive qualitative sample open to observer bias; self-reported quantitative data subject to social-desirability effects; reliance on a concept mock-up rather than live use; structural equation modeling that evidences association, not causation; a benefit-to-risk value ratio assuming equal weighting; a single-country sample limiting transfer to other cultures; and a spillover measured immediately after exposure, leaving its durability untested.

Delimitations. The research was deliberately bounded: to TAM, UTAUT, and VAM within an extended S-O-R framework, with alternative theories set aside; to a single use case (an AI agent for in-store coupon retrieval); to digitally literate, adult, urban Indian shoppers; and, methodologically, to a standardized concept mock-up rather than a live tool, with value operationalized as a usefulness-to-risk ratio (Davis, 1989; Venkatesh et al., 2003; Kim et al., 2007; Mehrabian and Russell, 1974).

Assumptions. The research assumed that participants responded honestly (mitigated through anonymity), that the mock-up conveyed the agent faithfully enough for considered evaluation, that behavioral intention proxies eventual use (Davis, 1989; Ajzen, 1991), that the Likert items validly indexed their constructs (tested in Chapter III), and that the sample adequately represented digitally literate urban Indian shoppers.

1.10 Definition of terms

AI agent. A system that perceives a context and acts within it on the user's behalf, unlike an assistant that only answers queries (Poole and Mackworth, 2010; Söderlund et al., 2022).

Digital coupon. An electronic voucher redeemed via a digital device for a discount at purchase (Danaher et al., 2015).

Behavioral intention. A shopper's stated readiness to use a technology, a reliable predictor of actual use (Davis, 1989; Venkatesh et al., 2003).

Attitude towards AI. A shopper's general evaluative disposition towards AI tools (Davis, 1989).

Perceived usefulness / ease of use. The degree to which the agent is expected to improve the task / the effort its use is expected to require (Davis, 1989).

Social influence. The extent to which a shopper perceives that important others endorse using the agent (Venkatesh et al., 2003).

Perceived risk. The negative utility associated with the agent, centred on data exposure, privacy, and trust.

Perceived value. A shopper's assessment of the agent's worth, balancing benefit against sacrifice (Kim et al., 2007); here operationalized as the ratio of usefulness to risk.

TAM / UTAUT / VAM. Adoption models based, respectively, on usefulness and ease of use (Davis, 1989); social influence and facilitating conditions (Venkatesh et al., 2003); and perceived value as benefit against sacrifice (Kim et al., 2007).

S-O-R framework. A structure in which stimuli evoke internal states that produce a response (Mehrabian and Russell, 1974); here, the overarching framework integrating TAM, UTAUT, and VAM is extended to a dual response (Jacoby, 2002).

Spillover effect. A shift in attitude towards an adjacent asset following a change in evaluation of a related attribute - applied, by analogy to Qin et al. (2025), to the transfer of a positive agent evaluation onto attitudes towards digital coupons.

Perception accelerator. A construct introduced here: the property of an AI agent that rapidly shifts a shopper's perception of an adjacent task in a favourable direction.

Category rehabilitator. A construct introduced here: the property of an AI agent that repairs a previously negative attitude towards an entire adjacent category - digital coupons as a whole - rather than a single offer.

Kirana store. A small, independently owned neighborhood store characteristic of India's unorganized retail (Deloitte and FICCI, 2025).

Background:

Over little more than a decade, artificial intelligence has moved from a back-office tool to a customer-facing layer of retail, yet this shift has concentrated online, where personalization has advanced from fixed segmentation to just-in-time relevance (Wilson and Daugherty, 2018; Lopes et al., 2024). The in-store environment remains comparatively untouched, even though most retail activity still occurs there. The digital coupon, a central personalization instrument, illustrates the gap: distributed at scale yet under-redeemed, because locating relevant offers amid email overload imposes effort that exceeds their perceived value (Danaher et al., 2015; Dickinger and Kleijnen, 2008) - a friction sharpest at the in-store point of purchase. These conditions are pronounced in India, among the largest and fastest-growing retail markets yet overwhelmingly physical, dominated by Kirana and unorganized stores (Deloitte and FICCI, 2025; IBEF, 2025). Indian shoppers nonetheless transact comfortably at the point of sale, as UPI adoption shows (NPCI, 2025), suggesting the barrier to an AI-mediated coupon system lies less in digital unfamiliarity than in awareness, trust, and the absence of a contextual layer. It is against this background that the research situates the adoption of an AI agent for in-store coupon retrieval.

CHAPTER 2:

REVIEW OF LITERATURE

2.1 Introduction

This chapter examines the literature that informs how shoppers in India may evaluate and adopt an AI agent for retrieving digital coupons during in-store purchases. Its purpose is twofold: to establish what is already understood about the concepts, technologies, and behaviors the research engages, and to identify the gaps it is designed to address.

The review begins with artificial intelligence itself - the nature and evolution of AI agents, and the challenges of trust, privacy, and risk that condition their adoption - before turning to digital coupons and their redemption within the Indian retail context. It then evaluates the three adoption models on which the research draws - the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Value-Based Adoption Model (VAM) - integrated within the overarching Stimulus-Organism-Response (S-O-R) framework. The chapter closes by drawing out the precise gaps these literatures leave open.

2.2 Inclusion Criteria

The literature reviewed was selected against a few deliberate criteria. Priority was given to peer-reviewed journal articles addressing technology adoption, artificial intelligence in retail, digital couponing, and consumer behavior, with foundational works retained for the established models (for example, Davis, 1989; Mehrabian and Russell, 1974) and recent studies, largely from 2020 onward, drawn upon to capture the fast-moving AI and Indian-market evidence. Because the application studied is emerging and academic coverage of it remains thin, authoritative industry and government sources - such as Deloitte and FICCI (2025), NPCI (2025), and IBEF (2025) - were included to establish market context where scholarly evidence was unavailable. Only English-language sources relevant to the constructs and to the Indian in-store setting were considered.

2.3 Artificial Intelligence and AI Agents: Concept and Evolution

Artificial intelligence is defined differently across the management and computing literatures, and the contrast matters for this research. In the business and marketing tradition, Kaplan and Haenlein (2019) define it as a system's ability to interpret external data correctly, to learn from that data, and to "achieve specific goals and tasks through flexible adaptation" - a definition that foregrounds data-driven learning and adaptation. In the computing tradition, Poole and Mackworth (2010) frame it as the study of "computational agents that act intelligently", where an agent is simply something that acts. Comparatively, the first lens suits the personalization logic of digital marketing, while the second - AI as an entity that *acts* on the user's behalf - is the more apposite for this research, since the tool it examines does not answer queries but acts: it retrieves and orders relevant coupons at the point of purchase. An *AI agent* is understood here in that agentic sense, as a system that perceives a context and acts within it for the user (Söderlund et al., 2022; Poole and Mackworth, 2010), as distinct from the information-dispensing assistants that dominate current retail practice. Several gaps in the existing literature follow from this. The most fundamental is conceptual: the term "AI agent" is applied loosely, gathering rule-based chatbots, recommender systems, and genuinely autonomous agents under a single label, which obscures the differing adoption considerations each entail (Gursoy et al., 2019).

2.4 The Challenges and Risks of Artificial Intelligence

If the case for AI in retail is compelling, its adoption is far from frictionless, and a critical review must give equal weight to the challenges. The most robust body of evidence concerns algorithm aversion - the documented tendency of people to resist algorithmic judgment even when it performs as well as, or better than, a human. Dietvorst et al. (2015) show that decision-makers lose confidence in an algorithm more quickly than in a person after seeing each make the same error. This means that an AI agent's objective competence does not guarantee its acceptance; a single visible mistake may disproportionately damage trust.

The picture is, however, more conditional than a blanket aversion, and this nuance matters for the present setting. Castelo et al. (2019) find that aversion is task-dependent,

pronounced for tasks perceived as subjective or requiring human judgment but weak for those seen as computational. Longoni et al. (2019) trace resistance in personal domains to uniqueness neglect - the fear that an algorithm cannot accommodate one's individual circumstances. Against these, Logg et al. (2019) document the opposite tendency, an algorithm appreciation in which people prefer algorithmic to human judgment under certain conditions. This means that whether a shopper resists or welcomes an AI coupon agent may depend on how the task is framed: coupon retrieval is a largely objective, computational task of the kind least prone to aversion, which could work in such an agent's favor - a proposition this research is positioned to examine rather than assume.

Trust and transparency present a second, more counterintuitive challenge. Schilke and Reimann (2025) find that disclosing AI involvement can erode trust, and Ngo (2025) reports that the relationship between transparency and adoption is non-linear rather than uniformly positive. This means that the design choices intended to build confidence in an AI agent may have ambivalent effects, and that trust cannot be treated as a simple function of openness.

A third challenge bears most directly on this research's treatment of perceived value. The personalization that makes an AI agent useful depends on access to personal data, generating the personalization-privacy paradox in which the same capability that confers benefit also imposes a sacrifice (Cloarec, 2024). This means that privacy risk is not peripheral to adoption, but constitutive of the value judgment a shopper makes - a benefit weighed against a cost - which is why perceived risk enters this research's framework as a sacrifice that may depress perceived value. Taken together, these challenges - aversion, fragile trust, and privacy sacrifice - explain why an account of AI-agent adoption confined to usefulness and ease of use would be incomplete, and why trust and perceived risk are treated here as conditions shaping how value and attitude form around an autonomous agent that shoppers will use.

2.5 Digital Coupons and Coupon Redemption in the Indian Retail Context

Coupons have long served as a core sales-promotion instrument, offering a price incentive intended to prompt trial, accelerate purchase, and build loyalty, and the past decade has seen their decisive migration from paper to digital and, increasingly, mobile form (Nayal and Pandey, 2020a). A digital coupon may be understood as an electronic voucher, issued or redeemed via a digital device, that a shopper redeems for a discount at the point of purchase (Danaher et al., 2015). This means that the coupon is no longer a physical object clipped in advance, but a piece of information surfaced, evaluated, and applied within the shopping moment itself -a shift that reframes redemption as a digital, and potentially automatable, act.

Research into what drives redemption has often treated it as a technology acceptance problem, examining how perceived usefulness, ease of use, and coupon proneness shape the intention to search for and redeem digital coupons (Ha and Im, 2014; Nayal and Pandey, 2020b). Two findings from this literature bear directly on the present research. First, perceived value and coupon proneness consistently emerge as the principal antecedents of redemption intention (Nayal et al., 2021), aligning the coupon domain with the value-based account of adoption developed earlier.

Yet a persistent puzzle attends digital coupons: despite their reach, redemption remains modest relative to distribution, a shortfall the literature attributes substantially to the effort of locating, comparing, and remembering relevant offers (Danaher et al., 2015). This means that the friction an AI coupon-retrieval agent is designed to remove - the search-and-application burden - is precisely the friction shown to depress redemption, which situates such an agent as a plausible response to a documented problem rather than a solution in search of one.

The Indian context sharpens these observations. India is among the fastest-growing markets for digital coupon use, with uptake propelled by rapid smartphone penetration, a young and value-conscious population, and intense festival-period promotion, with Generation Z a central, price-sensitive segment (Rakesh and Khare, 2012). Yet two features

of Indian retail complicate any straightforward transfer of existing findings. The market remains overwhelmingly physical, dominated by Kirana and unorganized stores, so the in-store environment - not the e-commerce setting in which most coupon research is conducted - is where the majority of Indian shopping, and therefore coupon redemption, actually occurs. This means that the existing evidence base, concentrated online and abroad, speaks only partially to an in-store, AI-mediated coupon encounter in India.

2.6 Technology Acceptance Model

The Technology Acceptance Model, introduced by Davis (1989), remains the most widely applied framework for explaining behavior towards technology (Marangunić and Granić, 2014). It holds that adoption depends on a user's attitude, which is in turn shaped by two beliefs: perceived usefulness - the degree to which a system is expected to enhance performance - and perceived ease of use, the degree of effort its use demands (Davis, 1989). In the context of AI agent adoption for coupon retrieval, both perceived usefulness and ease of use influence shoppers' willingness to adopt mobile coupons (Pandey et al., 2024).

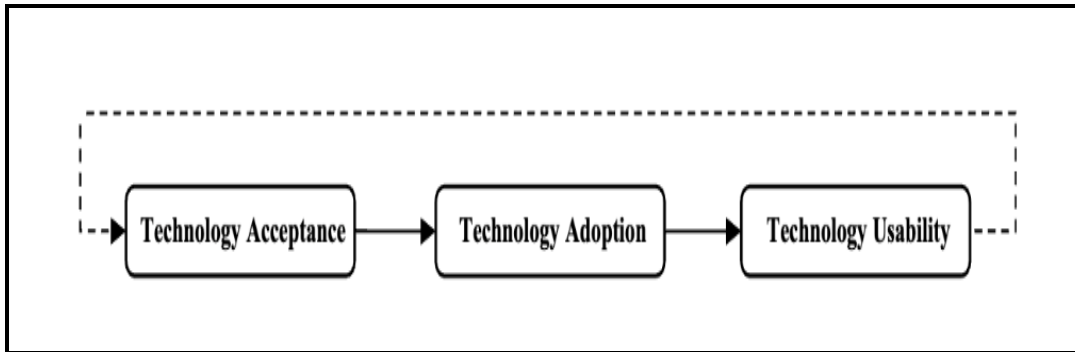


Figure 2.1

Relationship between Technology Acceptance, Technology Adoption, and Technology Usability (Liu et al., 2019)

TAM is one of the most widely applied models in the field of technology acceptance, developed to understand and explain the user's behavior towards using technology (Marangunić & Granić, 2014). In contrast to the hypothesis of a strictly sequential relationship, TAM reasons that technology adoption depends on individual attitudes, which in turn rely on three key variables: perceived usefulness, perceived ease of use, and trust

(Yeoha et al., 2024). In the years that followed, the TAM2 theory refined the model by slowly downplaying trust as a core construct.

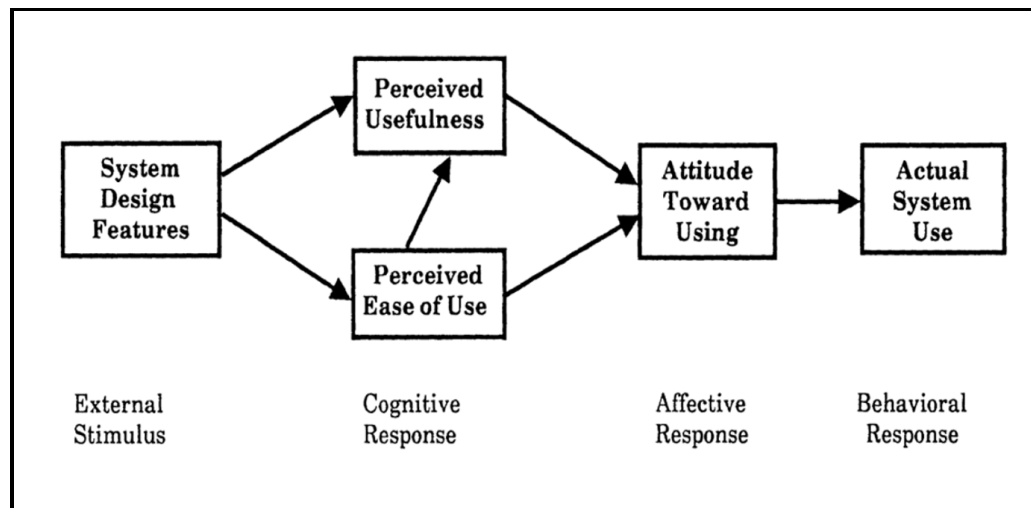


Figure 2.2

Technology Acceptance Model. Davis (1989)

TAM's enduring appeal lies in its simplicity. It explains technology adoption using a small number of core constructs. Yet that same simplicity is the basis of sustained critique. Bagozzi (2007) argues that the model assumes individuals make rational and deliberate adoption decisions, neglecting the affective, social, and cultural influences that shape technology behavior in practice, and that its parsimony limits its explanatory power across diverse technologies and contexts. In their study “What Makes a Consumer Redeem Digital Coupons? Behavioral Insights from Grounded Theory Approach”, Nayal & Pandey (2021) argue that in today’s scenario, past experiences, privacy risks, and media reviews have increased relevance. Subsequent work has sought to extend it: Featherman and Pavlou (2003) integrate perceived risk into TAM as a form of negative utility -distinguishing facets such as performance, financial, and privacy risk - and find that risk perceptions depress adoption intention while perceived ease of use mitigates them, with trust further offsetting perceived risk (Kesharwani and Bisht, 2012). In the paper ‘Extending the technology acceptance model by inclusion of perceived risk, Featherman (2001) adds another variable to the TAM model- perceived risk, theorized as a negative risk. With this method, the author aims to introduce a variable representing negative utility to better assess the

acceptance and adoption of new technology. Perceived risk negatively affects usage intention, and trust negatively affects perceived risk (Kesharwani & Bisht, 2012).

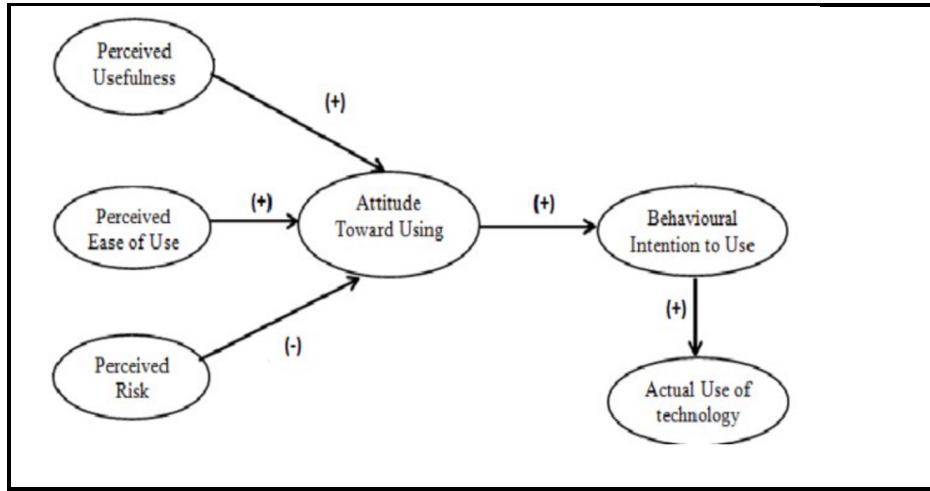


Figure 2.3

Technology Acceptance Model with Perceived Risk (Sinha et al., 2021)

The case of AI highlights a limitation: AI tools may be easy to use yet still raise concerns about data use and privacy (Ahmad et al., 2023). TAM cannot accommodate both. Additionally, although ease of use and usefulness of the technology strongly influence attitude and behavioral intention, studies have shown that additional factors, such as access to technology and the infrastructure that supports its use, are equally important. Subjective norms, such as social influence, also play a role in a user's propensity to adopt and use new technology (Marikyan & Papagiannidis, 2023). This means that while TAM offers a necessary foundation, it is insufficient on its own to explain the adoption of an AI agent in an authentic retail setting and must be situated within broader frameworks.

2.7 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology, formulated by Venkatesh et al. (2003), consolidates earlier acceptance models into a single framework explaining user intention and subsequent use. It holds that behavioral intention is shaped by three direct determinants - performance expectancy, effort expectancy, and social influence - while facilitating conditions, together with intention, drive actual use, with the relationships moderated by age, gender, experience, and voluntariness of use (Venkatesh et al., 2003;

Ursavaş, 2022). For this research, the model's value lies in two advances beyond TAM: the addition of social influence, which recognizes that adoption is seldom a solitary act, and the explicit use of demographic difference, since adoption varies across age, education, and income (Porter and Donthu, 2006). This means that UTAUT accommodates the real-world conditions - accessibility, prior experience, and social context - under which shoppers form intentions, which TAM's two beliefs leave aside.

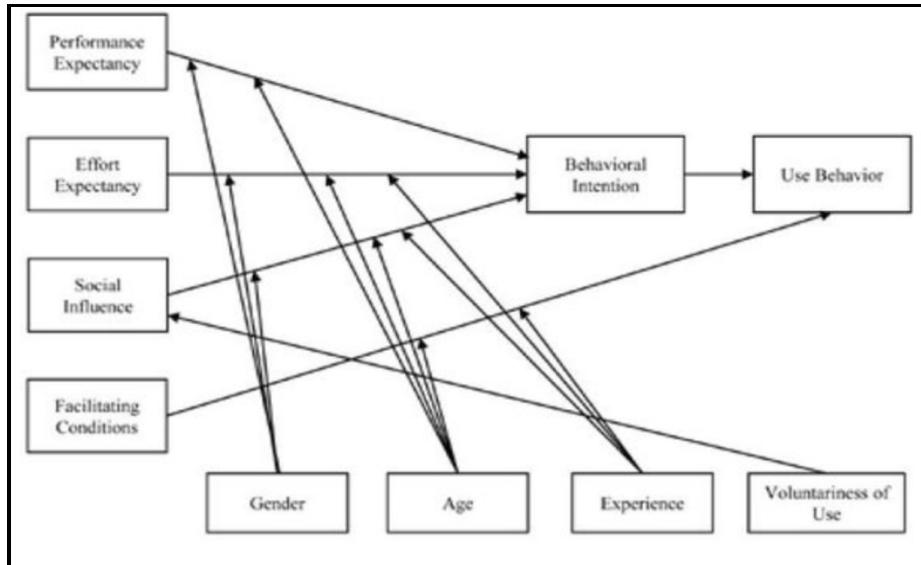


Figure 2.4

UTAUT MODEL (Chao, 2019)

Yet UTAUT's breadth is also the basis of its critique. Van Raaij and Schepers (2008) argue that, in absorbing eight models into one, UTAUT becomes more complex than TAM and TAM2, and that its strong explanatory power is achieved only through the addition of moderating variables rather than through superior theory. Bagozzi (2007) presses the point further, observing that the model's spread of predictors leaves technology-acceptance research "reaching a stage of chaos" and the model itself difficult to apply. This means that UTAUT's comprehensiveness comes at the cost of usability, offering little guidance on which constructs matter in a given context.

A further limitation is more consequential here. UTAUT, like TAM, was developed and validated in organizational settings, where users adopt mandated systems to perform their work. Gursoy et al. (2019) note that the adoption lens shifts when the subject is a shopper

rather than an employee: workplace users weigh technology against job performance, whereas shoppers also adopt technology voluntarily, and their decisions depend on perceived value, risk, trust, and convenience. This means that, for a voluntary consumer technology such as an AI coupon agent, neither TAM nor UTAUT fully accounts for the evaluation a shopper undertakes (Kim, Chan, and Gupta, 2007). Re-estimating a revised model, Dwivedi et al. (2019) show that attitude is in fact central - exerting a direct effect on behavioral intention and partially mediating the influence of performance expectancy, effort expectancy, social influence, and facilitating conditions. This means that a model built to predict intention while excluding attitude leaves out precisely the mechanism this research seeks to examine, since the present inquiry concerns not only whether shoppers intend to adopt an AI agent but how that adoption reshapes their attitudes towards digital coupons. Fourth, context: the moderating relationships specified in UTAUT may not hold across all settings (Dwivedi et al., 2019), which matters where the model is transposed from its original organizational, largely Western context to voluntary consumer adoption in India.

2.8 The Value-Based Adoption Model (VAM)

The Value-Based Adoption Model, introduced by Kim, Chan, and Gupta (2007), reframes adoption as a value judgment rather than a purely functional one. Developed specifically to explain consumer - rather than workplace - adoption of mobile internet, VAM holds that perceived value is the principal determinant of adoption intention, and that perceived value is itself the balance a user strikes between perceived benefits and perceived sacrifices (Kim et al., 2007). This means that, where TAM measures utility and UTAUT adds social and contextual breadth, VAM introduces the cost side of the ledger - the sacrifices weighed against the gains - which is precisely the dimension a privacy-sensitive AI tool engages.

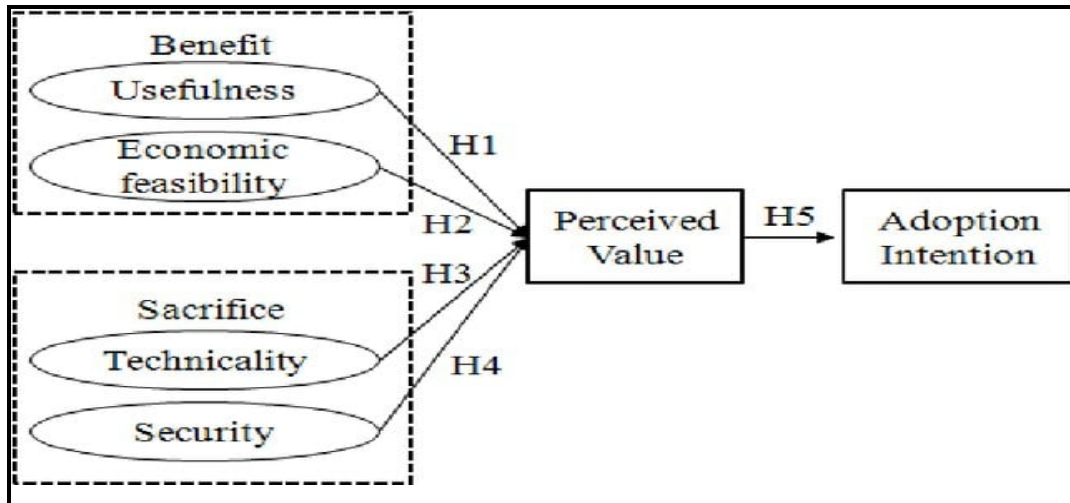


Figure 2.5

Value-Based Adoption Model (Kim et al., 2007)

The conception of value VAM draws on has deep roots in consumer research. Zeithaml (1988) defines perceived value as a shopper's overall assessment of a product's worth based on what is received against what is given, while Sweeney and Soutar (2001) show that value is multidimensional, spanning functional, emotional, and social dimensions rather than price alone. Within this research, the distinctive contribution of VAM is its treatment of sacrifice - including non-monetary cost such as privacy risk - as integral to value rather than peripheral to it (Kim et al., 2007). This means perceived benefit raises perceived value while perceived risk or intrusiveness depresses it, a tension especially salient where AI-enabled personalization trades convenience against the disclosure of personal data

The model's own limitation is that, unlike UTAUT, VAM models adoption as an individual's private benefit-sacrifice calculus and contains no social construct at all: social influence, peer norms, and word of mouth sit outside the model (Kim et al., 2007). This means that no single model suffices alone - TAM supplies the usefulness-ease foundation, UTAUT the social and demographic breadth, and VAM the value-risk negotiation - which is the rationale for integrating the three within a unifying framework. Second, and most consequentially for this research, VAM's notion of value is largely utilitarian - a weighing of usefulness and enjoyment against technicality and cost, and risks overlooking the emotional and relational drivers of intelligent-system adoption. Additionally, the model was developed and validated for mobile-internet adoption, so its specific benefit and

sacrifice factors are context-bound and may require specification when transposed to in-store AI coupon retrieval in India (Kim et al., 2007). This means that VAM is best treated not as a complete account but as the value-and-sacrifice component of a broader framework - supplying what TAM and UTAUT omit, while depending on them for the usefulness, social, and contextual dimensions it in turn leaves aside.

The preceding review suggests that no single acceptance model fully accounts for how a shopper might evaluate and adopt an AI agent during an in-store purchase. TAM, though simplicity, reduces adoption to just two beliefs - perceived usefulness and perceived ease of use - and sets aside risk, value, and social context (Davis, 1989). UTAUT widens the lens to include social influence and facilitating conditions, yet, as Dwivedi et al. (2019) demonstrate, it omits risk value. VAM supplies the benefit - sacrifice calculus that the others lack, but models a private, largely cognitive judgment that excludes social influence and underweights affect (Kim et al., 2007). This research, therefore, extends UTAUT by importing perceived value from the Value-Based Adoption Model (Kim et al., 2007) and by reinstating attitude as a mediating construct (Dwivedi et al., 2019). This means that the resulting model is a single, value-sensitive extension of UTAUT rather than a juxtaposition of competing frameworks - one that weighs usefulness, effort, and social influence alongside the value a shopper perceives once privacy risk is set against benefit.

2.9 Stimulus-Organism-Response Framework

The S-O-R construct is one of the most basic models in environmental psychology and has been widely employed in academic studies on retailing and consumers (Cao et al., 2023; Wu et al., 2022).

S-O-R is broken down as:

Stimulus (S): Environmental variables from outside that impact an individual, such as store ambiance, promotion, or digital interface quality (Cao et al., 2023; Wu et al., 2022).

Organism (O): Psychological processes and emotional states that mediate between the stimulus and its corresponding reaction (Wu et al., 2022). This factor is traditionally

described using three components: Pleasure, Arousal, and Dominance (PAD) (Bakker et al., 2014; Yani-de-Soriano & Foxall, 2006).

Response (R): Ultimately produced behavioral reaction, either approached (such as remaining, buying) or avoided (such as leaving, refusing to buy) (Cao et al., 2023; Wu et al., 2022).

The Stimulus-Organism-Response model has its roots in behavioral psychology, where Mehrabian and Russell (1974) introduced the organism as an intervening term between stimulus and response, displacing the mechanistic stimulus-response account that treated the mind as a closed box. Mehrabian and Russell (1974) formalized the paradigm in environmental psychology, proposing that environmental stimuli evoke internal emotional states - captured along the dimensions of pleasure, arousal, and dominance - that, in turn, produce approach or avoidance behavior. The model holds three elements: the stimulus, comprising external cues in the environment; the organism, denoting the cognitive and affective states through which those cues are interpreted; and the response, the resulting behavioral outcome. Its central claim is that a response is not determined by the stimulus directly, but through the mediating evaluations of the organism - a proposition that distinguishes S-O-R from the acceptance models, which tend either to omit such mediation or to treat it implicitly.

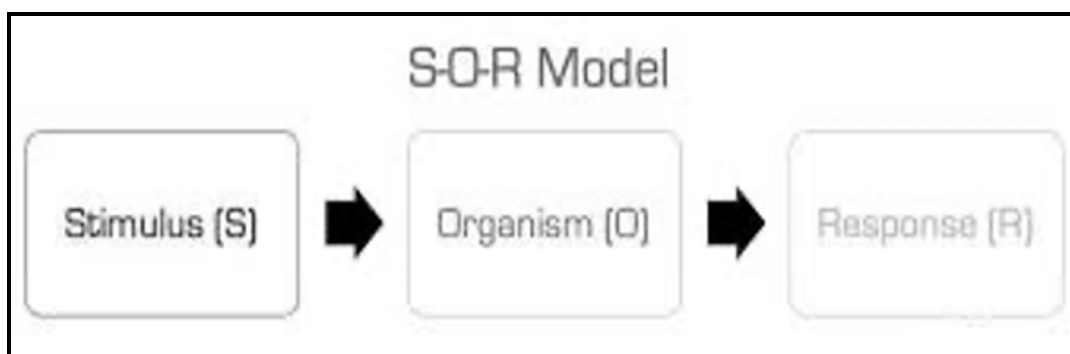


Figure 2.6

Stimulus-Organism-Response Model (Mehrabian & Russell, 1974)

The framework moved from environmental psychology into consumer research when Donovan and Rossiter (1982) adapted it to the retail store, demonstrating that the emotions

a store environment evokes shape shopping behavior and approach–avoidance outcomes. As retailing migrated online, Eroglu et al. (2001) extended the model to the virtual store, positing that the atmospheric cues of a website influence shopping outcomes through their intervening effect on shoppers' affective and cognitive states. This extension is significant for the present research: it establishes that S-O-R travels intact from physical to digital retail environments, and that interface and informational cues - not only ambient ones - qualify as stimuli. Since then, the paradigm has been applied across social commerce, mobile shopping, and live-streaming retail, thereby establishing its suitability for settings such as in-store AI coupon retrieval, where physical and digital stimuli converge during a single shopping episode.

The model is not without critique. Jacoby (2002) argues that S-O-R has too often been rendered as a static "box-and-arrow" construction that fails to build on prior theory and lacks simplicity and coherence. He proposes a reconceptualization that better accommodates the dynamic, sometimes automatic, processing by which stimuli become responses. Others note that the model's linear structure can understate the iterative, emergent character of real behavior.

Stimulus-Organism-Response theory is highly relevant in the Indian retail setting, given that more and more Indian shoppers are now using digital channels for their purchases. Shopping and stimuli come not only from within the store environment but also from outside it (Tandon, 2021). In the literature on Indian retail, Stimulus-Organism-Response theory has been used to explain how digital stimuli affect consumers' internal states (such as perceived value and impulsivity) (Chopdar & Balakrishnan, 2020). Recent industry data show that AI tools are now graduating from being mere assistants to 'value-optimizers' that help consumers (Capgemini Research Institute, 2026).

Spillover effects also help drive responses to stimuli. The spillover effect occurs when consumers' value perspective on a dynamic attribute alters their attitudes towards a static core asset (Qin et al., 2025). In the S-O-R model, the consumer's perception of the AI agent causes a spillover effect on the underlying static asset: the digital coupons. The outcomes

improve traditional skepticism, causing the consumer to perceive the underlying purchase task as "easier" or the coupons as "not spam" (Qin et al., 2025).

2.10 Gaps in Research

This review makes it clear that significant strides have been made in understanding personalized digital marketing and in using AI to drive this personalization. There still remains substantial scope to study the application of personalization across digital and in-store experiences. In particular, the application of AI tools to drive in-store purchase decisions remains unexplored.

Based on the literature review, the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which constitute the foundation of theories of technology adoption, need to be extended in order to incorporate factors like risk, trust, and privacy that are unique to AI systems. Evidence from the literature suggests that usefulness and perceived ease of use do not fully explain AI adoption, especially when value becomes a focal point of adoption decisions. In the world of AI, value could be a trade-off between costs and benefits (Dhiman et al., 2023).

Another gap can be observed at the intersection of AI technology adoption and its impact on attitudes towards the underlying tools, processes, or tasks it supports. Current models tend to investigate the adoption process for AI tools. They rarely address the possibility that real-time AI-based agents could change consumers' attitudes towards promotional instruments. Specifically, there is a lack of studies concerning whether a positive evaluation of an AI agent could result in a spillover effect, causing consumers to reconsider digital coupons as promotional noise and instead perceive them as tools of relevance. Such spillover effects become highly important against the backdrop of the rapidly developing digital experience of the Indian retail market. Therefore, the current research aimed to extend TAM/UTAUT models by introducing the factors of perceived value, risk, trust, and spillover effect in the S-O-R model of AI-enabled in-store coupon redemption in India.

Numerous gaps, therefore, converge in this research. At the theoretical level, the established acceptance models each leave something unaccounted for: TAM reduces

adoption to perceived usefulness and ease of use, setting aside the value, risk, and social context that a voluntary consumer technology engages (Davis, 1989); UTAUT, though broader, omits attitude, which a meta-analytic re-examination found to be central to acceptance and use (Dwivedi et al., 2019); and VAM, while supplying the benefit–sacrifice calculus the others lack, models a private, largely cognitive judgement that excludes social influence and underweights the affective response increasingly shown to drive the adoption of intelligent systems (Kim et al., 2007; Gursoy et al., 2019). No single model, therefore, accounts for an attitude-sensitive, value- and risk-laden, voluntary adoption of the kind examined here - a gap this research addresses by extending UTAUT to include perceived value and attitude and situating it within a stimulus-organism-response structure. A second gap is contextual to artificial intelligence itself: the adoption of autonomous, delegatory AI agents remains under-examined, documented largely in organizational or practitioner sources, and the challenges that condition it - algorithm aversion, fragile trust, and the personalization-privacy paradox - have been studied in isolation rather than as joint determinants of value and attitude (Dietvorst et al., 2015; Schilke and Reimann, 2025; Cloarec, 2024). The coupon literature treats redemption largely as an online technology-acceptance decision, leaving the in-store and AI-mediated context under-examined; the Indian evidence, though growing, remains thin and similarly skewed towards e-commerce; and, most consequentially, existing research stops at the act of redemption, saying little about whether the experience of an AI agent mediating coupons might reshape a shopper's broader attitudes towards digital coupons themselves. It is this last possibility - a spillover from agent adoption to coupon attitudes - that this research develops.

2.11 Conclusion

This review of the theoretical literature establishes that the adoption of an AI agent for in-store coupon retrieval cannot be explained by any single framework. The Technology Acceptance Model, the most widely employed of the three, accounts for adoption through perceived usefulness and ease of use; the Unified Theory of Acceptance and Use of Technology extends this by admitting social influence, facilitating conditions, and demographic moderators such as age, gender, and experience. Yet the review indicated that UTAUT itself requires extension in AI-driven settings, where privacy concerns, limited

trust, and psychological burden bear on behavioral intention. Read together, these literatures suggest that the decision to adopt is less a functional judgment than a value-exchange negotiation entailing utility, cost, context, value, and risk - one that no model captures in isolation. For this reason, the present research adopted an integrated position drawing on TAM, UTAUT, and the Value-Based Adoption Model.

Central to this position is the treatment of risk and value. The review showed that perceived risk has been incorporated into adoption discussions as a form of negative utility, with trust offsetting risk and, in turn, dampening usage intention; several academic extensions of UTAUT formalize this by adding risk-related variables. Perceived value, defined as shoppers' assessment of gains against losses, emerged as a critical determinant of behavioral intention, particularly given the well-documented tension between AI-enabled personalization and the privacy and ethical concerns it raises. In personalizing the shopping experience, therefore, the question is not merely whether the tool is useful or easy to use, but whether its benefits outweigh the sacrifice of privacy. The review accordingly supports a framework in which value and risk are not peripheral additions but central to willingness to adopt - a position best captured by VAM, which, unlike TAM's focus on utility, treats perceived value as the core driver, balancing functional benefit against non-monetary cost.

Finally, the review extended beyond adoption to the attitudinal shift an AI agent may itself produce. Because relevant coupons are difficult to retrieve from a crowded inbox at the point of purchase, their irrelevance has fostered negative attitudes towards digital coupons as a whole. The Stimulus-Organism-Response model offered a supplementary lens, whereby exposure to the AI coupon-retrieval agent serves as an external stimulus that may reshape these attitudes and lead to a post-exposure improvement in how shoppers regard digital coupons. This consideration is reinforced by the coupon paradox evident in the literature: digital coupons are portrayed as effective instruments of personalization that benefit marketers and shoppers alike, yet remain persistently under-redeemed due to limited access, poor timing, email overload, and trust and privacy concerns. The object of this research is therefore not technology adoption in general, but the adoption of an AI-driven tool that may ease access to coupons and lighten the burden of in-store decision-making.

CHAPTER 3:

METHODOLOGY

3.1 Introduction

This research investigated the factors influencing shoppers' adoption of an AI agent for retrieving digital coupons during in-store shopping in India, and whether positive evaluations of the agent spill over into attitudes towards digital coupons themselves. Although digital coupons are widely distributed, redemption rates remain low due to retrieval friction, weak contextual delivery, and concerns about privacy and trust, and the adoption of AI agents in physical retail remains largely unexamined in emerging markets.

The constructs most relevant to adoption in this setting are not well established in prior work, and their applicability to Indian shoppers could not be assumed. Moving directly to a survey risked forcing respondents into pre-set adoption constructs that may not hold in this context. An exploratory phase was therefore needed to surface the attitudinal and contextual factors most salient to Indian shoppers and to inform the quantitative instrument before structured measurement.

The choice of method was guided by the problem rather than preference (Creswell, 2009). Qualitative inquiry suits the exploration of poorly defined constructs and lived experience (Merriam, 2009), while quantitative inquiry suits hypothesis testing and generalization (Bryman, 2016). Because this research required both, an exploratory sequential mixed-methods design was adopted, in which qualitative interviews with 20 digitally aware shoppers surfaced themes - such as data-sharing and trust, the personalization–privacy trade-off, and emotional reactions to AI - that shaped the Likert items subsequently tested through a quantitative survey of construct relationships (Creswell and Plano Clark, 2018; Edmonds and Kennedy, 2017).

The two phases rest on complementary paradigms: the qualitative phase is interpretivist, seeking to understand shoppers' perceptions of AI-based shopping support, while the quantitative phase is positivist, testing the strength and significance of relationships among

constructs operationalized from TAM, UTAUT, and VAM (Bryman, 2016; Sekaran and Bougie, 2016). The sections that follow set out the operationalization of constructs, population and sampling, instrumentation, data collection, and analysis.

3.2 Operationalization of Theoretical Constructs

Operationalization is the process of translating abstract theoretical constructs into measurable variables and indicators, thereby bridging the gap between a conceptual framework and the data gathered to test it (Bryman, 2016; Saunders, Lewis, and Thornhill, 2019). Constructs such as perceived usefulness, perceived risk, or social influence cannot be observed directly; they become researchable only once defined through concrete indicators - here, Likert-scale items - that stand in for the underlying concept. The soundness of the latter analysis rests on this step, since poorly specified indicators would measure the wrong concept and erode construct validity. Based on the literature review, understanding the factors that determine the adoption of an AI agent for coupon retrieval cannot be addressed by a single theory. Hence, this research incorporates elements from three existing theories within the overall Stimulus-Organism-Response (S-O-R) framework. The theoretical foundations for construct selection are established in Chapter II; this section defines how those constructs were translated into measurable variables.

Because operationalization must serve both discovery and measurement, this research operationalized its constructs through two theoretically distinct but complementary routes. The qualitative route, grounded in an interpretivist position, was used to surface and contextualize indicators: the established constructs from TAM, UTAUT, and VAM were carried into semi-structured interviews so that their salience, wording, and meaning could be tested against the lived realities of Indian shoppers before any scale was fixed, guarding against the risk of importing Western adoption items wholesale into a setting where they may not hold. The quantitative route, grounded in a positivist position, then rendered the refined constructs measurable as validated Likert items, allowing the relationships among them to be tested statistically and generalized to the wider population (Bryman, 2016). Neither route would have sufficed alone - qualitative operationalization could contextualize indicators but could not test relationships, while quantitative

operationalization could measure relationships but would have imposed pre-set constructs without contextual validation. The exploratory sequential logic, therefore, required both qualitative operationalization to establish *what* to measure and quantitative operationalization to establish *how strongly* each construct mattered (Creswell and Plano Clark, 2018).

Extended S-O-R Framework as an Overarching Lens: In line with the current literature, this research applied the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974) to organize constructs derived from TAM, UTAUT, and VAM into a coherent model of individual adoption. In line with the current literature, the traditional S-O-R model was modified to account for the unique characteristics of AI use in retail interactions, particularly in-store purchases. The following constructs were measured as part of the three steps of the model:

Stimulus (S) - Exposure to the concept of AI-enabled coupon retrieval in a store shopping context. Unlike traditional retail stimuli, the stimulus introduced in the research was informational, as it presents consumers with the option to use an AI agent to personalize and offer targeted in-store digital coupons.

Organism (O) - Internal cognitive evaluation of the presented stimulus. Cognitive evaluation was measured using constructs such as perceived usefulness, perceived ease of use, social influence, perceived risk, and perceived value, which were derived from TAM, UTAUT, and VAM.

Response (R) - As recommended by Jacoby (2002), this study extended the traditionally limited one-step S-O-R approach by suggesting two parallel response outcomes in line with the current literature:

Response 1 - Behavioral intention to use the AI agent.

Response 2 - Changed Attitude toward Digital Coupons due to exposure to the AI concept, representing a spillover effect (Qin et al., 2025).

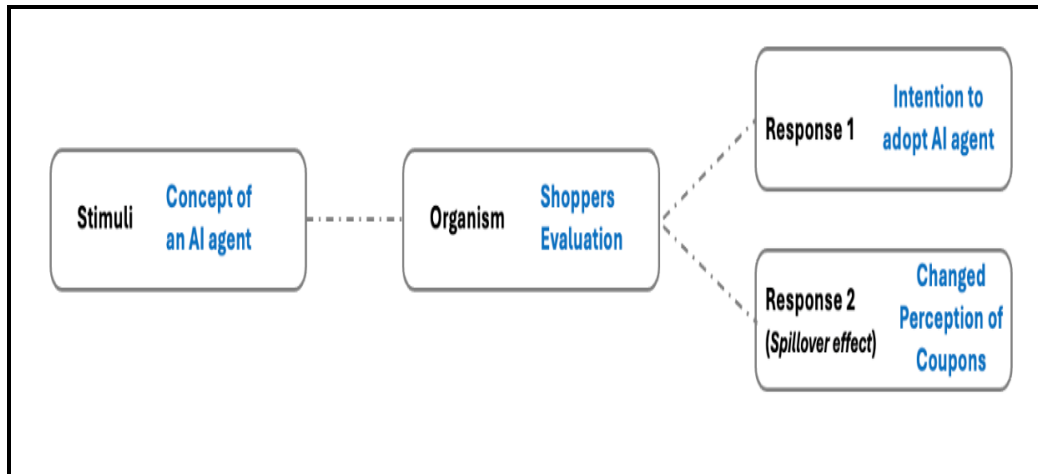


Figure 3.1

Extended Stimulus-Organism-Response Model (Mehrabian & Russell, 1974)

To summarize, this research operationalized the following constructs within the extended S-O-R framework to examine the drivers of adoption of an AI agent for in-store coupon retrieval:

Attitude towards AI tools in general: the shopper's pre-existing affective disposition towards AI tools, measured at baseline as the entry condition to the organism stage and tested as a predictor of behavioral intention. Demographic variables: Age, gender, income, education, occupation, and digital literacy were included as moderators to assess differences in behavioral intention across population segments (Venkatesh et al., 2003). Perceived Usefulness: The degree to which a shopper believes the AI agent would improve the efficiency and outcome of retrieving and redeeming digital coupons (Davis, 1989). Perceived Ease of Use: The degree to which a shopper believes that using the AI agent would be free of effort (Davis, 1989). Social Influence: The extent to which a shopper perceives that people important to them, or wider social adoption, would encourage their own use of the AI agent (Venkatesh et al., 2003). Perceived Risk: The shopper's perceived potential for loss when using the AI agent, chiefly around data privacy, security, and unwanted exposure of personal email content (Kim et al., 2007). Perceived Value: The shopper's overall assessment of perceived usefulness against perceived risk (Kim et al., 2007; Chew et al., 2006). Perceived Value is "a derived variable from the constructs

'Usefulness' and 'Risk'. Hence, it is calculated as the ratio of benefit to risk. A ratio captured the idea that risk can reduce or even cancel out the value of usefulness.

The research framework is illustrated in the figure below:

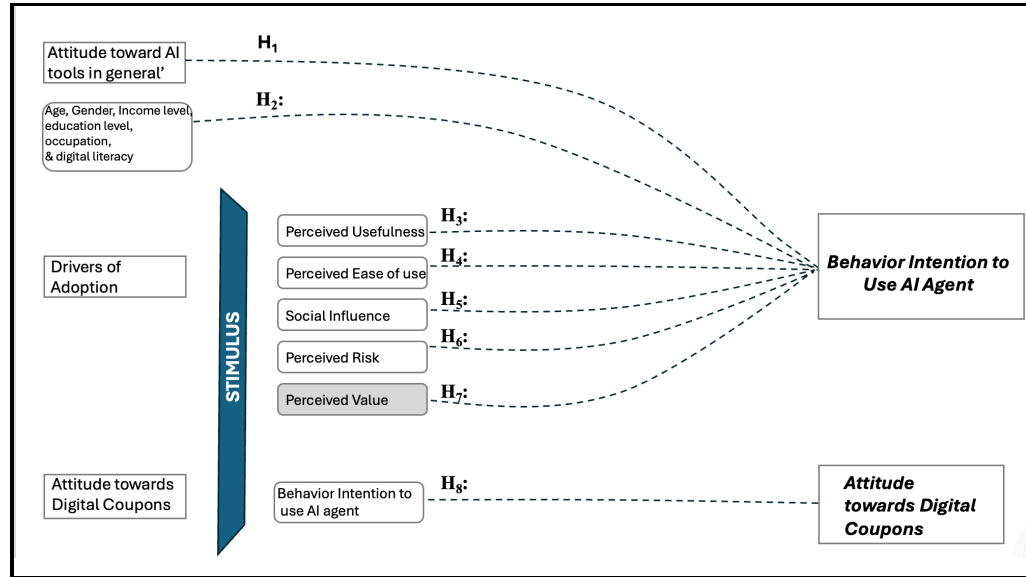


Figure 3.2

Research Structure and Variables

Figure 3.2 translates the extended S-O-R framework into the research structure tested in this study. The stimulus -exposure to the AI agent concept for in-store coupon retrieval - is shown as the vertical band from which all evaluation flows. To its left are the grouped inputs: the shopper's pre-existing attitude towards AI tools, demographic characteristics (age, gender, income, education, occupation, and digital literacy), and the drivers of adoption. The drivers comprise the five organism-stage constructs operationalized from TAM, UTAUT, and VAM - perceived usefulness, perceived ease of use, social influence, perceived risk, and perceived value - each measured through validated Likert items.

The dashed paths map the eight hypotheses onto the two response outcomes. The primary outcome, behavioral intention to use the AI agent, is predicted by attitude towards AI (H1), tested for demographic differences (H2), and modeled as a function of the five adoption drivers (H3 to H7). The second, parallel outcome captures the spillover effect: attitude towards digital coupons, measured before and after exposure to the concept, with H8 testing whether that attitude shifts as a result. Together, the figure shows the complete S-

O-R pathway - stimulus, organismic evaluation, and two parallel responses - and locates each hypothesis on the structure it tests.

Attitude toward Digital Coupons was included as an outcome construct measured before and after exposure to the AI agent concept. This construct captures whether the AI-enhanced coupon retrieval concept produces a spillover effect that shifts consumer perceptions of digital coupons from promotional noise to tools of relevance (Qin et al., 2025).

All constructs were operationalized using validated Likert-scale items adapted from recognized technology adoption models - TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), and VAM (Kim et al., 2007) - consistent with recommended practice for drawing on previously validated measures (MacKenzie, Podsakoff and Podsakoff, 2011). The wording of these items was then refined in light of the qualitative findings to ensure clarity and contextual relevance for the Indian retail shopper, in keeping with the instrument-development logic of exploratory sequential design (Creswell and Plano Clark, 2018). This operationalization provided the basis for moving from conceptual descriptions to empirical testing, using constructs that, in turn, informed the overall research design.

3.3 Research Design

Research design sets the stage for the overarching framework through which a study's objectives, theoretical constructs, methods, and analysis are brought into clear alignment, ensuring that the process of data collection, measurement, and analysis is orderly, useful, and capable of creating findings that address the research questions posed (Creswell, 2012).

Three characteristics of the research problem shaped the design choice:

- AI-assisted in-store coupon retrieval is a novel concept that does not yet exist as a commercially available product in the Indian market. Consumers have no prior lived experience with such a tool, so their perceptions, concerns, and motivations cannot be inferred from existing literature alone. A qualitative phase was therefore essential to explore how consumers interpret and evaluate this concept before imposing structured

measurement scales drawn from contexts that may not be directly comparable (Merriam, 2009).

- Established adoption frameworks such as TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), and VAM (Kim et al., 2007) provide validated constructs for technology adoption research; however, their application to real-time, AI-enabled retail interactions in-store in emerging markets remains insufficiently examined, as established in the literature review, especially in an integrated manner. The qualitative phase allowed the researcher to verify which of these established constructs were salient in the Indian retail context and to identify AI Agent-specific dimensions that these frameworks do not account for, such as AI trust, ease of use of an AI agent, and the risk associated with an AI agent. This is consistent with the instrument development variant of exploratory sequential design, in which qualitative findings inform the construction or refinement of quantitative measures (Creswell and Plano Clark, 2018; Edmonds and Kennedy, 2017)
- This research needed a sequential ordering - qualitative before quantitative - because moving directly to a large-scale survey risked forcing respondents into pre-determined adoption constructs that may not have captured the full range of factors influencing AI adoption in this specific context. Qualitative interviews could reveal themes that would not have emerged from closed-ended survey questions alone, including consumers' perception of coupons as spam unless delivered in context, concerns about AI accessing personal email content, and the expectation that AI should reduce cognitive effort rather than add complexity. These insights could directly shape the wording, sequencing, and emphasis of the Likert-scale items in the quantitative instrument, thereby strengthening construct validity and reducing the risk of measurement error.

Design Choice: This research adopted an exploratory sequential mixed-methods design (Creswell, 2012). The mixed-methods approach combined the strengths of qualitative and quantitative research within a structured methodological framework. Sequential methods are those in which the researcher seeks to build on the results of one method by adding another. This may involve beginning with a qualitative technique for exploratory purposes and following up with a quantitative method with a large sample to generalize results to a

population. The incorporation of both quantitative and qualitative approaches improves authenticity using triangulation, augments analysis, and adds new insights (Bekmezci & Sürücü, 2025). To this end, a descriptive and interpretative research design was adopted for the quantitative components of the research. This is ideal when the constructs are not well-defined, prior understanding of the context needs to precede measurement, and the development of the instrument should be rooted in real-world experience rather than existing literature.

This research followed a sequential three-phase design: an exploratory qualitative phase, a pilot quantitative phase, and a final quantitative phase, all employing descriptive and interpretive approaches.

Diagrammatically, this can be explained as follows:

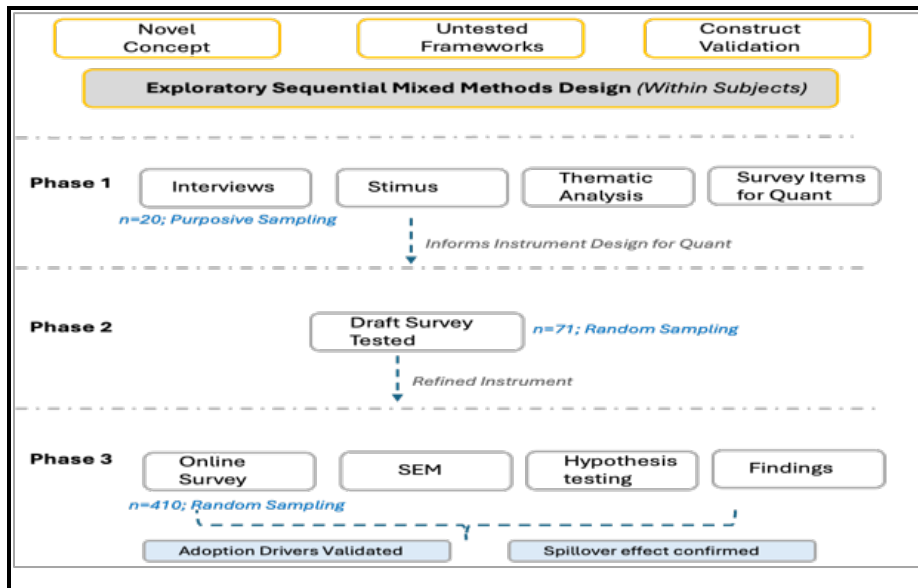


Figure 3.3

Research Design Diagram

The diagram shows the exploratory phase that involved conducting 20 semi-structured interviews (purposively sampled, digitally literate) with Indian consumers who participated in the qualitative phase of the research. Findings from this phase provided context on consumers' attitudes towards the use of AI technologies and digital coupons, understanding

of the perceptual and emotional reactions associated with exposure to AI agents, and informed the refinement of the constructs used in the later quantitative instrument.

Phase 2 was the Pilot Phase (N = 71): The main objective of this phase was to validate and refine the instrument. It involved assessment of item clarity, response variability, internal consistency, and the appropriateness of the analytic technique before conducting a full-fledged experiment.

Phase 3 was the Final Phase - Quantitative Approach (N = 410)

This involved using an online survey to examine the relationships between independent variables (attitude towards AI tools, perceived usefulness, perceived ease of use, social influence, perceived risk, and perceived value) and the dependent variable, behavioral intention to use the agent.

The use of inferential and descriptive statistical methods included

- Frequency distribution
- Structural equation modeling
- Non-parametric group comparison
- Correlation and paired samples T-test.

In particular, the hypotheses under consideration included: H1, H3-H6, structural equation model; H2, group comparison; H7, correlation; and H8, paired-sample t-test.

Once the research design, theoretical constructs, and analytical approach were established, the target population needed to be defined and the sample to be selected. This step helped assess the representativeness of the results and their applicability to the broader population of digitally proficient retail customers in India.

3.4 Population and Sample

The target population is the entire set of individuals who have features relevant to the research purpose (Ahmad et al., 2023). In this case, the target population included shoppers

in India who often buy products in brick-and-mortar stores and regularly engage with digital marketing messages, such as emails with digital coupons. Within this larger category, the focus was on digitally savvy people - individuals who knew mobile applications, were familiar with digital coupons, and understood basic aspects of AI technologies. The choice was made because respondents were needed who could evaluate both the technological and retail aspects of the issue under investigation.

The research was situated within the Indian retail environment. India was selected as an appropriate context for this research for three reasons. India possesses one of the world's largest and most rapidly growing consumer bases, a strong and sustained preference for in-store shopping, and increasing digital penetration (PWC India, 2023).

Qualitative sampling design: Sampling technique: Non-probability purposive sampling was used in this qualitative research, as it involves selecting participants based on specific attributes related to the research aims (Nikolopoulou, 2023). Sampling frame: Due to the exploratory nature of the qualitative phase of this research, the sampling frame comprised Indian consumers who are digitally savvy, regularly receive marketing offers via email, and often purchase products in physical stores. By choosing such a sampling frame, the researcher could ensure that participants had sufficient digital and retail experience for the research. Also known as judgmental sampling, this technique involves the intentional identification and selection of cases that contain rich information about the phenomenon under investigation (Merriam, 2009). Purposive sampling is widely used in qualitative and mixed-methods studies because it enables researchers to select participants with the specific experiential background needed for the study (Creswell, 2009). For this research, participants were selected based on the following criteria: digital savvy, regular in-store purchasing experience, prior use of digital coupons, and some familiarity with AI tools.

Sample size: 20 respondents were selected for in-depth interviews. The number of participants met the requirements for qualitative studies that involved thematic analysis. Specifically, researchers often recommend a sample of 15 to 30 respondents, as this size may provide thematic saturation, meaning that further interviews will not yield new themes (Braun & Clarke, 2006; Creswell, 2009).

Quantitative sampling design: Sampling Frame: The sampling frame for the quantitative phase was designed to include persons aged 18 or older, active digital media users, recipients of marketing proposals via email, frequent in-store buyers, and users of digital apps on smartphones. This sampling frame was used to ensure that the findings obtained in the quantitative phase were generalizable to the entire population of digitally literate consumers in the Indian retail market.

Sampling technique: In the quantitative phase, probabilistic sampling was used. It entailed simple random sampling, in which all eligible persons had an equal chance of participating in the research and answering the questionnaire (Nikolopoulou, 2023). By applying this approach, the external validity and generalisability of the findings to the specific population defined in the sampling frame were ensured. In contrast to the qualitative phase, where the sampling strategy aimed to maximize depth and understanding, the quantitative phase focused on increasing the breadth of coverage, in line with the positivist theory that underlay the second part of the research (Creswell, 2009).

Sample Size: For the determination of the sample size in the quantitative phase, a known formula by Cochran (1977) was used:

$$n = (z^2 \times p \times (1 - p)) / e^2$$

Where:

$z = 1.96$ (corresponding to 95% confidence level);

$p = 0.5$ (maximal variability, applicable when population proportion is unknown) and $e = 0.05$ (acceptable margin of error at 5%).

Calculation:

$$n = (1.96^2 \times 0.5 \times 0.5) / 0.05^2 = (3.8416 \times 0.25) / 0.0025 = 384.16.$$

Therefore, at a minimum, 384 people should have been involved in the research. To compensate for data lost during data cleaning, like missing data, bad respondents, and to increase the analytical strength of findings, in particular those obtained in structural equation modeling (SEM), which requires a minimum of 200 cases (with 10 respondents for each estimated parameter) (Kline, 2023; Hair et al., 2010), the sample size of 500

participants was targeted. In total, 578 responses were obtained, of which 410 were retained post-cleaning, with an approximate 60:40 gender balance (238 male and 172 female respondents).

Defining a population establishes who the research concerns in principle; participant selection operationalizes that definition at the point of recruitment by applying inclusion criteria that determine whether a given respondent has the experience necessary to evaluate the constructs under study (Patino and Ferreira, 2018). Because the research concerned an AI tool used for in-store coupon redemption, participants needed prior exposure to all three elements - in-store shopping, digital coupons, and AI tools - as those lacking experience of any one could not form a considered view of the relationships being tested. The criteria and screening procedures applied across the qualitative and quantitative phases are set out below.

For the qualitative component, respondents were required to be over 18 years of age, reside in India, and be actively engaged in in-store shopping. They were also expected to have prior exposure to marketing offers or coupons distributed via email, be regular in-store shoppers, and demonstrate digital literacy as tech-savvy app users. In addition, participants needed to be willing to participate in both online and face-to-face interviews. Using a non-probability purposive sampling method, twenty participants known to the researcher were interviewed - within the 15–30 range recommended for thematic saturation, beyond which further interviews yield few new themes (Braun and Clarke, 2006; Creswell, 2009).

For the quantitative section, the research needed to reach a geographically dispersed population at scale while affording respondents the anonymity that encourages candid responses to questions touching on privacy and risk (Evans and Mathur, 2018). Recruiting a representative sample at this scale, however, is difficult through organic or convenience channels within the time constraints of doctoral research. An online survey was best suited for this purpose. For the respondents, programmatic online sample marketplaces address this by providing access to large, pre-verified respondent panels with built-in quota management like geography, age group etc. with automated quality controls (Boas, et al., 2020). On this basis, respondents were recruited through PureSpectrum, a sample

marketplace that supplies verified Indian panelists and applies automated safeguards - digital fingerprinting, geolocation checks, speeder detection, and duplication prevention - to protect data quality (PureSpectrum, 2024). Additional screening criteria required that respondents be aged 18 or older and be based in metro cities. Within this panel frame, respondents were selected through random sampling: Pure Spectrum's invitation algorithm randomly selected panel members who matched the research's eligibility profile and routed survey invitations to them, eliminating self-selection bias and ensuring that respondents had no prior knowledge of the research's specific subject matter at the time of invitation. The initial screening questions checked whether respondents had been exposed to marketing offers or coupons via email. Participants who did not meet these criteria were excluded to ensure relevance to the research focus. Those who did not meet any inclusion criteria, as well as those who could not answer the embedded attention test question (Q14), were automatically excluded before taking the construct measurement questions. The double screening process was conducted at both the invitation stage and the questionnaire level to ensure that only eligible respondents participated in the research.

Demographic profile of respondents under the qualitative survey

This section describes the key demographic characteristics of the participants in the qualitative phase of the research.

Twenty urban, educated respondents aged 25 and above, familiar with digital coupons and AI, were chosen for semi-structured interviews.

Table 3.1

Demographic profile of respondents under the qualitative survey

Demographic Variables	Frequency	Percent
Age		
25 to 35 years	2	10%
36 to 50 years	15	75%
Above 50 years	3	15%
Total	20	100%
Gender		
Female	10	50%
Male	10	50%
Total	20	100%
Income in Lakhs		
5 to 25	7	35%
26 to 40	5	25%
More than 40	8	40%
Total	20	100%
Education		
Graduate	1	5%
Postgraduate	19	95%
Total	20	100%
Comfort with Digital Literacy		
Moderate Use of apps	3	15%
Frequent Use of apps	17	85%
Total	20	100%

Note. Compiled from primary data collection through a structured questionnaire survey.

The qualitative sample consisted of middle-aged, digitally savvy, and highly educated respondents. The bulk of respondents were aged 36-50 years (75%), followed by those aged 50+ years (15%) and those aged 25-35 years (10%). There was a fairly even gender split among respondents, with 52% female and 48% male. Income-wise, the sample was

skewed towards individuals earning high salaries, with 40% earning more than ₹40 lakhs per annum, 35% earning ₹5 lakhs to ₹25 lakhs per annum, and another 25% earning ₹26 lakhs to ₹40 lakhs per annum. Regarding educational qualifications, the vast majority of respondents had pursued postgraduate studies, suggesting they belonged to an extremely educated demographic. The sample also boasted a highly digitally savvy community, as 85% used apps frequently, while the remaining 15% used them occasionally.

Demographic Profile of Respondents under the Quantitative Survey

This section describes the key demographic characteristics of the participants, including age, gender, income, education, digital literacy, and occupation, as analyzed quantitatively. These will help better understand the findings and support subgroup analyses.

Table 3.2

Demographic profile of respondents under the quantitative survey

Demographic Variables	Frequency	Percent
Age		
18 years - 24 years	98	23.9%
25 years- 44 years	249	60.7%
45 years and above	63	15.4%
Total	410	100%
Gender		
Female	172	42%
Male	238	58%
Total	410	100%
Annual Income		
Less than ₹5 lakhs	83	20.2%
₹5 - 25 lakhs	226	55.1%
₹25 - 40 lakhs	66	16.1%
More than ₹40 lakhs	35	8.6%
Total	410	100%
Education		
Less than graduate	34	8.3%
Graduate (bachelor's degree)	194	47.3%
Postgraduate (master's degree or higher)	180	43.9%
Others	2	0.5%
Total	410	100%
Comfort with Digital Literacy		
Beginner	30	7.3%
Intermediate	183	44.6%
Advanced	197	48%
Total	410	100%
Occupation		
Technology / IT	284	69.3%

Others	126	30.7%
Total	410	100%

Note. Compiled from primary data collection through a structured questionnaire survey.

The quantitative sample consisted of 410 respondents, and their demographic characteristics provide important context for interpreting the findings and understanding subgroup variations in coupon behavior and AI adoption. The age distribution shows that the majority of respondents (60.7%) were between 25 and 44 years, representing the core working-age population most likely to engage with digital tools. Younger shoppers aged 18-24 accounted for 23.9%, while those aged 45 and above accounted for 15.4% of the sample. It should be noted that the qualitative sample was concentrated in the 36-50 age band (75%), while the quantitative sample had the highest concentration in the 25-44 cohort. This is an outcome of the purposive sampling used in the qualitative phase.

In terms of gender, 58% were male, and 42% were female, indicating a balanced representation of perspectives across genders. Annual income levels revealed that more than half of the respondents (55.1%) earned between ₹5 and ₹ 25 lakhs, while 20.2% earned less than ₹5 lakhs and 24.7% earned above ₹25 lakhs. This distribution reflects a predominantly middle-income consumer base, which aligns with the target population of digitally active in-store shoppers.

Educational attainment was relatively high, with 47.3% holding a bachelor's degree and 43.9% holding a postgraduate qualification, suggesting strong digital readiness and familiarity with technology-enabled retail experiences. Digital literacy levels further supported this, with 48% identifying as advanced users and 44.6% as intermediate, indicating that the sample was well equipped to evaluate AI-enabled shopping tools. Only 7.3% identified as beginners.

Regarding occupation, a significant proportion of respondents (69.3%) worked in technology or IT-related fields, while 30.7% were employed in other sectors. This occupational profile suggests that a large share of participants were already comfortable with digital ecosystems, making them suitable evaluators of AI-assisted coupon retrieval.

Overall, the demographic characteristics indicate that the sample consisted largely of digitally literate, working-age consumers with substantial exposure to technology, an appropriate population for examining the adoption of AI-enabled agents in in-store shopping contexts.

3.5 Instrumentation

This section describes the instruments developed for data collection across the qualitative and quantitative phases of the research. Two instruments were needed because the research design had two distinct objectives: first, an exploratory understanding of consumer perceptions, motivations, and concerns regarding an AI agent for coupon retrieval; and second, the quantitative measurement of the construct relationships specified in the conceptual framework. A semi-structured interview guide was developed for the qualitative phase to enable open exploration of participants' perspectives, and a structured online questionnaire was developed for the quantitative phase to operationalize constructs derived from TAM, UTAUT, and VAM. To ensure consistency of stimulus across all participants and minimize concept-related variance as a source of measurement error, identical visual mock-ups of the AI agent were used in both phases.

Qualitative Interview Guide: The qualitative instrument consisted of an open-ended interview guide conducted through face-to-face or online interviews. It included an introduction that included consent gathering and explaining the purpose of the research. The participants were shown a concept of an AI agent through digital mock-ups and a written description of its capabilities.



Figure 3.4

Concept Screen 1

Here are your email Vouchers!	
Sender	Subject line
W	Double the Joy: Free Item with Your Purchase!
Reliance Trends	Hurry! Mega Discounts on Electronics Await!
Zara	Save Big: Up to 70% Off on Bestsellers – For You!
Shoppers Stop	Here's Your Exclusive Coupon – Don't Miss Out!
Kalyan Sarees	Your Personalized Discount Voucher Is Here!

Figure 3.5

Concept Screen 2

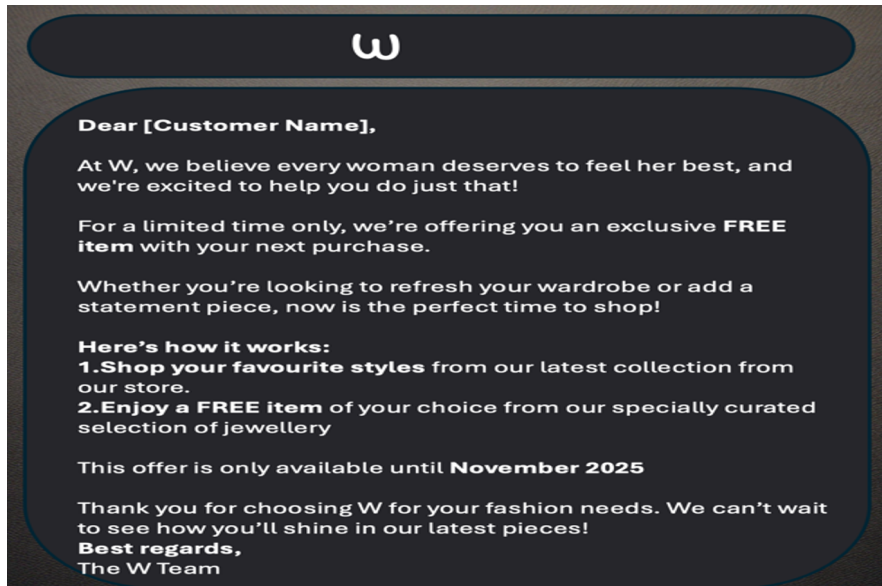


Figure 3.6

Concept Screen 3

All participants were shown the same mock-ups featuring three screens:

- Concept Screen 1: Input screen for entering the context of in-store visits and filtering emails
- Concept Screen 2: Screen showing categorized coupons by industry (retail, dining, etc.)
- Concept Screen 3: Final offer screen featuring a redeemable coupon selected for redemption

A semi-structured interview format consisting of four themed segments was created:

- Segment 1 focused on subjects' general perceptions of AI-based systems, the extent of their use, and the forces that could facilitate or hinder their adoption.
- Segment 2 delved into perceptions of electronic coupons sent via email, their frequency of use, channel preferences (digital vs. traditional), and factors that could encourage greater coupon use.
- Segment 3 explored the risks and potential fears associated with AI-based applications, the circumstances under which the subjects felt threatened and insecure, and the measures that can be taken to alleviate those threats after

presenting a prototype concept showing how an AI system could identify relevant offers by scanning emails and display them through an easy-to-use interface.

- Segment 4 collected data on future adoption intentions, identified any risks or fears about the agent, and recommended ways to boost respondents' confidence levels.

Quantitative Questionnaire: The quantitative component of the research employed a structured online survey designed and deployed using SurveyMonkey. This questionnaire was later distributed via an online panel from the sample platform PureSpectrum. The survey followed a monadic concept-testing design, in which each respondent evaluated the AI agent concept as a single stimulus without comparison with alternative tools. This approach is well-suited to evaluating novel concepts when no competing product exists in the market. The survey was structured in four sections to assist the Stimulus-Organism-Response logic of the research framework.

The first section captured demographic information and screened respondents against eligibility criteria, collecting data on age group, gender, annual household income, education level, self-rated digital literacy, occupation field, in-store shopping frequency, and prior exposure to email-based promotional coupons from brands. The second section introduced the AI Agent concept through 3 mock-up screens- similar to the qualitative questionnaire. This is the stimulus point in the S-O-R framework; everything before this captures the pre-existing state of decision to adopt the AI agent, and everything after captures the response. The third section- captured core measurement, where the conceptual framework's constructs are operationalized. Each question is a Likert-scale item measuring a construct. The last section captured the behavioral intention to use the AI agent and its spillover effect on digital coupons.

Pre-Testing of Questionnaire: The questionnaire was pre-tested through a pilot survey by an expert who completed it to refine its logic, flow, and measurement clarity. Testing was conducted using a questionnaire built and deployed with the SurveyMonkey survey tool to evaluate skip logic and question structure. It was distributed to a random sample via platforms such as LinkedIn. Feedback from testing improved sequencing, clarity, and elimination criteria. This step ensured instrument readiness before a pilot deployment.

Reliability of the Questionnaire: In this research, the reliability of the questionnaire was assessed using item-behavior analysis and correlation checks to ensure internal consistency across all constructs. This step was first applied in the pilot survey with 71 respondents, allowing refinement of the instrument before large-scale data collection.

In this research, validity was established through a multi-step process to ensure that the measurement model accurately captured the intended constructs.

Content validity: Content validity refers to the degree to which the items within a measurement instrument fully represent the full domain of the construct being measured. In the context of this research, content validity was established by ensuring that the survey items collectively captured all relevant dimensions of consumer perception and adoption of AI-enabled coupon retrieval agents, including attitudes, perceived usefulness, ease of use, social influence, perceived risk, and perceived value, without omission or redundancy (Lawshe, 1975). The items were developed based on established adoption frameworks, namely TAM, UTAUT, and VAM, and further informed by the themes that emerged from the qualitative phase. Expert review was undertaken by Mrs Julie Gandhi, Senior VP Market Research, and Mr Husain Burhanpurwala (Vice President, Market Research), who evaluated the relevance, clarity, and completeness of the items relative to the constructs being operationalized, thereby confirming that the instrument accurately represented the theoretical domain under investigation.

The empirical reliability and validity of the measurement model were tested post-data collection using structural equation modeling (SEM). Construct reliability (composite reliability and Cronbach's alpha), convergent validity (average variance extracted), and discriminant validity (Fornell & Larcker) are discussed in the Data Analysis Section.

3.6 Data Collection

The data collection for this research was conducted in two sequential phases consistent with the exploratory sequential mixed-methods design (Creswell & Creswell, 2018). Each phase employed distinct procedures, instruments, and protocols aligned with its respective methodological purpose.

Qualitative Data Collection: Qualitative data were collected through semi-structured, in-depth interviews with 20 purposively selected participants from the target population of urban Indian shoppers with prior exposure to digital coupons and varying levels of AI familiarity. Interviews were conducted via Google Meet, to enable geographic flexibility and broader participation across India, and has shown to produce data quality comparable to face-to-face interviewing while reducing logistical and scheduling barriers (Archibald et al., 2019) (Archibald et al., 2019). Each session lasted approximately 30-45 minutes and followed a four-segment open-ended interview guide structured around general AI perceptions, digital coupon attitudes, AI-related risks, and post-stimulus reactions to the AI agent concept (presented through the standardized mock-ups described in Section 3.7). Participants were encouraged to respond in their own words, allowing the researcher to probe emergent themes while maintaining consistency across sessions through the standardized guide (Braun and Clarke, 2006).

Qualitative Data Organization: All interviews were audio-recorded with prior informed consent using Fireflies.ai, which generated automated verbatim transcripts. Upon completion of each interview, audio recordings generated through Fireflies.ai were downloaded and stored in a secure local directory. Each recording was assigned a unique participant code (e.g., P01-P20) to replace all identifying information, ensuring anonymity from the point of storage onward.

Qualitative Data Cleaning and Coding: All transcripts were uploaded to Taguette. This open-source qualitative data analysis tool supports inline tagging of text excerpts and aggregation of tagged content across documents (Rampin and Rampin, 2021). A thematic codebook was developed iteratively through close reading of the transcripts. The final codebook comprised 23 thematic tags spanning demographic context; shopping and coupon behavior; baseline AI perceptions; concerns and fears regarding AI; and post-stimulus reactions to the AI agent, including perceived utility, ease of use, concerns, and feature requests. Each tag was applied to relevant excerpts across all 20 transcripts; tag-level frequencies and cross-document coverage were recorded by the tool, producing 529 tagged highlights in total. Taguette-tagged data were exported and organized in Microsoft Excel. Frequencies, document distribution, and sample quotes were extracted, from which

a matrix of themes per participant was developed. The theme matrix forms the basis of the thematic analysis in Chapter IV. It serves as the link between the qualitative research results and the concepts used in the quantitative component. In other words, the questions in the next chapter were drawn directly from participants' responses.

Quantitative Data Collection: The quantitative data were collected via a structured online survey administered through SurveyMonkey, as discussed in detail in Section 3.7. SurveyMonkey has explicit features that prevent a survey from being taken multiple times on the same device. The survey had a two-stage design: a pilot study was conducted before the main survey. The pilot study included 71 participants selected from the target population to test the logic and flow of the questions, their clarity, skip logic, and initial psychometric properties. The pilot data provided valuable insights into item performance, answer distributions, survey duration, and drop-off points. Minor adjustments to item wording, option order, and skip logic were made to improve the survey ahead of the main phase.

The pilot study ($N = 71$) preceded the main survey to assess instrument clarity, response variability, and the appropriateness of the analytical approach (Creswell, 2009).

The main survey was administered through Pure Spectrum. This online market research sample marketplace supports survey fielding by allowing researchers to define respondent targeting criteria, manage quotas, and access samples through participating supplier networks. The choice of Pure Spectrum was driven by its ability to recruit a geographically dispersed group of verified Indian respondents, set up nested quotas across multiple screening questions, and use automation for quality assurance, including digital fingerprinting, geolocation checks, speeder detection, and duplication prevention. These capabilities were necessary to achieve a controlled demographic distribution and high-quality results within a reasonable timeframe, which was not possible with convenience or snowball sampling, given the time constraints of doctoral studies. A total of 578 responses were collected, of which 410 were retained after data screening for incompleteness, straight-lining (a survey response pattern in which a respondent gives the same answer

repeatedly across many questions, especially in grid or Likert-scale questions), and irregular response patterns.

Quantitative Data Organization: Survey responses collected via SurveyMonkey were exported in CSV format and stored in a directory with restricted access. No personally identifiable information was collected. The raw dataset was assigned version identifiers to maintain an audit trail throughout the analysis process. Variables were renamed to correspond with their construct codes (e.g., PU_EFF, PEOU_R, PR_DATA) to ensure consistency with the measurement model and facilitate traceability between survey items and latent constructs. Response categories for Likert-scale items were numerically recoded to a 1-5 scale, and categorical demographic variables were assigned standardized labels. All datasets were backed up at regular intervals, and no personally identifiable information was retained at any stage.

Quantitative Data Cleaning and Coding: In the quantitative phase, incomplete responses were removed, eligibility criteria were verified, and coding consistency was maintained. Only responses that met the inclusion criteria and were valid were retained for analysis. Survey responses were systematically coded according to the latent constructs developed in this research. Each item was mapped directly to its conceptual construct, enabling traceability and analytical rigor. This coding facilitated internal consistency analysis, confirmatory factor analysis, and structural equation modeling.

Variable mapping of Statements Under ‘Attitude towards AI tools’:

Table 3.3

Survey Statements and Code Numbers for the Construct “Attitude towards AI Tools”

Statements Under Perception of AI tools	Code Number
I feel comfortable using AI-powered technologies in my daily life.	Per1
I enjoy experimenting with new AI powered tools and applications.	Per2
I feel confident in my ability to interact with AI driven systems.	Per3
AI technologies enhance my daily experiences and activities.	Per4
AI-powered tools help improve efficiency and save time.	Per5
I trust AI agents to provide accurate and reliable information.	Per6

I feel comfortable sharing personal information with AI-powered services.	Per7
I trust AI tools in my professional work only.	Per8

Note. Compiled by the researcher.

Variable mapping of statements under the ‘Usefulness of AI agent for coupon redemption.’

Table 3.4

Survey Statements and Code Numbers for the Construct “Usefulness of AI agent.”

Statements under Usefulness of AI agent for coupon redemption	Code Number
The AI Agent improves the efficiency of retrieving digital coupons.	Benf1
The AI Agent helps me find better discounts and promotions compared to my usual methods.	Benf2
Using the AI Agent can increase my total savings when shopping.	Benf3
The AI Agent helps me discover personalized coupon offers that I wouldn’t normally find.	Benf4
The AI Agent improves my overall shopping experience by offering valuable deals.	Benf5
The AI Agent helps me plan my shopping by suggesting relevant discounts in advance.	Benf6
I am more likely to shop at a store that offers AI-driven coupon recommendations.	Benf7

Note. Compiled by the researcher.

Variable mapping of statements under ‘Ease of use of AI agent.’

Table 3.5

Survey Statements and Code Numbers for the Construct “Ease of use of AI agent.”

Statements under Ease and intuitiveness of AI agent	Code Number
The AI agent looks easy to navigate and interact with.	Ease1

The AI agent appears to be intuitive and user friendly for retrieving digital coupons.	Ease2
It looks like I can quickly learn how to use the AI agent without assistance.	Ease3
The AI agent will reduce the time I spend searching for discounts in my emails.	Ease4
I feel comfortable using the AI agent even if I am not tech-savvy.	Ease5
The AI agent will make my shopping experience easier.	Ease6
The AI agent provides clear instructions and guidance for first time users.	Ease7

Note. Compiled by the researcher.

Variable mapping of Statements Under Social Influence on AI Agent Usage

Table 3.6

Survey Statements and Code Numbers for the Construct “Social Influence on usage of AI agent.”

Statements Under Social Influence on AI Agent Usage	Code Number
I would use if people whose opinions I value (friends, family, colleagues) would approve of me using the AI Agent	SID1
I am more likely to use the AI Agent if my friends or family members are using it.	SID2
If other shoppers in the store are using the AI Agent, I would be more inclined to try it.	SID3
Positive online reviews or ratings would increase my likelihood of using the AI Agent.	SID4
Retailer promotions (e.g., staff recommendations, ads) would encourage me to use the AI Agent.	SID5
Seeing social media influencers or well-known personalities endorse the AI Agent would make me more likely to use it.	SID6

Hearing success stories from other users (e.g., how much they saved) would make me more interested in trying the AI Agent.	SID7
If the AI Agent becomes widely adopted, I would feel more comfortable using it.	SID8

Note. Compiled by the researcher.

Variable Mapping of statements under Risk Perception of AI Agent

Table 3.7

Survey Statements and Code Numbers for the Construct “Risk Perception of AI Agent”

Statements Under Risk Perception of AI Tool	Code Number
I am concerned about how my personal data will be used when using the AI Agent.	Risk1
I worry that the AI Agent might collect too much personal information.	Risk2
I am hesitant to use the AI Agent because of potential security risks (e.g., hacking, data leaks).	Risk3
I fear that using the AI Agent might lead to unwanted marketing messages or spam.	Risk4
I worry that relying on the AI Agent for discounts might make me miss out on better deals elsewhere.	Risk5
I am uncomfortable with the possibility that the AI agent may access other information on my phone.	Risk6
I am concerned that the AI Agent might not always handle my personal data accurately or securely.	Risk7

Note. Compiled by the researcher

Variable Mapping of statements under “Attitude Towards Digital Coupons Before Ad Exposure.”

Table 3.8

Survey Statements and Code Numbers for the Construct “Attitude Towards Digital Coupons Before Ad Exposure”

Statements Under Attitude Towards Digital Coupons Before Ad Exposure	Code Number
I frequently use digital coupons when shopping.	Attd1
Digital coupons make my shopping experience more convenient.	Attd2
I actively search for digital coupons before making a purchase.	Attd3
Digital coupons influence where I choose to shop.	Attd4
I trust digital coupon emails and find them relevant, rather than spam.	Attd5
I prefer receiving fewer but more personalized digital coupon emails.	Attd6
I am more likely to buy a product if I receive a digital coupon for it in my email.	Attd7

Note. Compiled by the researcher.

Variable Mapping of statements under “Attitude Towards Digital Coupons After Ad Exposure

Table 3.9

Survey Statements and Code Numbers for the Construct “Attitude Towards Digital Coupons After Ad Exposure”

Statements Under Attitude Towards Digital Coupons After Ad Exposure	Code Number
I will frequently use digital coupons when shopping.	AttitudeAft1
Digital coupons will make my shopping experience more convenient.	AttitudeAft2
I will actively search for digital coupons before making a purchase.	AttitudeAft3
Digital coupons will influence where I choose to shop.	AttitudeAft4

I trust digital coupon emails more and will find them relevant, rather than perceiving them as spam.	AttitudeAft5
I would still prefer receiving fewer but more personalized digital coupon emails.	AttitudeAft6
I am now more likely to buy a product if I receive a digital coupon for it in my email.	AttitudeAft7

Note. Compiled by the researcher.

3.7 Data Analysis Method

The data analysis followed an exploratory sequential mixed-methods design (Creswell and Creswell, 2018), proceeding in two distinct stages - qualitative followed by quantitative - so that exploratory and confirmatory work remained methodologically separate and aligned to the research objectives. The qualitative stage identified underlying behavioral drivers (perceptions of risk and value, attitudes toward AI tools), while the quantitative stage examined the factors influencing adoption of the AI agent and the effect of AI exposure on perceptions of digital coupons.

The qualitative data, comprising 20 interview transcripts, were analyzed using Braun and Clarke's (2006) six-phase thematic analysis, selected for its structured yet flexible approach to identifying, analyzing, and reporting patterns. The procedure moved from familiarization through close reading of all transcripts, to systematic coding in Taguette using descriptive and interpretive tags applied to research-relevant text segments, to collating codes into candidate themes, reviewing those themes for internal coherence and mutual distinctiveness, defining and naming each theme, and finally weaving data extracts and interpretive commentary into a coherent narrative. The emergent themes were then mapped onto constructs drawn from TAM, UTAUT, and VAM - both to validate the theoretical constructs against participants' language and experience, and to surface emergent items for operationalization in the quantitative survey instrument.

The quantitative analysis was conducted using SPSS version 26 and AMOS version 21, across four stages: descriptive analysis, cross-tabulation, structural equation modeling, and

pre-post comparison. Descriptive analysis used frequency distributions and percentages for all demographic, behavioral, and Likert-scale variables, along with measures of central tendency (mean, median, mode) and dispersion (standard deviation), to characterize response patterns across constructs. Cross-tabulations examined how key variables - coupon receipt, redemption frequency, AI-tool usage, and behavioral intention - were distributed across demographic subgroups prior to inferential testing. Normality of the dependent variable, Behavioral Intention, was then assessed using the Shapiro-Wilk and Kolmogorov-Smirnov tests, and skewness and kurtosis were examined for the pre-post attitude difference score to determine the appropriate inferential procedures.

Hypothesis testing employed structural equation modeling following the two-step approach of Anderson and Gerbing (1988). The measurement model was first estimated through confirmatory factor analysis and evaluated against established model fit indices (CMIN/df, GFI, CFI, TLI, SRMR, RMSEA). Construct reliability was assessed using Cronbach's alpha and composite reliability; convergent validity through the Average Variance Extracted (AVE); and discriminant validity through the Fornell-Larcker criterion, comparing the square root of each construct's AVE against its inter-construct correlations. Once the measurement model was validated, the structural model tested the hypothesized directional paths from Attitude toward AI Tools, Usefulness, Ease of Use, Social Influence, and Risk Perception to Behavioral Intention (H1, H3-H6). The influence of demographics on Behavioral Intention (H2) was tested using non-parametric subgroup comparisons - the Mann-Whitney U test for binary variables (gender, occupation) and the Kruskal-Wallis H test, with pairwise follow-up comparisons, for multi-category variables (age, income, education, digital literacy) - these being selected because Behavioral Intention departed from normality. The relationship between Perceived Value (operationalized as the ratio of perceived benefits to perceived risks) and Behavioral Intention (H7) was tested using both Pearson's correlation and Spearman's rho. Finally, the effect of AI-agent exposure on attitudes toward digital coupons (H8) was tested with a paired-sample t-test, with Cohen's d reported as the effect size.

3.8 Data Analysis Limitations and Delimitations

This research employed a rigorous design to meet its objectives. Nevertheless, there were still some limitations of this research that need to be acknowledged.

The qualitative research used purposive sampling to identify digitally savvy in-store shoppers. This could lead to bias, such as observer bias. Additionally, the qualitative phase was skewed towards respondents aged 36-50 (75%); hence, the themes identified may not fully capture the attitudes and adoption motivations of the 25-44 cohort, identified quantitatively as the group with the highest behavioral intention. The quantitative research is entirely based on self-reported data. Hence, there could be respondent bias, as participants may provide socially acceptable responses. The sample may not be representative, as it is drawn through random sampling and relies on online respondents. The sample may not represent all regions across India.

Since this research relied on participants being exposed to digital mock-ups of the agent rather than using an AI agent, the responses may reflect misunderstandings of how the tool works.

The structural model was estimated using Structural Equation Modeling (SEM), which evaluates the fit between hypothesized relationships and observed data but cannot establish causal directionality (Hoyle, 2023). The R^2 , therefore, reflects the model's explanatory fit with the sample rather than the causal influence of the predictors on Behavioral Intention, and the possibility of reverse causation or unmeasured common causes cannot be ruled out.

Value Perception was operationalized as the ratio of usefulness to risk, rather than as an independent latent variable with its own indicators (Kim et al., 2007). In the current research, this means that the perceived value of the AI agent was understood in terms of whether its usefulness outweighed its risks. This method has two shortcomings. First, the method assumes equal influence of usefulness and risk on the value perception. Second, calculating the value ratio prevents the researcher from testing H7 alongside H1 and H3-H6; hence, H7 was investigated separately using correlation analysis.

This research is context-specific to AI agents for in-store shopping experiences, specifically coupon retrieval; it may not generalize easily to other AI tools.

Another important consideration is that this research is conducted only for shoppers within India. Hence, its findings may not be easily applicable across other regions or cultures.

Delimitations are the boundaries a researcher deliberately sets - the choices of what to include and exclude that keep a study focused and feasible - and are therefore distinct from limitations, which stem from constraints beyond the researcher's control (Theofanidis and Fountouki, 2018). This research was bounded in several deliberate ways.

Conceptually, it was confined to the integration of TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), and VAM (Kim et al., 2007) within an extended S-O-R framework (Mehrabian and Russell, 1974); alternative adoption theories were set aside to preserve a coherent and testable model. The scope was further narrowed to a single application - an AI agent for retrieving digital coupons during in-store purchases - rather than AI agents in general, allowing adoption to be examined in a concrete, bounded context. The research was also delimited geographically to India, with the population restricted by design to digitally literate, adult, metro-based shoppers - the segment best placed to evaluate the proposed agent - and non-digital, rural, and under-18 shoppers excluded.

Methodologically, because no comparable AI agent yet exists commercially for use in India, the research relied on concept exposure through standardized digital mock-ups rather than live use, a deliberate boundary that ensured a consistent stimulus across all participants. Perceived value was likewise operationalized as the ratio of perceived usefulness to perceived risk, following Kim et al. (2007), rather than as an independent latent construct.

These were considered choices made to preserve analytical focus and feasibility within the bounds of doctoral research, and should be read as scope conditions on the findings rather than as shortcomings (Theofanidis and Fountouki, 2018).

3.9 Ethics Related to Human Subject Participation

Given that the research engaged human participants and elicited views on personal data, privacy, and trust, ethical integrity was treated as a first-order concern at every stage. Participation was entirely voluntary, and informed consent was obtained from each respondent before data collection commenced; participants were briefed on the purpose and scope of the research, advised that there were no right or wrong answers, and informed of their right to withdraw at any stage without consequence. For the qualitative phase, interviews were audio-recorded only with prior consent, and each participant was assigned a unique code so that identifying information was removed from the point of storage onward, thereby preserving anonymity throughout transcription and analysis. The research accordingly upheld the principles of informed consent, voluntary participation, confidentiality, and anonymity consistent with established standards for research involving human subjects. In the quantitative phase, respondents to the pilot (N=71) and the final survey (N=410) were presented with a consent statement at the outset of the online questionnaire and could proceed only after agreeing to participate; no personally identifying details were collected, responses were recorded anonymously, and participants could exit the survey at any point. Across both phases, all data were stored securely and used solely for academic purposes, with no personal information disclosed in the reporting of findings. These safeguards were considered especially pertinent because the research itself concerns shoppers' apprehensions about data sharing and surveillance - it would have been incongruous to investigate privacy-related risk while handling participants' own data without comparable care. The research accordingly upheld the principles of informed consent, voluntary participation, confidentiality, and anonymity consistent with established standards for research involving human subjects.

3.10 Conclusion

This chapter outlined the methodological framework used to investigate consumer perceptions and adoption intentions regarding an AI-enabled coupon-retrieval agent among in-store shoppers in India. The research employed an exploratory sequential mixed-methods design (Creswell and Creswell, 2018), proceeding through three phases:

qualitative exploration through semi-structured interviews with 20 purposively selected participants, pilot validation with 71 respondents, and a final quantitative survey administered to 410 respondents via SurveyMonkey.

The qualitative phase utilized Braun and Clarke's (2006) six-phase thematic analysis to uncover underlying perceptions, attitudes, and behavioral cues related to AI-assisted coupon retrieval. The emergent themes informed the development and refinement of constructs operationalized in the quantitative instrument, ensuring alignment between exploratory findings and the extended S-O-R theoretical framework. The quantitative phase employed a structured survey incorporating five-point Likert scale items mapped to constructs drawn from TAM, UTAUT, and VAM. Reliability was established using Cronbach's alpha and composite reliability, while validity was assessed using convergent validity (AVE) and discriminant validity (Fornell-Larcker criterion). Structural Equation Modeling using AMOS was employed to test the measurement and structural models, supplemented by correlation analysis, paired-samples t-tests for pre-post attitudinal comparisons, and non-parametric tests (Mann-Whitney U and Kruskal-Wallis) for demographic subgroup analysis.

Throughout the research process, ethical principles of informed consent, anonymity, and data confidentiality were upheld. The methodological choices at each stage were guided by the research questions and the nature of the data, ensuring coherence between the qualitative and quantitative phases. The following chapter presents the findings from these three phases of analysis.

CHAPTER 4:

RESULTS

4.1 Introduction

This chapter reports the empirical findings of the research. The qualitative findings emerged from thematic analysis of twenty semi-structured interviews, and the quantitative findings from the final survey of 410 respondents, analyzed through descriptive statistics, structural equation modeling, non-parametric group comparisons, correlation, and a paired-samples *t*-test. The findings are organized by research question, with the qualitative findings presented first and the quantitative findings second, each reported against the four research questions in turn.

4.2 Organization of Data Analysis

The data analysis was carried out in two distinct stages: qualitative and quantitative, each aligned with the research's objectives. The qualitative analysis focused on identifying underlying behavioral drivers, particularly perceptions of risk and value, as well as attitudes toward AI tools. The quantitative analysis examined the factors influencing shoppers' adoption of the AI agent and assessed the impact of AI exposure on perceptions of digital coupons. By structuring the analysis separately, the research ensured methodological coherence and avoided mixing exploratory and empirical findings. The qualitative data were analyzed using Braun and Clarke's (2006) six-phase thematic analysis framework. This approach was selected for its structured yet flexible method of identifying, analyzing, and reporting patterns within qualitative datasets.

The six phases proceeded as follows:

First, the researcher engaged in familiarization by reading all 20 transcripts in depth to develop an understanding of the data's breadth and depth (Braun and Clarke, 2006). Second, initial highlights were generated systematically using Taguette, with descriptive and interpretive tags applied to text segments relevant to the research questions. Third, responses were collated and categorized into potential themes reflecting broader

patterns across the dataset. Fourth, themes were reviewed for internal coherence and distinctiveness, ensuring that each theme was supported by sufficient data and clearly differentiated from the others. Fifth, each theme was defined and named to capture its essence.

Sixth, the final list of key themes was produced by weaving together data extracts and interpretive commentary into a coherent narrative.

The emergent themes from this phase informed the refinement of constructs subsequently operationalized in the quantitative survey instrument, consistent with the exploratory sequential mixed-methods design (Creswell and Creswell, 2018).

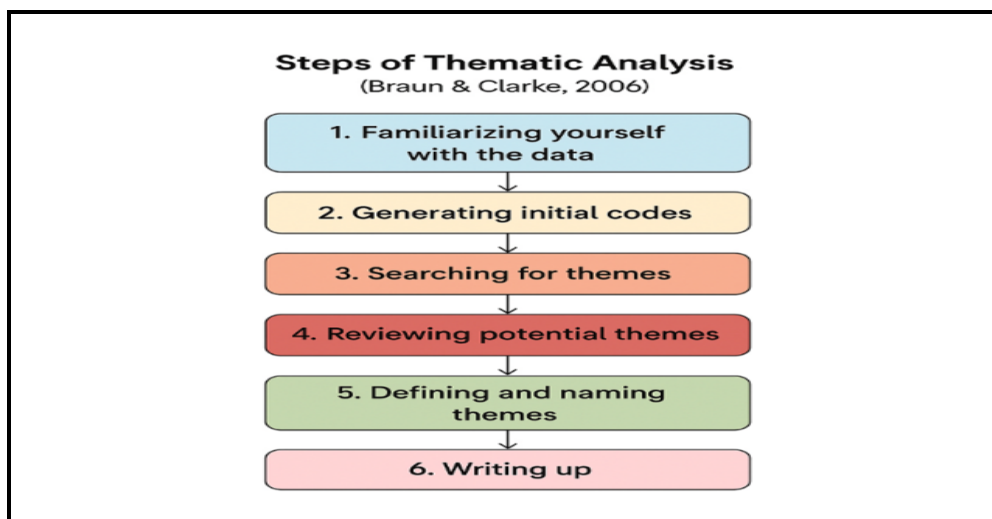


Figure 4.1

Steps of Thematic Analysis

Note. Compiled by the researcher.

Qualitative Themes and Constructs:

The themes were then mapped onto the constructs within the conceptual framework derived from TAM, UTAUT, and VAM. This mapping served two functions: first, to validate the theoretical concepts by linking them to the participant's language and experiences; second, to identify any emergent themes that would help develop the constructs into items for use during the quantitative phase. The table below presents the key insights and the corresponding constructs for these themes.

Table 4.1

Key insights with the Corresponding Constructs for the themes from Qualitative

Theme	Key Insight	Linked Construct(s)
Digital Coupons: Frequent but forgotten	Redemption hindered by effort, spam, and irrelevance; 83% negative sentiment	Perceived Value, Ease of Use, Attitude toward Digital Coupons
AI Attitudes: Comfort Meets Caution	Positive attitudes toward AI efficiency (30% confident, 25% cite time savings) coexist with privacy fears (40%) and transparency concerns (30%); trust is category-dependent	Attitude toward AI Tools, Perceived Risk
Belief in Functional Utility	AI agent recognized as solving retrieval pain points; 40% cited efficiency gains	Perceived Usefulness
Perceived Risk: Conditional Trust	Trust conditional on transparency, privacy, and control; strongest qualitative backing (45% cited data concerns)	Perceived Risk, Attitude toward AI
Ease and Speed Expectations	Demand for one-click, effortless functionality; 40% cited timesaving as core utility	Perceived Ease of Use
Just-in-Time Relevance and Value	Value = benefit minus intrusiveness; context and timing drive perceived worth	Perceived Value
Social Influence (Weak)	Only 2-3 respondents cited peer/social cues; primarily theory-driven construct	Social Influence

Note. Compiled by the researcher.

Together, the qualitative and integration with constructs establish a methodological and conceptual foundation for the quantitative phase. The themes identified through qualitative inquiry informed the structure of measurable constructs, and the systematic mapping documented above ensures traceability between respondent narratives and survey items. The qualitative findings also provided interpretive depth for the quantitative results: the emergent pattern of conditional adoption - enthusiasm tempered by privacy and effort concerns - foreshadowed the structural model's finding that benefit-oriented constructs cluster positively against the countervailing force of Risk Perception.

Table 4.2

Constructs from theories with Qualitative Grounding

Construct	Total Survey Items	Qual.-Grounded Items	Items with Weak/No Qualitative Grounding
Attitude toward Digital Coupons	7	7	None
Attitude toward AI Tools	8	6	Comfortable sharing personal info (reverse-coded); Professional use only (15%)
Perceived Usefulness	7	7	None
Perceived Ease of Use	7	5	Comfortable to use even if not tech-savvy (5%); Clear first-time instructions (5%)
Social Influence	8	2	6 items theory-driven from UTAUT- but limited Qualitative grounding
Risk Perception	7	7	None - strongest qualitative grounding

Note. Compiled by the researcher.

The table below presents every survey item across all six constructs, showing the exact number of qualitative mentions and the emergent theme from which it was derived.

Table 4.3

Item-Level Qualitative Theme to Quantitative Survey Construct tagging's

Code	Survey Item	Mentions (n=20)	%	Qualitative Theme / Evidence
Attd1	I frequently use digital coupons when shopping	4	20%	Redeems frequently (apps), once in a while
Attd2	Digital coupons make my shopping experience more convenient	5	25%	Happy when getting discount, saves money
Attd3	I actively search for digital coupons before making a purchase	3	15%	Not actively sought, used only if available (inverse framing)
Attd4	Digital coupons influence where I choose to shop	3	15%	Coupon doesn't tempt me to shop, only if already planning
Attd5	I trust digital coupon emails and find them relevant, rather than spam	4	20%	Views as spam/clutter, irrelevant, pushing brands (inverse)
Attd6	I prefer receiving fewer but more personalized digital coupon emails	5	25%	Wants relevance, tied to needs, from brands they like
Attd7	I am more likely to buy a product if I receive a digital coupon for it	6	30%	Only if need exists, fantastic offer, commercial value
Per1	I feel comfortable using AI-powered	4	20%	General Comfort; uses for shopping/comparison

	technologies in my daily life			
Per2	I enjoy experimenting with new AI powered tools and applications	6	30%	Fun to experiment, willing to explore, open to future use
Per3	I feel confident in my ability to interact with AI driven systems	4	20%	Similar to comfort
Per4	AI technologies enhance my daily experiences and activities	6	30%	Makes shopping easier, virtual try-on, life made easy
Per5	AI-powered tools help improve efficiency and save time	5	25%	Saves time on mundane tasks, price comparison, grammar
Per6	I trust AI agents to provide accurate and reliable information	6	30%	Useful for research/professional tasks, always double-checks
Per7	I feel comfortable sharing personal information with AI-powered services	0	0%	No positive support; 40% cited privacy fears (inverse only)
Per8	I trust AI tools in my professional work only	3	15%	Won't rely on AI for purchase decisions; professional use only
Benf1	The AI Agent improves the efficiency of retrieving digital coupons	8	40%	Don't have to search through emails, one click

Benf2	Helps me find better discounts and promotions vs usual methods	6	30%	Surfaces forgotten offers, shows best available
Benf3	Using the AI Agent can increase my total savings when shopping	5	25%	Commercial value, redeeming coupons that would otherwise lapse
Benf4	Helps me discover personalized coupon offers I wouldn't normally find	5	25%	Highlights vouchers from specific brands, offers user might miss
Benf5	Improves my overall shopping experience by offering valuable deals	6	30%	Gives everything at once, solves "can't find coupon at counter"
Benf6	Helps me plan my shopping by suggesting relevant discounts in advance	3	15%	Push notifications, reminders, alarm-like feature for expiring coupons
Benf7	I am more likely to shop at a store that offers AI-driven recommendations	4	20%	Would consider, influences store choice based on offers
Ease1	The AI agent looks easy to navigate and interact with	5	25%	Looks simple, clear interface
Ease2	Appears to be intuitive and user friendly for retrieving coupons	4	20%	Like an assistant, similar to other apps

Ease3	I can quickly learn how to use the AI agent without assistance	4	20%	No learnability issue, adaptability not a challenge
Ease4	Will reduce the time I spend searching for discounts in my emails	8	40%	Core utility - saves time fetching from inbox
Ease5	I feel comfortable using the AI agent even if I am not tech-savvy	1	5%	Not explicitly supported; low-tech respondents remained hesitant
Ease6	The AI agent will make my shopping experience easier	6	30%	Eliminates manual email search, everything at once
Ease7	Provides clear instructions and guidance for first-time users	1	5%	“Show me how” option, demo/video requested by one respondent
SID1	I would use if people whose opinions I value would approve	2	10%	See somebody else use it and check their experience
SID2	More likely to use if my friends or family members are using it	2	10%	Same peer-experience theme as SID1
SID3	If other shoppers in the store are using the AI Agent, I’d try it	0	0%	Not directly mentioned by any respondent
SID4	Positive online reviews or ratings would increase my likelihood	0	0%	Not directly mentioned by any respondent

SID5	Retailer promotions (staff recommendations, ads) would encourage me	0	0%	Not directly mentioned by any respondent
SID6	Social media influencers endorsing the AI Agent would make me use it	0	0%	Not directly mentioned by any respondent
SID7	Hearing success stories from other users would make me try it	1	5%	“See somebody else use this app and what is their experience”
SID8	If the AI Agent becomes widely adopted, I’d feel more comfortable	0	0%	Not directly mentioned by any respondent
Risk1	Concerned about how my personal data will be used	9	45%	How companies use data, data governance, what’s floating where
Risk2	Worry that the AI Agent might collect too much personal information	7	35%	Accesses beyond coupons, reads banking/personal emails
Risk3	Hesitant due to potential security risks (hacking, data leaks)	5	25%	Bank account hacking, data breaches, scams
Risk4	Fear that using the AI Agent might lead to unwanted marketing/spam	6	30%	Endless recommendations, targeted ads, pop-ups

Risk5	Worry that relying on the AI Agent might make me miss better deals	2	10%	Vendor bias, agent might privilege certain brands
Risk6	Uncomfortable with the possibility that the AI agent may access other phone info	4	20%	Contacts, chats, files, full phone access concerns
Risk7	Concerned the AI Agent might not handle my data accurately/securely	4	20%	Apps store data even after deletion (Uber example), cyber threats

Note. Compiled by the researcher.

Quantitative Data Analysis: The quantitative data were analyzed in four stages: descriptive analysis, cross-tabulation, structural equation modeling, and pre-post comparison testing. All statistical analyses were conducted using SPSS version 26 and AMOS version 21.

Descriptive Analysis: A frequency distribution is a tabular summary showing the number of observations (frequencies) falling within each category or response option of a variable. At the same time, the corresponding percentages represent the proportion of total responses that each category accounts for. This is calculated as:

Percentage = (Frequency of a category / Total number of responses) × 100
For example, if 213 out of 410 respondents indicated they were "Likely" to use the AI agent, the percentage would be $(213/410) \times 100 = 52.0\%$.

Frequency distributions and percentages were applied to all demographic variables (age, gender, annual income, education level, digital literacy, and occupation), all behavioral variables (frequency of physical shopping, coupon receipt, coupon redemption frequency, and AI tool usage), and all Likert-scale construct items (Perception of AI Tools: Per1, Per3,

Per4, Per6; Usefulness: Benf3, Benf4, Benf6, Benf7; Ease of Use: Ease3, Ease5, Ease7; Social Influence: SID5, SID6, SID7; Perceived Risk: Risk2, Risk4, Risk6, Risk7; Attitude Toward Digital Coupons before and after exposure: Attd1-Attd7; and Behavioral Intention) (Hair et al., 2010).

These distributions enabled the identification of dominant response categories, opinion skewness, and overall sentiment across constructs.

Table 4.4

Constructs in Quantitative Research with agreement percentage

Construct	Item	Strongly Disagree %	Disagree %	Neither Agree nor Disagree %	Agree %	Strongly Agree%	Total Agree %
Perception of AI Tools	Per1	4.4	4.9	23.9	37.1	29.8	66.9
	Per3	3.9	6.8	17.8	42.4	29	71.4
	Per4	3.9	5.6	18.3	42.7	29.5	72.2
	Per6	3.9	7.1	24.1	36.3	28.5	64.8
Usefulness of AI Agent	Benf3	3.9	2.4	28.5	32.2	32.9	65.1
	Benf4	4.6	3.2	29.3	35.4	27.6	63
	Benf6	4.6	3.9	29	34.9	27.6	62.5
	Benf7	3.9	3.9	24.6	37.8	29.8	67.6
Ease and Intuitiveness	Ease3	0.5	14.1	13.4	36.3	35.6	71.9
	Ease5	0.7	14.9	15.4	37.1	32	69.1
	Ease7	0.5	13.4	10.7	38.8	36.6	75.4
Social Influence	SID5	3.4	9.5	19.8	42.2	25.1	67.3
	SID6	3.7	10.7	18.8	41.5	25.4	66.9
	SID7	3.2	9.3	21	39.3	27.3	66.6
Risk	Risk2	14.6	24.1	26.6	22.7	12	34.7
Perception	Risk4	15.4	28.5	30	8.3	17.8	26.1

	Risk6	13.9	29.8	25.4	15.4	15.6	31
	Risk7	14.4	29.3	30.5	11.2	14.6	25.8
Attitude -	Attd1	2.9	12.4	26.6	42.2	15.9	58.1
Pre-	Attd2	2.9	8.3	18	48	22.7	70.7
Exposure	Attd3	3.7	15.1	21.2	38	22	60
	Attd4	2.9	12.9	20	42.4	21.7	64.1
	Attd5	3.4	19.3	29.3	31.2	16.8	48
	Attd7	2.4	12	20.5	40.2	24.9	65.1
Attitude -	AttAft1	1.5	6.8	22	49.3	20.5	69.8
Post-	AttAft2	1.5	2.2	15.6	52	28.8	80.8
Exposure	AttAft3	1.2	7.6	20.7	44.6	25.9	70.5
	AttAft4	1	6.1	23.2	46.6	23.2	69.8
	AttAft5	1.5	7.1	26.3	44.6	20.5	65.1
	AttAft7	1.2	6.3	18.5	47.1	26.8	73.9

Note. Compiled by the researcher.

Agree+ = combined Agree and Strongly Agree percentage.

Measures of central tendency were computed for each Likert-scale item to describe the typical response pattern across constructs (Field, 2013). The mean is the arithmetic average of all observed values for a variable, calculated as:

$$\text{Mean } (\bar{x}) = \sum x_i / N$$

where x_i represents each response, and N is the total number of responses. The mean was used to assess the average level of agreement across items within each construct. The mean scores for items under Perception of AI Tools (Per1 = 3.83, Per3 = 3.86, Per4 = 3.88, Per6 = 3.79) indicated moderate-to-high agreement with the construct. The median is the middle value when all observations are arranged in ascending order. For an even number of observations, it is the average of the two central values (Field, 2013). The median was computed for all Likert-scale items to identify the central response tendency, particularly where distributions were skewed. Across the construct items, the median was consistently

4.00, indicating that most responses clustered around "Agree." The mode is the most frequently occurring value in a distribution. The mode was used to identify the single most common response for each item(Field, 2013). Across all construct items, the mode was consistently 4.00, indicating that "Agree" was the most frequently selected response.

Standard deviation measures the average dispersion of individual responses around the mean, calculated as:

$$SD = \sqrt{[\Sigma(xi - \bar{x})^2 / (N - 1)]}$$

A lower standard deviation indicates that responses are tightly clustered around the mean, while a higher value indicates greater variability (Field, 2013). Standard deviations were computed for all Likert-scale items to assess response variability within each construct. For example, standard deviations for Perception of AI Tools items ranged from 1.02 to 1.06, indicating moderate and consistent variability across the construct. Mean, median, mode, and standard deviation were computed for all items across the following constructs: Perception of AI Tools (Per1, Per3, Per4, Per6), Usefulness of AI Agent (Benf3, Benf4, Benf6, Benf7), Ease and Intuitiveness (Ease3, Ease5, Ease7), Social Influence (SID5, SID6, SID7), Perceived Risk (Risk2, Risk4, Risk6, Risk7), Attitude Toward Digital Coupons before exposure (Attd1-Attd7), and Attitude Toward Digital Coupons after exposure.

Table 4.5

Constructs in Quantitative Research with Mean, Median, Mode, and Standard Deviation

Construct	Item	N	Mean	Median	Mode	SD
Perception of AI	Per1	410	3.83	4	4	1.05
Perception of AI	Per3	410	3.86	4	4	1.04
Perception of AI	Per4	410	3.88	4	4	1.02
Perception of AI	Per6	410	3.79	4	4	1.06
Usefulness	Benf3	410	3.88	4	5	1.03
Usefulness	Benf4	410	3.78	4	4	1.03

Usefulness	Benf6	410	3.77	4	4	1.04
Usefulness	Benf7	410	3.86	4	4	1.02
Ease of Use	Ease3	410	3.92	4	4	1.05
Ease of Use	Ease5	410	3.85	4	4	1.06
Ease of Use	Ease7	410	3.98	4	4	1.03
Social Influence	SID5	410	3.76	4	4	1.04
Social Influence	SID6	410	3.74	4	4	1.07
Social Influence	SID7	410	3.78	4	4	1.05
Risk Perception	Risk2	410	2.93	3	3	1.24
Risk Perception	Risk4	410	2.85	3	3	1.29
Risk Perception	Risk6	410	2.89	3	2	1.27
Risk Perception	Risk7	410	2.82	3	3	1.24
Attitude (Pre)	Attd1	410	3.56	4	4	1
Attitude (Pre)	Attd2	410	3.79	4	4	0.98
Attitude (Pre)	Attd3	410	3.6	4	4	1.1
Attitude (Pre)	Attd4	410	3.67	4	4	1.04
Attitude (Pre)	Attd5	410	3.39	3	4	1.08
Attitude (Pre)	Attd7	410	3.73	4	4	1.04
Attitude (Post)	AttAft1	410	3.8	4	4	0.89
Attitude (Post)	AttAft2	410	4.04	4	4	0.81
Attitude (Post)	AttAft3	410	3.86	4	4	0.93
Attitude (Post)	AttAft4	410	3.85	4	4	0.88
Attitude (Post)	AttAft5	410	3.76	4	4	0.91
Attitude (Post)	AttAft7	410	3.92	4	4	0.9

Note. Compiled by the researcher.

Cross-Tabulation Analysis: Cross-tabulations were conducted to examine the distribution of key variables, including coupon receipt, coupon redemption frequency, AI tool usage, and behavioral intention, across demographic categories such as age, gender, income, education, digital literacy, and occupation. This helped identify systematic patterns and subgroup differences before inferential testing.

Normality Assessment: Before inferential testing, normality was assessed to determine the appropriate statistical tests. The Shapiro-Wilk test evaluates whether a sample is drawn from a normally distributed population by computing the ratio of the best linear unbiased estimate of variance to the sample variance (Shapiro and Wilk, 1965). It is computed as:

$$W = (\sum a_i x_{(i)})^2 / \sum (x_i - \bar{x})^2$$

where $x_{(i)}$ are the ordered sample values and a_i are constants derived from the expected values of normal order statistics. A significant result ($p < 0.05$) indicates departure from normality (Shapiro and Wilk, 1965). The Kolmogorov-Smirnov test compares the empirical cumulative distribution function of the sample with a specified theoretical distribution (Field, 2013). The test statistic is:

$$D = \max |F_n(x) - F(x)|$$

where $F_n(x)$ is the empirical distribution and $F(x)$ is the theoretical normal distribution. A significant result ($p < 0.05$) indicates the sample does not follow a normal distribution (Field, 2013).

Both tests were applied to the dependent variable (Behavioral Intention) across all demographic categories: Age (18-24, 25-44, 45+), Gender (male, female), Annual Income (four categories), Education (four categories), Digital Literacy (beginner, intermediate, advanced), and Occupation (Technology/IT, Others).

Results across all categories yielded $p < 0.05$ on both tests, confirming that Behavioral Intention was not normally distributed, thereby necessitating non-parametric inferential procedures for demographic subgroup comparisons (Hair et al., 2010).

Skewness and kurtosis: Skewness and kurtosis were assessed for the difference in attitude scores (pre- versus post-exposure) as a prerequisite for the paired sample t-test. Skewness measures the asymmetry of the distribution around the mean, while kurtosis measures the peakedness relative to a normal distribution (Field, 2013). These were applied to the

variable Difference in Attitude (Mean_Attitudebef – Mean_AttitudeAft), yielding a skewness of 1.325 and a kurtosis of 3.845.

Inferential Analysis (Hypothesis testing):

Structural Equation Modeling: SEM is a multivariate statistical method that enables the simultaneous testing of relationships between observed indicators and latent constructs, as well as directional relationships among latent constructs themselves (Thakkar, 2020). SEM was employed in this research using AMOS version 21 to test the hypothesized adoption framework, following the two-step approach recommended by Anderson and Gerbing (1988).

Step 1 Measurement Model (Confirmatory Factor Analysis)

The measurement model was estimated through CFA to assess how well the observed items represented their intended latent constructs (Anderson and Gerbing, 1988). This step assessed construct reliability and validity before structural path estimation. Model fit indices assess the degree to which the proposed model reproduces the observed covariance structure (Hu and Bentler, 1999).

The following indices were used to evaluate both the measurement and structural models:

- CMIN/df (Chi-square/degrees of freedom) is the ratio of the chi-square statistic to the degrees of freedom, providing a parsimony-adjusted measure of overall fit. Values ≤ 2 indicate a good fit (Ullman, 2006). Formula: $CMIN/df = \chi^2 / df$.
- GFI (Goodness-of-Fit Index) represents the proportion of variance in the observed covariance matrix explained by the model. Values > 0.90 indicate acceptable fit (Hair et al., 2010). Formula: $GFI = 1 - (\chi^2_{model} / \chi^2_{null})$.
- CFI (Comparative Fit Index) compares the fit of the proposed model against a baseline (null) model. Values > 0.90 indicate acceptable fit (Bentler, 1990). Formula: $CFI = 1 - (\max(\chi^2_{model} - df_{model}, 0) / \max(\chi^2_{null} - df_{null}, 0))$.

- TLI (Tucker-Lewis Index) adjusts the CFI for model parsimony by penalizing model complexity. Values > 0.90 indicate a good fit (Bentler, 1990). Formula: $TLI = [(\chi^2_{null} / df_{null}) - (\chi^2_{model} / df_{model})] / [(\chi^2_{null} / df_{null}) - 1]$.
- SRMR (Standardized Root Mean Square Residual) is the average standardized difference between the observed and predicted correlations. Values < 0.08 indicate a good fit (Hu and Bentler, 1999). Formula: $SRMR = \sqrt{[\sum(s_{ij} - \hat{\sigma}_{ij})^2 / k]}$, where k is the number of unique elements in the correlation matrix.
- RMSEA (Root Mean Square Error of Approximation) estimates the discrepancy between the model and population covariance per degree of freedom. Values < 0.06 indicate a close fit (Hu and Bentler, 1999). Formula: $RMSEA = \sqrt{[(\chi^2 - df) / (df \times (N - 1))]}$

Table 4.6

Model Fit Statistics of the Measurement Model

Fit Index	Recommended	Obtained	Source
CMIN/df	≤ 2	1.785	Ullman (2006); Schumacker and Lomax (2004)
GFI	> 0.90	0.944	Hair et al. (2010)
CFI	> 0.90	0.988	Bentler (1990)
TLI	> 0.90	0.986	Bentler (1990)
SRMR	< 0.08	0.021	Hu and Bentler (1998)
RMSEA	< 0.06	0.044	Hu and Bentler (1998)

Note. Compiled by the researcher.

The measurement model achieved satisfactory fit across all indices. The relative chi-square value (CMIN/df = 1.785) falls below the recommended ceiling of 2.0, indicating a good fit (Ullman, 2006; Schumacker and Lomax, 2004). The Goodness-of-Fit Index (GFI = 0.944), Comparative Fit Index (CFI = 0.988), and Tucker-Lewis Index (TLI = 0.986) all surpass the acceptable threshold of 0.90, confirming the model's adequacy (Hair et al., 2010). The Standardized Root Mean Square Residual (SRMR = 0.021) and Root Mean Square Error of Approximation (RMSEA = 0.044) are well within the acceptable limits (Hu and Bentler,

1998), further confirming the soundness of the model's structure and its appropriateness for further analysis.

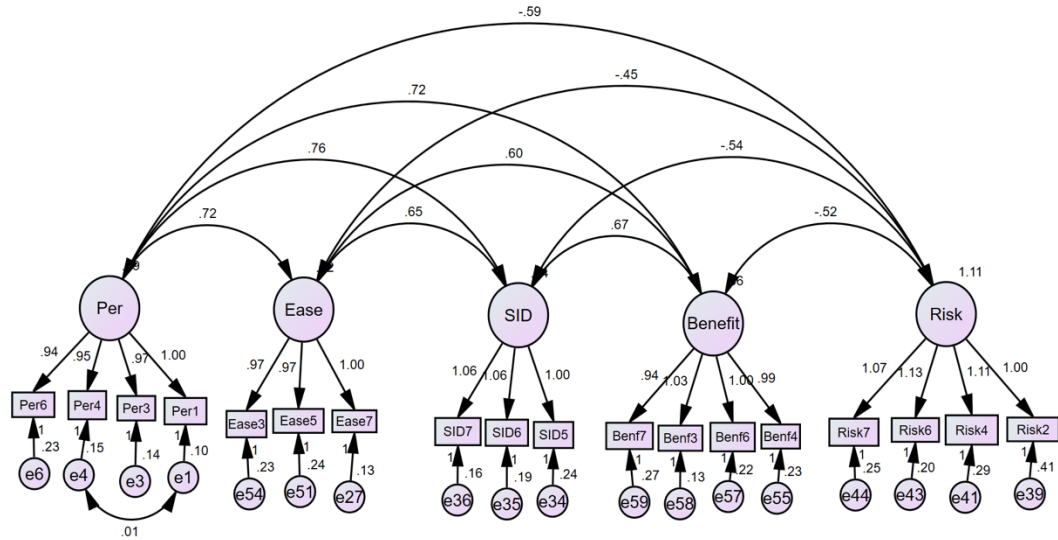


Figure 4.2

Measurement Model of Perception (Per), Ease of Use (Ease), Usefulness (Benefit), Social Influence (SID), and Risk Perception (Risk)

Note. Output generated from IBM SPSS AMOS

The measurement model reveals strong item-construct loadings, which suggest good construct validity; conceptually coherent correlations among the constructs; a clear negative relationship between the Risk- and benefit-based constructs; no multicollinearity; and a stable measurement model. From a substantive perspective, the model visually supports the thesis argument, in which the adoption constructs cluster positively, with Risk as the countervailing force, similar to the value-exchange negotiation framework.

Table 4.7

The constructs and their final indicator variables

Construct	Items / Variables
Attitude towards AI Tools	Per1, Per3, Per4, Per6
Usefulness of AI Agent for Coupon Redemption	Benf3, Benf4, Benf6, Benf7

Ease and Intuitiveness of AI Agent	Ease3, Ease5, Ease7
Social Influence on AI Agent Usage	SID5, SID6, SID7
Risk Perception of AI Tool	Risk2, Risk4, Risk6, Risk7

Note. Compiled by the researcher.

Step 2: Reliability and Validity testing of the model

Following the structural equation modeling methodology outlined by Anderson and Gerbing (1988), the measurement model was analyzed before estimating the structural model. Such a procedure allows for the assessment of the validity and reliability of the theoretical constructs under consideration before drawing any conclusions about their associations.

Reliability of the Questionnaire: Reliability testing of the measurement instrument was conducted through two processes using two measures to ensure that the constructs under study exhibit consistent internal stability preliminary assessment. In the pilot survey (n = 71), inter-item and item-total correlations were computed to assess whether any items do not contribute substantially to their respective constructs. This preliminary step enabled the modification and elimination of problematic items before the main research was conducted.

Reliability testing of the measurement instrument was conducted through two processes, using two measures, to ensure that the constructs under research have achieved consistent internal stability:

- Cronbach's Alpha (α), where $\alpha \geq 0.70$, was used as the acceptance criterion (Hajjar, 2018).
- Composite Reliability (CR) index, wherein CR was computed based on the standard factor loadings and error variances obtained from the measurement model. CR was considered the ideal reliability test statistic in SEM analysis, and $CR \geq 0.70$ indicated acceptable reliability (Hair et al., 2019). Composite reliability was computed because Cronbach's alpha assumes that all items contribute equally, which can underestimate reliability.

Cronbach's alpha is a statistical measure commonly used to assess the internal consistency or reliability of a set of observed variables designed to measure a latent concept. It produces a single value representing the intercorrelation among the observed variables, indicating how well the set of items captures the variance of the latent concept. Cronbach's alpha is a gauge of the true reliability of a measuring instrument, and it may underestimate that reliability (Hajjar, 2018). A Cronbach's alpha value above 0.70 is considered an indicator of satisfactory internal consistency (Olaniyi, 2019). The table below presents the Cronbach's alpha values for each construct.

Table 4.8

Cronbach's alpha values for each construct

Construct	No. of Items	Cronbach's α
Attitude towards AI Tools	4	0.96
Usefulness of AI Agent for Coupon Redemption	4	0.941
Ease and Intuitiveness of AI Agent	3	0.93
Social Influence on AI Agent Usage	3	0.933
Risk Perception of AI Tool	4	0.946

Note. Output generated from IBM SPSS Statistics

All five constructs demonstrate excellent internal consistency, with Cronbach's alpha values ranging from 0.930 to 0.960, well above the recommended threshold of 0.70. In particular, Attitude towards AI Tools ($\alpha = 0.960$) and Risk Perception ($\alpha = 0.946$) exhibit the highest reliability, while Ease and Intuitiveness ($\alpha = 0.930$) have the lowest, yet still indicates excellent reliability. These results confirm that the items within each construct are highly intercorrelated and consistently measure their respective latent variables.

Composite reliability (CR): In a measurement model, CR is a statistical index that assesses the internal consistency or reliability of a latent construct measured by multiple observed indicators. Unlike Cronbach's alpha, the composite reliability coefficient takes into account the different outer loadings of the items on the corresponding latent construct (Memon and Shaikh, 2021). Composite reliability is calculated as the ratio of the squared sum of standardized factor loadings to the sum of squared factor loadings plus the sum of

error variances (Thakkar, 2020). A composite reliability value above 0.70 generally indicates that the observed variables are very consistent and are reliable indicators of the construct (Hair et al., 2010). The table below presents the standardized factor loadings and composite reliability for each construct.

Table 4.9

Table Standardized factor loadings and composite reliability for each construct

Sr. No.	Construct	Item	Loading	CR
1	Attitude towards AI Tools	Per1	0.951	0.959
		Per3	0.932	
		Per4	0.924	
		Per6	0.889	
2	Usefulness of AI Agent	Benf3	0.937	0.941
		Benf4	0.887	
		Benf6	0.891	
		Benf7	0.861	
3	Ease and Intuitiveness	Ease3	0.889	0.93
		Ease5	0.885	
		Ease7	0.936	
4	Social Influence	SID5	0.881	0.932
		SID6	0.911	
		SID7	0.925	
5	Risk Perception	Risk2	0.854	0.946
		Risk4	0.908	
		Risk6	0.935	
		Risk7	0.913	

Note. CR = Composite Reliability; Values computed by the researcher using Microsoft Excel based on standardized factor loadings from IBM SPSS AMOS output. CR > 0.70 confirms construct reliability (Hair et al., 2019; Fornell & Larcker, 1981)

All items demonstrate strong standardized factor loadings ranging from 0.854 to 0.951, exceeding the minimum recommended threshold of 0.70. Composite reliability values for

all five constructs range from 0.930 to 0.959, confirming excellent internal consistency. These results affirm that each observed variable reliably represents its underlying latent construct and that the measurement model is strong enough for further structural analysis.

Validity Testing: Validity testing assesses the degree to which the conceptual framework used for measurement accurately reflects the constructs it purports to measure. Reliability concerns the stability of measurements of a particular construct, and validity concerns whether the construct is measured correctly. Two types of validity tests were performed at this juncture. First, convergent validity was assessed by calculating the Average Variance Extracted (AVE) for each construct. This test measures the amount of variance shared by items belonging to a single construct, so they may be said to reflect the same construct conceptually.

An important metric used to assess convergent validity is the Average Variance Extracted (AVE), which estimates the proportion of variance in the indicators explained by the construct relative to that explained by measurement error. The cut-off criterion for AVE is 0.50 or higher, which suggests that more than half of the variance in the indicators is accounted for by the construct, thereby providing strong evidence of convergent validity (Bagozzi and Yi, 1988; Lim, 2024). The table below presents the AVE values for each construct.

Table 4.10

AVE values for each construct

Sr.	Construct	Item	Loading	AVE
1	Attitude towards AI Tools	Per1	0.951	0.854
		Per3	0.932	
		Per4	0.924	
		Per6	0.889	
2	Usefulness of AI Agent	Benf3	0.937	0.8
		Benf4	0.887	
		Benf6	0.891	
		Benf7	0.861	

3	Ease and Intuitiveness	Ease3	0.889	0.817
		Ease5	0.885	
		Ease7	0.936	
4	Social Influence	SID5	0.881	0.821
		SID6	0.911	
		SID7	0.925	
5	Risk Perception	Risk2	0.854	0.815
		Risk4	0.908	
		Risk6	0.935	
		Risk7	0.913	

Note. AVE = Average Variance Extracted. Values computed by the researcher in Microsoft Excel using standardized factor loadings from IBM SPSS AMOS output. AVE > 0.50 confirms convergent validity (Hair et al., 2019; Fornell & Larcker, 1981)

All constructs exceed the 0.50 AVE threshold, with values ranging from 0.800 to 0.854. Specifically, Attitude towards AI Tools (AVE = 0.854), Usefulness (AVE = 0.800), Ease and Intuitiveness (AVE = 0.817), Social Influence (AVE = 0.821), and Risk Perception (AVE = 0.815) show that their respective constructs explain a large amount of the variance in their respective indicators. Taken together, the results provide evidence that the selected items effectively measure their respective constructs, and convergent validity is established for the measurement model.

Discriminant validity is a subcomponent of construct validity that examines the extent to which the measures of different constructs are not highly correlated. It examines whether the measurement tool can differentiate between constructs and does not substantially overlap with measures of unrelated constructs. It is assessed using the Fornell and Larcker Criterion by comparing the square root of the AVE of each construct with the inter-construct correlations. High discriminant validity indicates that the measurement tool can differentiate between the constructs, providing evidence that each construct is measured uniquely and correctly in the model (Anderson and Gerbing, 1988). A measurement model demonstrates discriminant validity if the square root of AVE for each construct is greater than its correlation with any other construct. The table below presents the discriminant

validity matrix, with the square root of AVE on the diagonal (shown in bold) and inter-construct correlations in the off-diagonal cells.

Table 4.11

The Discriminant Validity Matrix (Forner and Lacker)

	Attitude	Useful.	Ease	Risk	Social
Attitude towards AI Tools	0.924				
Usefulness of AI Agent	0.781	0.894			
Ease and Intuitiveness	0.757	0.676	0.904		
Risk Perception	-0.560	-0.532	-0.441	0.903	
Social Influence	0.835	0.785	0.733	-0.561	0.906

Note. Output generated from IBM SPSS AMOS

For every construct, the square root of AVE (diagonal) exceeds all corresponding inter-construct correlations (off diagonal), confirming that each construct captures variance unique to itself and is empirically distinct from the others. The negative correlations between Risk Perception and all benefit-oriented constructs are theoretically coherent, reflecting the countervailing role of perceived risk in the value exchange framework. This pattern visually supports the thesis argument, in which the adoption constructs cluster positively, and Risk is the countervailing force, consistent with the value-exchange negotiation framework. Discriminant validity is therefore established for the measurement model.

Step 3 Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) is a multivariate quantitative method used to explain relationships among observed variables. In simple terms, it is a way to test a theory of how things influence each other when behaviors people care about, like ‘trust’, ‘risk’, etc., are not directly measurable. This method assists the researcher in validating the theoretical model for theory testing and development. The multivariate analysis helps the researcher carry out in-depth explanatory analysis while maintaining statistical efficiency.

Structural Equation Modeling (SEM) is a method of testing a theory that has the following characteristics:

Some constructs are not directly apparent to be studied (e.g., Perceived Usefulness, Trust, Ease of Use, Adoption Intention).

Several survey questions (indicators/items) are used to measure those concepts. The relationships between the concepts (for example, Usefulness → Intention) are examined while taking into account measurement error.

SEM is a combination of two tasks:

Measurement model (CFA part): “Are my survey items measuring the constructs correctly?”

Structural model (path part): “Do the constructs relate to each other the way my theory says?”

SEM can determine whether the data fit the causal narrative, but it cannot prove causality. In this research, it can be used to determine whether the model supports the hypothesized directional relationships (Hoyle, 2023). After establishing the measurement model's adequacy, the structural model was estimated to test the directional relationships among latent constructs (Anderson and Gerbing, 1988).

The structural model tested the following hypothesized paths:

- Attitude Toward AI Tools - Behavioral Intention (H1)
- Usefulness - Behavioral Intention (H3)
- Ease of Use - Behavioral Intention (H4),
- Social Influence - Behavioral Intention (H5)
- Risk Perception - Behavioral Intention (H6).

Furthermore, H2 (the impact of demographics on Behavioral Intention) was tested using nonparametric subgroup comparison procedures described below.

The Mann-Whitney U test was used for binary demographic variables (Gender, Occupation) to determine whether two independent groups differ significantly on a continuous outcome (Nachar, 2008). The Mann-Whitney U test revealed no statistically significant difference in Behavioral Intention between female respondents (mean rank = 203.38) and male respondents (mean rank = 207.03), with $U = 20,104.000$ and $p = .747$. The Mann-Whitney U test revealed a statistically significant difference in Behavioral Intention across occupation categories ($U = 15,153.000$, $p = .009$). Technology/IT professionals reported a higher mean rank (215.14) compared to respondents from other occupations (183.76).

The Kruskal-Wallis H test was used for multi-category demographic variables (Age, Annual Income, Education, Digital Literacy) to assess significant differences among three or more independent groups (McKight and Najab, 2010). When the Kruskal-Wallis test was significant, pairwise comparisons were conducted to identify which specific category pairs differed. The Kruskal-Wallis H test revealed a statistically significant difference in Behavioral Intention across age groups ($H = 7.955$, $p = .019$). Subsequent pairwise comparisons identified the specific locus of the difference: a statistically significant difference was observed between respondents aged 18-24 years (mean rank = 189.21) and those aged 25-44 years (mean rank = 217.99), with $p = .032$. No significant differences were found between the 45+ age group and either the 18-24 group ($p = 1.000$) or the 25-44 group ($p = .065$). The 25-44 age group demonstrated the highest Behavioral Intention. The Kruskal-Wallis H test revealed no statistically significant difference in Behavioral Intention across income categories ($H = 2.819$, $p = .420$).

The Kruskal-Wallis H test revealed no statistically significant difference in Behavioral Intention across education levels ($H = 3.334$, $p = .343$). The Kruskal-Wallis H test revealed a statistically significant difference in Behavioral Intention across digital literacy levels ($H = 15.038$, $p < .001$). Pairwise comparisons indicated significant differences between the Beginner and Advanced groups ($p = .015$) and between the Intermediate and Advanced groups ($p = .003$). No significant difference was observed between the Beginner and Intermediate groups ($p = .842$). Advanced digital literacy users (mean rank = 227.07)

exhibited significantly higher Behavioral Intention than both Intermediate users (mean rank = 188.93) and Beginner users (mean rank = 164.97).

Correlation Analysis: Correlation analysis examines the power and direction of the linear association between two variables (Field, 2013). In this research, correlation analysis was conducted to test H7, which suggests that perceived value (operationalized as the ratio of benefits to risks) significantly influences behavioral intention to use the AI agent. This is because Perceived Value is a derived construct representing the ratio of perceived benefits (Usefulness) to perceived costs (Risk). Both Pearson's correlation and Spearman's rho were computed to account for potential deviations from normality. The Pearson r measures the degree of linear relationship between two continuous variables. At the same time, the Spearman rho provides an alternative measure of the same in the form of a non-parametric test. Both tests were computed to assess the correlation between perceived value and behavioral intention (H7), with Spearman's rho used because Behavioral Intention was non-normally distributed. The results indicate a significant positive association between Perceived Value and Behavioral Intention: Pearson's $r = .511$ ($p < .001$) and Spearman's $\rho = .662$ ($p < .001$)

Pre-Post Comparison (Paired-Sample t-test): To test H8, which posits that exposure to the AI agent positively influences attitudes toward digital coupons, a paired-sample t-test was conducted (Field, 2013). The paired sample t-test compares the means of two related measurements taken from the same participants at two time points, and is calculated as:

$$t = \bar{d} / (SD_d / \sqrt{N})$$

where $\bar{d}$ is the mean of the paired differences, SD_d is the standard deviation of the differences, and N is the number of pairs (Field, 2013). The test was applied to the difference between mean attitude scores before exposure (Mean_Attitudebef) and after exposure (Mean_AttitudeAft) to the AI agent concept.

Before conducting the paired-sample t-test, the measurement properties of the Attitude towards Digital Coupons construct were verified at both time points. Before exposure, all factor loadings ranged from 0.736 to 0.830, with a composite reliability of 0.907, a

Cronbach's α of 0.906, and an AVE of 0.619. After exposure, factor loadings ranged from 0.682 to 0.806, with composite reliability of 0.887, Cronbach's α of 0.886, and AVE of 0.567. All values exceeded the minimum threshold criteria, confirming that the construct was reliably and validly measured at both time points.

The difference scores (post minus pre) had a skewness of 1.325 and kurtosis of 3.845, indicating a departure from normality. But, with a large sample size ($N = 410$), the paired-sample t-test remains steady to such departures.

Table 4.12

Paired-Sample t-Test for Attitude Toward Digital Coupons (Pre vs. Post Exposure)

Pair	Mean Diff.	SD	SE Mean	95% CI Lower	95% CI Upper	t	Sig.
Pre - Post	-0.25	0.576	0.028	-0.306	-0.195	-8.805	< .001

Note: $df = 409$. Difference calculated as $Mean_AttitudeBefore - Mean_AttitudeAfter$, hence a -ve value. Output generated from IBM SPSS Statistics

The paired-sample t-test yielded a mean difference of -0.25 ($SD = 0.576$, $SE = 0.028$), with a 95% confidence interval ranging from -0.306 to -0.195. The t-value was -8.805 ($df = 409$, $p < .001$), confirming a statistically significant positive shift in attitudes toward digital coupons following exposure to the AI agent concept.

Effect size was assessed using Cohen's d , calculated as the mean difference divided by the standard deviation of the difference scores ($d = 0.25 / 0.576 = 0.43$; Cohen, 1988). By conventional benchmarks, a d of 0.43 falls in the small-to-medium range, indicating that the observed attitudinal shift, while modest in magnitude, is meaningful and unlikely to be attributable to chance alone.

4.3 Qualitative Findings (Thematic Analysis)

Thematic analysis of the twenty interview transcripts yielded six emergent themes that captured the main patterns in the dataset. These themes are reported below, supported by illustrative participant quotations and frequency counts.

RQ1 - HOW DOES A SHOPPER'S ATTITUDE TOWARDS AI INFLUENCE INTENTION TO USE THE AI AGENT?

Participants' pre-existing attitudes toward AI tools revealed a dual pattern of comfort and caution. On the positive side, respondents demonstrated genuine openness to AI: six participants (30%) expressed confidence in their ability to interact with AI-driven systems, describing it as fun to experiment with and expressing willingness to explore future applications. A further six (30%) stated that AI technologies enhance their daily experiences, citing examples such as virtual try-on features, simplified shopping, and general life convenience. Five participants (25%) specifically noted that AI-powered tools improve efficiency and save time on mundane tasks such as price comparison and grammar correction. Six (30%) trusted AI to provide accurate and reliable information, although most qualified this by saying they always double-check AI output. Four participants (20%) enjoyed experimenting with new AI-powered tools and applications, using them for shopping comparisons and general exploration.

On the negative side, the same interviews revealed substantial reservations. Privacy concerns emerged as the single most frequently cited barrier to AI comfort, with eight participants (40%) expressing fears about data being shared, phones listening in on conversations, targeted advertisements appearing after searches, and AI systems accessing email. Six participants (30%) cited a lack of trust in AI or insufficient transparency, noting that they did not know who built the tools, how their data was being used, or what regulations governed AI applications. Four participants (20%) expressed concern that AI is biased toward promoting shopping, describing endless recommendations and impulse buying nudges as manipulative. Three participants (15%) reported accuracy concerns, that they could not fully rely on AI and preferred to double-check its outputs. A further three (15%) expressed a preference for human interaction over AI bots, citing negative chatbot experiences and the impersonal nature of AI-driven interactions. Notably, no participant

expressed positive comfort with sharing personal information with AI - this item functions purely as a risk-detection indicator, which is noted for methodological transparency.

“I have not had a very pleasant experience because sometimes I’m trying to explain a situation, like a return, and that option is not there to connect to a person. But otherwise, when it’s like gen AI like ChatGPT or Copilot, that’s useful because it helps me improve efficiency in my work. It depends on which category of AI I am using.”

“I feel as if my privacy has been invaded literally because what I am thinking in my mind and this AI has got it immediately.”

Three participants (15%) stated that they trust AI tools only for professional work and would not rely on them for personal purchase decisions. In contrast, four (20%) described themselves as having low familiarity with AI or not being particularly interested in technology. The pattern that emerged was one of category-dependent trust: participants were comfortable with AI for productivity and information tasks (ChatGPT, Copilot, price comparison) but became cautious or resistant when AI intersected with personal data, financial transactions, or autonomous decision-making.

This dual pattern - comfort with AI capability alongside caution about AI boundaries - directly informed the Attitude toward AI Tools construct tested under H1. The finding that attitudes were shaped by the specific AI context (professional versus personal, transparent versus opaque) provides qualitative depth to interpreting the quantitative result that Attitude toward AI Tools was the strongest predictor of Behavioral Intention ($\beta = 0.281$). Consumers do not hold a monolithic attitude toward AI; rather, their attitudes are context-dependent, and the AI coupon agent sits precisely at the boundary between welcomed efficiency and guarded personal space.

RQ2 - What differences in behavioral intention exist across demographic groups?

Demographic differences in behavioral intention are, by their nature, a quantitative question, examined through group comparisons reported in the quantitative findings. The qualitative phase, drawn from a small purposive sample, did not surface demographic-

based differences as a distinct theme, and this research question is therefore addressed through the quantitative findings.

RQ3 - What drives shoppers to accept and adopt the AI agent for retrieving digital coupons in-store?

Perceived usefulness: Respondents demonstrated a strong belief in the utility of AI tools for simplifying routine tasks. When presented with the concept of the AI coupon agent, participants quickly grasped its potential to address known pain points, particularly the discovery of valid offers at the point of purchase. Eight participants (40%) specifically mentioned that the agent would improve coupon retrieval efficiency by eliminating the need to search manually through emails. Six participants (30%) noted that the agent could surface better discounts and promotions compared to their usual methods. Five participants (25%) believed the agent could increase their total savings by redeeming coupons that would otherwise lapse, and a further five (25%) valued its ability to discover personalized offers they would not normally find.

“Would be helpful for finding deals.”

The strength of this theme - grounded in 40% of respondents citing retrieval efficiency and 30% citing superior discount discovery - provided strong qualitative grounding for the Perceived Usefulness construct subsequently tested in H3.

Perceived ease of use: Participants consistently expressed a need for effortless functionality and “one-click” interaction. The utility most frequently cited was saving time spent fetching coupons from inboxes (40% of participants). Five participants (25%) described the agent as easy to navigate, with a clear interface, and four (20%) found it intuitive and similar to other apps they already use. Six participants (30%) emphasized that the agent would make their overall shopping experience easier by eliminating the need for manual email searches. The redemption process was expected to be automated, requiring minimal interaction or eligibility checking.

“I don’t need to rather go look into things and just with one click I’m gonna get everything I need.”

Two items in the subsequent quantitative instrument - “comfortable using even if not tech-savvy” and “clear instructions for first-time users” - had minimal qualitative grounding (one respondent each, 5%) and were included based on the TAM and UTAUT theoretical frameworks rather than emergent qualitative themes. This is noted for methodological transparency. The broader theme, however, provided robust grounding for the Perceived Ease of Use construct tested in H4.

Social influence: Social influence was the weakest area in the qualitative data. Only two participants (10%) wished to see someone else use the agent before trying it, and one (5%) cited success stories from other users. No participant mentioned retailer promotions, influencer endorsements, online reviews, in-store observation of other shoppers, or widespread adoption as motivators.

Perceived risk: Conditional Trust in AI

Functional optimism about AI was prevalent, yet trust in AI was conditional. This theme had the strongest qualitative backing of any construct area, with nearly every survey item tracing directly to multiple respondent statements. The primary concerns raised by participants were: how personal data would be used, including data governance and what information is “floating where” (45% of participants); the possibility that the AI agent might collect too much personal information by accessing content beyond coupons, such as banking or personal emails (35%); fear of unwanted marketing messages, targeted ads, and pop-ups (30%); security risks such as hacking and data breaches (25%); discomfort with the agent accessing other phone information such as contacts, chats, and files (20%); and concern that the agent might not handle data accurately or securely, with one participant citing an example of an app storing data even after account deletion (20%).

“Concerns about data privacy and how data might be used, especially regarding microphone permissions and potential data breaches.”

“It was not a fear of the AI, rather the fear of the app... I was not sure if the things which I enter on the app... was going to be misused.”

Trust was higher when boundaries were visible or when information was transparent. This theme reflects the cost side of the value exchange and provides direct qualitative grounding for the Risk Perception construct tested in H6.

Perceived value: Coupon utility was related not only to the discount value but also to its timing and delivery context. Participants preferred an agent that could surface offers in-store or at checkout, making them salient at the moment of purchase. Six participants (30%) noted that the agent would improve their overall shopping experience by offering valuable deals at the right moment, and five (25%) wanted the agent to suggest relevant discounts in advance via push notifications or reminders about expiring coupons. Four participants (20%) stated they would be more likely to shop at a store that offers AI-driven coupon recommendations.

“Helpful to quickly find available vouchers while shopping.”

Respondents also strongly expressed a limit to intrusiveness beyond which perceived value was lost - the risk of AI reading sensitive emails or the perception of manipulation by advertisers caused disengagement. Two participants (10%) specifically cited concerns about vendor bias, in which the agent might privilege certain brands over others. This duality of benefit and cost within a single theme directly supports the Perceived Value construct tested in H7 and the thesis's central premise that adoption is a value exchange negotiation.

RQ4 - Does exposure to the AI agent shift shoppers' attitudes towards digital coupons?

At baseline, all twenty participants (100%) reported receiving promotional offers via email or SMS, yet sentiment towards digital coupons was predominantly negative, with 83% expressing unfavorable views. Four drivers of this negativity emerged: forgetfulness (35%), cumbersome redemption (25%), perception as spam (20%), and irrelevance of offers (30%). Redemption was more common in online than in-store settings. *"I don't even remember I had them until it's too late."*

On exposure to the concept of an AI agent that retrieves, classifies, and displays digital coupons in real time at checkout, participants displayed cautious enthusiasm. They recognized practical benefits - time saved, increased redemption through reduced forgetfulness, and timely, contextual offers - and even those skeptical of AI expressed openness to trying the agent. The prevailing pattern was one of conditional adoption: shoppers wanted a trustworthy, non-intrusive agent that eased shopping without requiring privacy trade-offs.

4.4 Findings from Quantitative Study

Frequency Distributions

The frequency distribution tables for all retained variables are provided in the Data Analysis section. All questionnaire items pertain to seven constructs; each item uses a five-point Likert scale, with N = 410 observations per item. Among all retained questionnaire items, the proportion of agreement-side responses (i.e., Agree + Strongly Agree) spanned from the minimum of 25.8% for Risk7 to the maximum of 80.8% for AttAft2.

In six out of the seven constructs, there was a majority in all the retained items, with percentages in each item for Agree+ falling in the range of 60% to 80%. The constructs with the largest percentage in Agree+ were the Ease and Intuitiveness items, reaching their highest percentage in Ease7 with 75.4%, and also the Post-Exposure Attitude items, with their highest percentage in AttAft2 at 80.8%-the highest percentage in the entire

questionnaire. Pre-Exposure Attitude was the only construct in this cluster that included an item with a minority-agreement response: Attd5 (attitude towards trust in coupons via email messages), with 48.0% agreement. By comparison, all post-exposure attitude constructs showed majority agreements. For the Risk Perception construct, all retained items showed minority agreement responses, with percentages ranging from 25.8% to 34.7%, along with disagree responses ranging from 38.7% to 43.9%. A notable portion of respondents also indicated neutral positions in the constructs of Usefulness (25-29%), Risk Perception (25-31%), and Pre-Exposure Attitude (18-29%).

The measures of central tendency support the findings on the distribution of agreement levels reported above. All but one of the seven constructs had a mean greater than 3.0, the midpoint of the scales. Most items had median and mode scores of 4.00, indicating that respondents generally preferred the Agree option when responding to the questionnaire items. Ease and Intuitiveness were characterized by the highest item means (3.85-3.98). Perception of AI tools, Usefulness, and Post-Exposure Attitude were next in terms of the highest item means, ranging from 3.74 to 4.04. Pre-Exposure Attitude items were marked by somewhat lower item means (3.39 to 3.79), with Attd5 (trusting coupon emails) the lowest (less than 3.5). Risk Perception was the only construct where the means of all items were lower than 3.0 (2.82 to 2.93), implying neutrality rather than negativity. All standard deviations were higher than 0.81 and lower than 1.29. Risk Perception items recorded the highest SDs, whereas Post-Exposure Attitude items recorded the lowest ones, implying a high level of convergence in assessments following exposure to AI technology.

RQ1 - How does a shopper's attitude towards AI influence intention to use the AI agent?

This part of the research operationalizes the “attitude” pathway primarily via investigating attitude towards AI tools in general. The hypothesis used to validate this is:

H1_o: *Attitude toward AI tools does not significantly influence behavioral intention to use the AI agent.*

H1_a: *Attitude toward AI tools significantly and positively influences behavioral intention to use the AI agent.*

The structural model results indicate that the path from Attitude towards AI Tools to Behavioral Intention to Use the AI Tool was positive and statistically significant ($\beta = 0.281$, $t = 4.511$, $p < .05$). Hence, for every one standard deviation increase in a consumer's attitude towards AI tools, behavioral intention to use the AI agent increases by 0.281 standard deviations, holding all other predictors constant. This result leads to the rejection of the null hypothesis (H_{1o}). The alternative hypothesis (H_{1a}) is therefore supported: Attitude toward AI tools significantly and positively influences behavioral intention to use the AI agent for coupon redemption.

Among the five predictors in the structural model, Attitude towards AI Tools was jointly the strongest predictor of Behavioral Intention (tied with Social Influence at $\beta = 0.281$).

RQ2: What are the differences in behavioral intention when using AI agents across various demographic groups?

H2_o: *There is no significant difference in behavioral intention to use the AI agent across [demographic] groups.*

H2_a: *There is a significant difference in behavioral intention to use the AI agent across [demographic variable] groups.*

The distribution of Behavioral Intention was tested for normality across all demographic categories using the Kolmogorov-Smirnov and Shapiro-Wilk tests. All categories returned p-values below 0.05, indicating that the normality assumption was violated. Non-parametric tests were therefore applied: the Mann-Whitney U test for binary demographic variables (Gender, Occupation) and the Kruskal-Wallis H test for multi-category variables (Age, Annual Income, Education, Digital Literacy).

Gender: The Mann-Whitney U test revealed no statistically significant difference in Behavioral Intention between female respondents (mean rank = 203.38) and male respondents (mean rank = 207.03), with $U = 20,104.000$ and $p = .747$. The null hypothesis is not rejected. Gender does not significantly influence Behavioral Intention to use the AI agent.

Occupation: The Mann-Whitney U test revealed a statistically significant difference in Behavioral Intention across occupation categories ($U = 15,153.000$, $p = .009$). Technology/IT professionals reported a higher mean rank (215.14) compared to respondents from other occupations (183.76). The null hypothesis is rejected. Occupation significantly influences Behavioral Intention, with Technology/IT professionals exhibiting stronger intention to use the AI agent.

Age: The Kruskal-Wallis H test revealed a statistically significant difference in Behavioral Intention across age groups ($H = 7.955$, $p = .019$). The null hypothesis is rejected. Subsequent pairwise comparisons identified the specific locus of the difference: a statistically significant difference was observed between respondents aged 18-24 years (mean rank = 189.21) and those aged 25-44 years (mean rank = 217.99), with $p = .032$. No significant differences were found between the 45+ age group and either the 18-24 group ($p = 1.000$) or the 25-44 group ($p = .065$). The 25-44 age group demonstrated the highest Behavioral Intention.

Annual Income: The Kruskal-Wallis H test revealed no statistically significant difference in Behavioral Intention across income categories ($H = 2.819$, $p = .420$). The null hypothesis is not rejected. Annual income does not significantly influence Behavioral Intention to use the AI agent.

Education: The Kruskal-Wallis H test revealed no statistically significant difference in Behavioral Intention across education levels ($H = 3.334$, $p = .343$). The null hypothesis is not rejected. Education level does not significantly influence Behavioral Intention to use the AI agent.

Digital Literacy: The Kruskal-Wallis H test revealed a statistically significant difference in Behavioral Intention across digital literacy levels ($H = 15.038$, $p < .001$). The null hypothesis is rejected. Pairwise comparisons identified that the significant differences lay between Beginner and Advanced groups ($p = .015$) and between Intermediate and Advanced groups ($p = .003$). No significant difference was observed between Beginner and Intermediate groups ($p = .842$). Advanced digital literacy users (mean rank = 227.07)

exhibited significantly higher Behavioral Intention than both Intermediate users (mean rank = 188.93) and Beginner users (mean rank = 164.97).

Table 4.13

Summary of Hypothesis Testing Results for H2 Across Demographic Variables

Variable	Test	Test Statistic	p-value	Decision
Gender	Mann-Whitney U	20,104.000	.747	Fail to Reject H ₀
Occupation	Mann-Whitney U	15,153.000	.009	Reject H ₀
Age	Kruskal-Wallis H	7.955	.019	Reject H ₀
Annual Income	Kruskal-Wallis H	2.819	.420	Fail to Reject H ₀
Education	Kruskal-Wallis H	3.334	.343	Fail to Reject H ₀
Digital Literacy	Kruskal-Wallis H	15.038	< .001	Reject H ₀

Note. Output generated from IBM SPSS Statistics

To summarize, only three of the six demographic variables - Occupation, Age, and Digital Literacy - significantly influence Behavioral Intention to use the AI agent, while Gender, Annual Income, and Education do not. The strongest demographic differentiator is Digital Literacy ($p < .001$), followed by Occupation ($p = .009$) and Age ($p = .019$).

RQ3: What drives shoppers to accept and adopt an AI agent for retrieving digital coupons in-store?

RQ3 is addressed through five hypotheses (H3-H7), each testing a distinct adoption construct from the extended S-O-R framework.

H3: Perceived Usefulness Influencing Behavioral Intention

H3₀: *Perceived usefulness does not significantly influence behavioral intention to use the AI agent.*

H3_a: *Perceived usefulness significantly and positively influences behavioral intention to use the AI agent.*

The structural model results indicate that the path from Perceived Usefulness to Behavioral Intention was positive and statistically significant ($\beta = 0.123$, $t = 2.407$, $p < .05$). The null hypothesis is rejected, and H3_a is supported. Perceived Usefulness significantly and positively influences Behavioral Intention, although its effect size is the smallest among the five structural predictors.

H4: Perceived Ease of Use Influencing Behavioral Intention

H4_o: *Perceived ease of use does not significantly influence behavioral intention to use the AI agent.*

H4_a: *Perceived ease of use significantly and positively influences behavioral intention to use the AI agent.*

The path from Ease and Intuitiveness of the AI Agent to Behavioral Intention was positive and statistically significant ($\beta = 0.182$, $t = 3.922$, $p < .05$). The null hypothesis is rejected, and H4_a is supported. Perceived Ease of Use significantly and positively influences Behavioral Intention. This construct ranks as the third-strongest predictor in the model.

H5: Social Influence influencing Behavioral Intention

H5_o: *Social influence does not significantly affect behavioral intention to use the AI agent.*

H5_a: *Social influence significantly and positively affects behavioral intention to use the AI agent.*

The path from Social Influence to Behavioral Intention was positive and statistically significant ($\beta = 0.281$, $t = 4.477$, $p < .05$). The null hypothesis is rejected, and H5_a is supported. Social Influence significantly and positively affects Behavioral Intention. This construct is jointly the strongest predictor in the model (tied with Attitude towards AI Tools at $\beta = 0.281$).

H6: Perceived Risk Influencing Behavioral Intention

H6₀: *Perceived risk does not significantly influence behavioral intention to use the AI agent.*

H6_a: *Perceived risk significantly and negatively influences behavioral intention to use the AI agent.*

A significantly negative correlation existed between Risk Perception and Behavioral Intention ($\beta = -0.101$, $t = -2.960$, $p < .05$). The null hypothesis was falsified and H6_a confirmed. The variable ‘Perceived Risk’ showed a significant negative effect on Behavioral Intention. This construct is the only one that has a negative effect; it serves as an opposing power to all the constructs representing some kind of benefits. This finding is consistent with the theory of value-exchange negotiation, which forms the basis of the current research. The effect size is moderate ($\beta = -0.101$) and negative in direction.

H7: Perceived Value Influencing Behavioral Intention

H7₀: *‘Perceived value’ does not significantly influence behavioral intention to use the AI agent.*

H7_a: *‘Perceived value’ significantly influences behavioral intention to use the AI agent.*

H7 was tested through correlation analysis, as ‘Perceived Value’ is a derived construct i.e. the ratio of perceived benefits (Usefulness) to perceived costs (Risk). Both Pearson’s correlation and Spearman’s rho were computed to account for potential deviations from normality. As per the results, a significant positive relationship existed between ‘Perceived Value’ and Behavioral Intention: Pearson’s $r = .511$ ($p < .001$) and Spearman’s $\rho = .662$ ($p < .001$)

Table 4.14

Correlation Analysis Between Perceived Value and Behavioral Intention

Test Applied	Correlation	Sig. Value
---------------------	--------------------	-------------------

Pearson Correlation	.511	< .001
Spearman's rho	.662	< .001

Note. Output generated from IBM SPSS Statistics

The null hypothesis is rejected, and H7_a is supported. Perceived Value significantly and positively influences Behavioral Intention. The correlations are moderate-to-strong (particularly Spearman's $\rho = .662$)

Table 4.15

Summary of Hypothesis Testing Results for RQ3 (H3-H7)

Hypothesized Path	β	t-value	p-value	Decision
Usefulness $\rightarrow$ BI (H3)	0.123	2.407	< .05	Reject H ₀
Ease of Use $\rightarrow$ BI (H4)	0.182	3.922	< .05	Reject H ₀
Social Influence $\rightarrow$ BI (H5)	0.281	4.477	< .05	Reject H ₀
Risk Perception $\rightarrow$ BI (H6)	-0.101	-2.960	< .05	Reject H ₀
Value $\rightarrow$ BI (H7)*	$r = .511 / \rho = .662$	-	< .001	Reject H ₀

*Note. *H7 tested via correlation analysis; β and t-value not applicable. Output generated from IBM SPSS Statistics*

All five hypotheses under RQ3 are supported. The structural model explains 73.3% of the variance in Behavioral Intention ($R^2 = 0.733$). The relative strength of the predictors, in descending order of standardized regression weight, is: Attitude towards AI Tools and Social Influence (both $\beta = 0.281$) > Ease of Use ($\beta = 0.182$) > Perceived Usefulness ($\beta = 0.123$) > Risk Perception ($\beta = -0.101$).

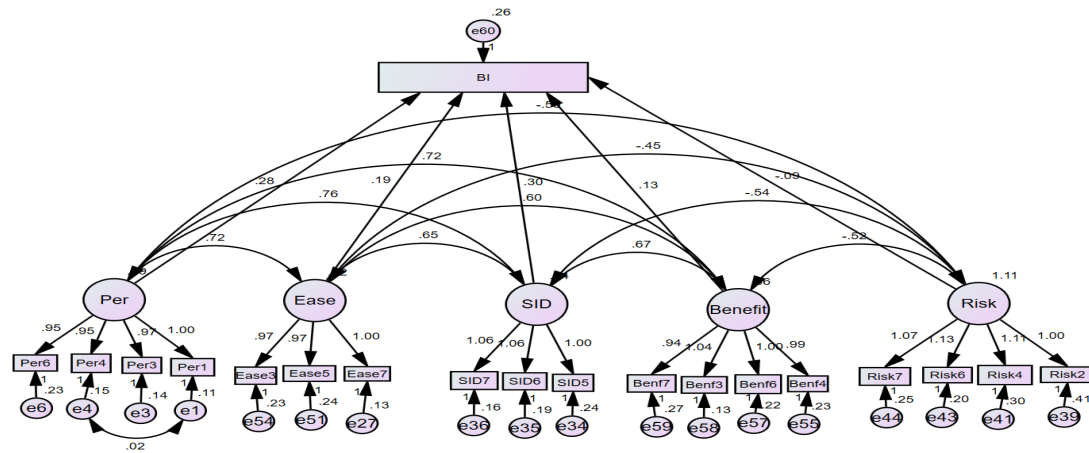


Figure 4.3

Structural Model Illustrating the Influence of Perception (Per), Ease of Use (Ease), Usefulness (Benefit), Social Influence (SID), and Risk Perception (Risk) on Behavioral Intention (BI).

Note. Output generated from IBM SPSS AMOS

RQ 4: What is the impact of the AI agent on the shopper's perception and attitude towards digital coupons in general?

H8₀: *There is no significant difference in shoppers' attitudes toward digital coupons before and after exposure to the AI agent concept.*

H8_a: *Shoppers' attitudes toward digital coupons are significantly more positive after exposure to the AI agent concept than before exposure.*

The results of the data analysis reveal a statistically significant difference between attitudes before and after exposure, with a mean difference of -0.25 (S.D.=0.576; S.E.=0.028), and a 95% confidence interval of [-0.306, -0.195]. The difference was calculated as Mean_AttitudeBefore minus Mean_AttitudeAfter; a negative difference indicates that, after being exposed to the idea of AI agents, people developed stronger attitudes towards digital coupons. The confidence interval does not include any positive values; this change in attitude is unlikely to be due to sampling error and reflects an actual change. Cohen's d equals 0.43; the effect size is small to medium, which means that the observed attitude change is real and meaningful.

Hypothesis H8_o is rejected, while Hypothesis H8_a is accepted, as consumers develop much more positive attitudes towards digital coupons after exposure to the AI agent concept than before.

4.5 Summary of Findings

The summary of all hypotheses put together shows the following:

Table 4.16

Consolidated Summary of All Hypothesis Testing Results

H	Hypothesis Statement	Supported ?	Key Statistic
H1	Attitude toward AI → BI	Yes	$\beta = 0.281, p < .05$
H2	Demographics → BI	No	Only 3 of 6 variables do not support- Gender income and education have $p = 0.747, 0.420$ and 0.343 respectively
H3	Perceived Usefulness → BI	Yes	$\beta = 0.123, p < .05$
H4	Perceived Ease of Use → BI	Yes	$\beta = 0.182, p < .05$
H5	Social Influence → BI	Yes	$\beta = 0.281, p < .05$
H6	Perceived Risk → BI	Yes	$\beta = -0.101, p < .05$
H7	Perceived Value → BI	Yes	$\rho = .662, p < .001$
H8	AI exposure → Attitude shift	Yes	$t = -8.805, p < .001$

Note. Output generated from IBM SPSS AMOS

Table 4.4 presents an overview of the results obtained for each of the eight hypotheses. H1-H7 were all confirmed, while for H2, 3 of the 6 demographic characteristics did not show a significant correlation with Behavioral Intention.

4.6 Conclusion

Having established the empirical results for all four research questions and eight hypotheses, the next chapter discusses the theoretical implications of these findings within the extended S-O-R framework, their practical relevance for retailers and AI product designers, and the limitations that bound their interpretation. The next chapter discusses the theoretical and practical implications of these findings.

CHAPTER 5:

DISCUSSION

5.1 Introduction

This chapter interprets and critiques the findings reported in Chapter 4 through the extended S-O-R framework, drawing on the wider literature on AI adoption, technology acceptance, and consumer behavior to establish where the results confirm, dispute, or extend existing scholarship.

The central findings can be stated briefly. Seven of the eight hypotheses were supported: attitude towards AI, perceived usefulness, perceived ease of use, social influence, perceived value, and perceived risk each significantly influenced behavioral intention, and exposure to the AI agent produced a significant positive shift in attitudes towards digital coupons. Behavioral intention differed significantly across three of the six demographic groups - occupation, age, and digital literacy.

Taken together, the results suggest that adoption among Indian in-store shoppers was shaped less by functional utility than by attitudinal, social, and value-based evaluations, and that exposure to the agent generated a measurable spillover effect onto the underlying retail task.

Each section below states the relevant finding, interprets and critiques it against the supporting tables, figures, and quotes, and positions it within the existing literature.

5.2 Discussion of Research Question One

RQ1: How does a customer's attitude towards AI influence their intention to use an AI agent?

H1: Attitude towards AI tools significantly influences behavioral intention to use the AI agent - Supported

The research found attitude towards AI tools to be among the strongest predictors of intention to adopt the agent, with a positive and significant path to behavioral intention ($\beta = 0.281$, $t = 4.511$, $p < .05$) - jointly the highest of the five constructs. This means a shopper's general disposition towards AI, more than the agent's utility alone, shaped their intention to use it. The result confirms the reasoned-action view of attitude as a proximal antecedent of intention (Ajzen, 1991), and aligns with the core TAM proposition that attitude toward technology is a primary determinant of behavioral intention (Davis, 1989). Yet it departs from classic TAM, where usefulness usually dominates (Davis, 1989): here attitude outweighed usefulness ($\beta = 0.123$), suggesting that for an emerging, personally intrusive technology, how shoppers feel about AI in general may matter more than its measurable utility - a reading supported by the qualitative pattern of category-dependent trust.

The qualitative data provided interpretive depth: participants' attitudes were not binary but context-conditional. Consumers who viewed AI as useful and trustworthy in professional settings (e.g., ChatGPT, Copilot) were more willing to extend that trust to a retail application. In contrast, consumers who associated AI with privacy invasion or manipulation approached the agent with greater resistance. This context dependence is consistent with Chopdar and Balakrishnan's (2020) finding that digital stimuli in Indian retail operate through perceived value and impulsivity, with the consumer's pre-existing orientation mediating the stimulus-response pathway.

From the value-exchange negotiation perspective, a positive attitude toward AI lowers the psychological entry cost of the negotiation. When consumers already view AI as beneficial and trustworthy, the cognitive friction of adopting a new AI application decreases, making the coupon agent's perceived benefits more salient than its perceived risks. Conversely, a negative baseline attitude raises the entry cost, requiring stronger compensatory signals (greater usefulness, more transparency, social endorsement) to shift the negotiation toward adoption. Within the extended S-O-R model, when a person is predisposed negatively toward AI, the burden of overcoming this friction lies with the stimulus itself. On the other hand, when the person is positively predisposed to the technology, the same stimulus is seen as confirmation rather than persuasion.

This finding is consistent with the findings of Pillai et al. (2020) and Gursoy et al. (2019), in which a positive attitude towards AI is considered one of the main precursors of adoption intention in automated retail and service environments.

5.3 Discussion of Research Question Two

RQ 2: What are the differences in behavioral intention when using AI agents across various demographic groups?

H2: Shopper demographics significantly influence behavioral intention - Supported in 3 of 6 variables, not supported in 3

The results reveal a consistent pattern: fixed demographic characteristics (gender, income, education) do not significantly differentiate Behavioral Intention, whereas capability-related factors (digital literacy, occupation) and life-stage factors (age) do. Gender showed no significant difference ($U = 20,104$, $p = .747$), nor did income ($H = 2.819$, $p = .420$) or education ($H = 3.334$, $p = .343$). In contrast, digital literacy was the strongest differentiator ($H = 15.038$, $p < .001$), followed by occupation ($U = 15,153$, $p = .009$) and age ($H = 7.955$, $p = .019$).

The digital literacy finding was particularly noteworthy. Pairwise comparisons revealed significant differences between Advanced and Intermediate users ($p = .003$) and between Advanced and Beginner users ($p = .015$), with no significant difference between the Beginner and Intermediate groups ($p = .842$). This suggests a threshold effect: it is specifically advanced digital competence that drives heightened intention to adopt, rather than a linear relationship across all literacy levels. This finding is consistent with UTAUT's proposition that experience and facilitating conditions moderate adoption (Venkatesh et al., 2003) but also suggests that what really drives adoption is exposure to digital and AI environments rather than socioeconomic background. Gender, income, and education - variables typically assumed to proxy technology access - showed no significant effect, while age, digital literacy, and field of work did. Experience, in other words, worked through direct exposure rather than through income or schooling.

When shoppers decide whether to adopt an AI agent, demographics influence the starting position of the negotiation but do not determine its outcome. Consumers with higher digital competence enter with lower perceived effort, higher perceived control, and greater tolerance for automation, meaning they require less compensatory value to adopt. Consumers with lower competence require stronger signals of simplicity, transparency, and benefit to reach the same adoption threshold. Demographics, therefore, play a moderating rather than a primary role in the S-O-R pathway, consistent with UTAUT's positioning of individual differences as contextual moderators rather than direct predictors (Venkatesh et al., 2003).

5.4 Discussion of Research Question Three

RQ 3: Drivers of AI Agent Adoption (H3-H7): What drives shoppers to accept and adopt an AI agent for retrieving digital coupons in-store?

RQ3 represents the core of the organism stage in the extended S-O-R model: it tests the five cognitive-affective constructs through which consumers process the AI agent stimulus and form Behavioral Intention (Response 1). The structural model accounted for 73.3% of the variance in Behavioral Intention ($R^2 = 0.733$). This means that, for behavioral intention among the 410 individuals surveyed, 73.3% is explained by the model's predictors. The remaining 26.7% reflects variance associated with factors outside the model's scope, such as individual experience, contextual variables, or measurement noise. Consistent with the inherent limitations of SEM, this figure describes the model's explanatory fit with the observed data only.

The relative strength of the five predictors, in descending order of standardized regression weight, was: Social Influence and Attitude toward AI ($\beta = 0.281$ each) > Ease of Use ($\beta = 0.182$) > Perceived Usefulness ($\beta = 0.123$) > Risk Perception ($\beta = -0.101$). All five paths were statistically significant ($p < .05$), and the positive clustering of benefit constructs against the negative risk construct directly supports the value-exchange negotiation premise.

H3: Perceived Usefulness influencing behavioral Intention Supported ($\beta = 0.123$, $t = 2.407$, $p < .05$).

Perceived Usefulness, which influenced behavioral Usefulness, had a significant positive effect on Behavioral Intention, validating the foundational TAM proposition that the belief in a technology's ability to enhance task performance is a primary driver of adoption (Davis, 1989). In this context, usefulness referred specifically to the AI agent's ability to improve coupon retrieval efficiency, surface better discounts, and increase total savings. The qualitative data reinforced this: 40% of participants cited retrieval efficiency as the core utility, and 30% valued the agent's ability to surface offers they would otherwise miss.

Usefulness had the smallest effect size among the positive predictors ($\beta = 0.123$), suggesting that while consumers recognize the agent's functional value, other factors - particularly social endorsement and pre-existing AI attitudes - carry more weight in shaping adoption intention. As part of the consumer's benefit-versus-risk evaluation, usefulness represents the benefit side of the equation. Its significance confirms that consumers evaluate the AI agent's functional contribution before committing to adoption; its modest effect size confirms that functional benefit alone is insufficient without supporting conditions of trust, ease, and social validation.

The identified moderate influence of PU aligns with the results reported by Sinha et al. (2021) and Chao (2019), which show that, despite PU's reliability as a predictor, its dominance is undermined when other AI-related variables are taken into account. It contradicts the hierarchical model of TAM (Davis, 1989) and confirms recent findings on the influence of emotional and contextual aspects over functionality in the context of AI use (Lopes et al., 2024; Raut et al., 2024; Pandey et al., 2024).

H4: Perceived Ease of Use influencing Behavioral Intention Supported ($\beta = 0.182$, $t = 3.922$, $p < .05$).

Ease of Use exerted a stronger positive effect than Usefulness ($\beta = 0.182$ vs. 0.123), ranking as the third-strongest predictor. This is consistent with TAM's theoretical hierarchy in which ease of use influences intention both directly and indirectly through usefulness

(Davis, 1989), and with the qualitative finding that participants consistently demanded “one-click” functionality and an “invisible” experience at checkout. In retail environments, particularly at physical checkout, any perceived complexity becomes a deterrent because consumers are time-constrained and cognitively occupied with the purchasing task (Schmutz et al., 2009).

In the consumer’s assessment of whether the tool is worth using or in a value-exchange negotiation, ease of use reduces the effort cost on the equation's left-hand side. When the agent is perceived as intuitive and requiring minimal interaction, the cognitive cost of adoption decreases, making the net value proposition more favorable. This finding supports extending TAM to context-specific retail scenarios in which effort reduction may be more salient than functional enhancement (Huang, 2010).

This dominance of Ease of Use over Usefulness in the present research supports the results obtained by Chew et al. (2006) and Porter & Donthu (2006), whose examples show that effort minimization is especially relevant in consumer technology usage contexts. The latest research studies on technology adoption under the UTAUT2 framework in emerging economies such as India (Dinh et al., 2025; Yeoh et al., 2024; Pandey et al., 2024) have also supported the idea of perceived effort as an important threshold for adoption.

H5: Social Influence influencing Behavioral Intention Supported ($\beta = 0.281$, $t = 4.477$, $p < .05$).

Social Influence was jointly the strongest predictor in the model, tied with Attitude toward AI Tools at $\beta = 0.281$. This is a striking finding because Social Influence was the weakest theme in the qualitative data, with only two to three respondents mentioning peer or social cues. The discrepancy between weak qualitative emergence and strong quantitative effect is itself a substantive finding: social influence may operate below conscious awareness in individual interviews but emerge powerfully in survey responses when prompted by specific scale items. This pattern is consistent with UTAUT’s proposition that social influence operates as a normative pressure rather than an individually articulated motivation (Venkatesh et al., 2003).

Rather than treating this divergence as a methodological inconsistency, this research interprets it as a substantive finding in its own right: social influence for a novel, unfamiliar technology operates not as an explicit motivator that consumers speak about, but as a latent, underlying risk-reduction mechanism they activate without conscious awareness. When no established adoption norm exists for a technology - as is the case for an AI coupon agent in the Indian market - consumers use social proof as a cognitive shortcut to lower perceived uncertainty: if peers, influencers, or fellow shoppers have adopted and endorsed the tool, the unknown becomes familiar, and the risk threshold shifts downward (Hofstede, 2001). The strength of this effect indicates that validation from peers, influencers, and fellow shoppers acts as a catalyst, increasing confidence and normalizing the use of AI in retail settings. In value-exchange negotiations, social endorsement reduces perceived uncertainty: when others have adopted the technology and reported positive outcomes, the consumer's estimated risk decreases and the estimated benefit increases, shifting the negotiation toward adoption. This is particularly relevant in the Indian retail context, where social proof and community validation carry substantial weight in purchase decisions (Chopdar and Balakrishnan, 2020).

Another key finding is the divergence between the qualitative and quantitative findings on Social Influence. In qualitative interviews, only two or three interviewees mentioned peer influence as an inducer of adoption intention. Conversely, Social Influence emerged as one of the most influential variables in the Structural Model, with the same weight as Attitude toward AI Tools ($\beta = 0.281$). This discrepancy can be understood in light of three assumptions.

First, social influence often operates as a latent normative pressure that respondents do not articulate until prompted; UTAUT theorists note that it acts through internalized norms rather than explicit appeals (Venkatesh et al., 2003). Second, Indian consumers display significant levels of in-group collectivism (Hofstede, 2001), in which factors such as family, peers, and community shape consumers' decision-making in retail purchase choices, as communicated through a tightly knit digital social network structure. Recent literature on omnichannel and retail adoption in India indicates that this social factor is a

key driver of consumer technology adoption (Kushwaha & Gupta, 2019; Gupta et al., 2024).

Finally, since the AI coupon agent represents a novel technology without a standardized adoption model, social proof serves as a mental tool that reduces perceived risk, often unconsciously. This suggests a consideration for research methodology: pure qualitative studies conducted before the introduction of a technology might fail to account for social influences in new markets, further justifying mixed methods.

H6: Perceived Risk influencing behavioral Intention Supported ($\beta = -0.101$, $t = -2.960$, $p < .05$).

Perceived Risk was the only construct exerting a negative influence on Behavioral Intention, confirming its role as the countervailing force in the value-exchange negotiation. The qualitative data provided the richest grounding for this construct: 45% of participants cited concerns about data usage, 35% worried about excessive data collection, and 30% feared unwanted marketing. These concerns are consistent with the perceived risk literature in technology adoption (Featherman, 2001; Kesharwani and Bisht, 2012) and with the VAM proposition that perceived sacrifice moderates the benefit-intention relationship (Kim et al., 2007).

The modest absolute effect size ($\beta = -0.101$) relative to the benefit-oriented constructs suggests that functional optimism can offset risk concerns when the agent's value proposition is sufficiently compelling. Still, risk does not disappear; it acts as a threshold condition. Within the S-O-R model, risk represents the evaluative counterweight in the Organism stage: even when usefulness, ease, and social endorsement are high, consumers will not adopt if their risk threshold is exceeded. The finding supports the inclusion of risk as a core construct in AI adoption models, extending TAM and UTAUT by demonstrating that adoption decisions involve explicit risk evaluation alongside benefit assessment (Davis, 1989; Venkatesh et al., 2003; Kim et al., 2007).

Featherman and Pavlou (2003) recognized perceived risk as a determinant in TAM-based studies. The present research extends their assertion to AI-supported retail settings,

showing that risk acts as an ongoing but moderate balancing force to benefit-based concepts. The above finding aligns with the prevailing trend observed in digital/AI adoption studies, where data privacy and trust issues influence consumer assessments (Kesharwani and Bisht, 2012; Rana et al., 2023).

H7: Perceived Value influencing Behavioral Intention Supported (Pearson's $r = .511$, Spearman's $\rho = .662$, $p < .001$).

Perceived Value, operationalized as the ratio of perceived benefit (usefulness) to perceived cost (risk), showed a strong positive correlation with Behavioral Intention. The Spearman's ρ of .662 is the strongest bivariate relationship observed in the research. This finding directly substantiates the thesis's central proposition: consumers do not evaluate the AI agent's usefulness in isolation; they weigh it against risk to form a complete value judgment, and this net value predicts intention. This is consistent with the VAM framework, which positions perceived value as the proximal determinant of adoption and integrates both benefit and sacrifice constructs (Kim et al., 2007).

The qualitative evidence of “just-in-time relevance” provides the interpretive mechanism: when the AI agent delivers the right coupon at the precise moment of checkout, it maximizes perceived utility while minimizing effort costs, thereby producing a high net value that outweighs privacy apprehensions. This finding is one of the research's most important contributions, as it validates the value-exchange negotiation lens and demonstrates its empirical tractability through the combined use of SEM and correlation analysis.

The strong correlation between Perceived Value and Behavioral Intention ($\rho = .662$) corroborates the fundamental premise of VAM theory that customers form judgments about value by weighing benefits and costs (Zeithaml, 1988; Chew et al., 2006). The findings also support extending the UTAUT model by Pitchayadejanant (2011) to VAM and resonate with recent trends indicating that benefit-cost considerations remain a prevalent rationale for adoption in AI-driven retail scenarios (Harjati et al., 2025).

Table 4.3 consolidates the hypothesis-testing outcomes for the five adoption constructs examined under RQ3 (H3-H7), reporting the standardized path coefficients, significance levels, and the decision reached for each hypothesis.

5.5 Discussion of Research Question Four

RQ 4: The Spillover Effect on Attitude Toward Digital Coupons

What is the significant impact of the AI agent on the shopper's perception and attitude towards digital coupons in general?

H8: Attitude towards the AI agent positively influences the shopper's attitude towards digital coupons. *Supported* ($t = -8.805$, $df = 409$, $p < .001$).

The paired-sample t-test confirmed a statistically significant positive shift in attitudes toward digital coupons after exposure to the AI agent concept (mean difference = -0.25, calculated as pre minus post, indicating improvement). The item measuring perceived convenience (AttAft2) achieved the highest post-exposure mean of 4.04, compared with a pre-exposure mean of 3.79, and the item measuring trust in coupon relevance (AttAft5) rose from 3.39 to 3.76. Following exposure, 86.4% of respondents reported being likely or very likely to use the AI agent, compared with 83% at baseline who held negative views about coupons.

Within the extended S-O-R model, this finding represents Response 2 - the spillover effect. Following Jacoby's (2002) recommendation for dual-response S-O-R models, this research tested whether the AI stimulus elicits not only a direct behavioral response (intention to use the agent) but also an indirect attitudinal response (a change in perception of the underlying task). The significant positive shift confirms the spillover mechanism proposed by Qin et al. (2025): the AI agent not only drives its own adoption but also acts as a catalyst, re-legitimizing digital coupons as valuable retail tools.

The interpretive mechanism is straightforward: before exposure, digital coupons were perceived as burdensome, intrusive, and irrelevant because retrieving them required effort

that exceeded their perceived benefits. The AI agent addresses these specific pain points by automating discovery, classifying offers, and delivering them at the precise moment of purchase. This intervention shifts the effort-value equation: the cost of coupon usage drops (automated retrieval replaces manual search), while the benefit increases (contextual relevance replaces generic spam). The result is a perceptual transformation in which coupons are re-evaluated from marketing noise to opportunities for personalized value.

This finding has significant theoretical implications. It demonstrates that AI agents function not only as transactional enablers but also as perceptual intermediaries - they change how consumers evaluate the tools, processes, and tasks that AI supports. In a value-exchange negotiation framework, the AI agent acts as a category rehabilitator. By resolving the friction that caused coupons to be devalued, it re-establishes the conditions under which the value exchange becomes favorable to the consumer.

The attitudinal shift observed after exposure provides empirical evidence supporting Qin et al.'s (2025) argument that artificial intelligence (AI) technologies act as catalysts for changes in perceptions, rather than merely adoptable technologies. The results support the concept of the experience turn in retail studies (Becker and Jaakkola, 2020; Hoyer et al., 2022; Stevens et al., 2024).

The effect size (Cohen's $d = 0.43$) can be classified as small to medium based on traditional standards (Cohen, 1988), and this is important from a methodological standpoint since the duration of stimulus exposure was short; respondents observed three concept screens in a single survey and did not have the chance to communicate with the actual live agent. The fact that a single exposure led to any measurable and significant attitudinal change shows how rapid the process of reframing perception can be when the stimulus acts on an already existing pain point. An effect of greater magnitude cannot be expected in such circumstances; therefore, the current effect size is a conservative estimate of the possible influence of live communication.

Another explanation that warrants serious consideration is that the reported change might be partly due to the phenomenon of demand characteristics, that is, the tendency of

respondents to modify their post-stimulus answers in such a way that they correspond to the assumed goals of the research (Orne, 1962; Corneille & Lush, 2023). Such issues become especially acute in the case of a within-subjects design, since, according to Orne (1962, p. 779), repeated measurement after some intervening treatment makes the expected occurrence of change very evident. This problem cannot be avoided entirely, but two aspects of the current experiment help minimize its potential impact. First, participants were not informed that the pre-test and post-test measures would be compared to test the hypotheses. Second, the attitude items presented after the exposure phase were related to the secondary construct, thereby reducing respondents' ability to align their responses with a presumed hypothesis (Strohmetz, 2008). The shift is therefore unlikely to be entirely driven by demand.

5.6 Conclusion

This chapter integrated the results obtained in Chapter 4 in an extended version of the S-O-R model (Mehrabian & Russell, 1974; Jacoby, 2002), drawing on the constructs of TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), and the VAM (Kim et al., 2007) models. Across all four research questions, there is agreement that Indian consumers' willingness to adopt an AI coupon-retrieving application stems not from its functional utility but from attitude, social, and value-based evaluations. That experience with the application affects both its adoption and perceptions of a previously devalued technological tool.

The discussion has concluded that Attitude toward AI is the key determinant of behavioral intention and that experience, rather than demographics, can determine adoption readiness. Social Influence and Attitude toward AI emerged as the two strongest predictors of intention. Notably, the significant difference between the relatively low prominence of social influence as a predictor in qualitative research and its strong effect in quantitative versions could be viewed as meaningful and indicative of how social proofs operate as an unconscious mechanism of reducing perceived risk when interacting with new technology in collectivist cultures (Venkatesh et al., 2003; Hofstede, 2001; Chopdar & Balakrishnan, 2020).

The most notable result came from RQ4, which showed a significant positive change in attitude toward digital coupons due to exposure ($t = -8.805, p < .001$). This finding supports the view that the AI agent not only aids the transaction process but also serves as an intermediary in shaping favorable perceptions of the technology. It is; therefore, a perception accelerator and category rehabilitator that eliminates friction associated with coupons and creates favorable conditions for the value exchange. A single exposure that leads to an observable effect on attitude (Cohen's $d = 0.43$) shows that reframing occurs swiftly when a pain point is targeted, thus positioning the AI agent as a perception accelerator. The category rehabilitator is defined as the property of an AI agent where it repairs a previously negative attitude towards an entire adjacent category, not merely towards a single offer or brand within it. It is, by contrast, an *outcome* construct - it describes the direction, valence, and level of the change. Its empirical signature was the movement from a baseline in which 83% of respondents held unfavorable views of digital coupons to a post-exposure position in which 86.4% reported intention to use the agent, with the perceived-convenience and trust-in-relevance items both rising. This means the agent served as a perceptual intermediary for the entire coupon category, rather than promoting any one voucher.

In light of these findings, one might conclude that the observed effect warrants significant further investigation. Overall, this chapter extended the explanatory reach of the TAM, UTAUT, and VAM frameworks beyond the question of whether a shopper adopts an AI agent. It went on to show that an AI agent's influence could also spill over onto the adjacent category it supports, reshaping how shoppers evaluate digital coupons as a whole rather than only the agent itself.

CHAPTER 6:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

This research seeks to identify the drivers of consumers' use of an artificial intelligence (AI) agent to retrieve digital coupons while shopping in a brick-and-mortar store in India, and to test whether exposure to such an agent leads to a spillover effect on attitudes towards digital coupons in general. A long-standing contradiction inspires the current research in retail marketing: although digital coupons are widely distributed, redemption rates remain low due to retrieval frictions, lack of relevance, and privacy and trust issues. AI agents represent a new tool that can overcome these frictions, yet empirical research on their use in emerging retail markets is limited. This research addresses this gap by extending the Stimulus-Organism-Response framework to integrate constructs from the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and the Value-Based Adoption Model.

Structured around 4 research questions tracing the S-O-R pathway, this research used 8 hypotheses to study the drivers of adoption of AI agents in an in-store retail experience for customers and spillover effects, like perception acceleration, if any, on the tools, processes, or tasks that such agents support, in this case, digital coupons.

The findings substantiate the central thesis: AI adoption in retail in-store experiences in India is driven less by utility but more by attitudinal, social, and value-exchange negotiations. The research findings also establish the ability of AI agents to act as perception accelerators that extend beyond the tool by changing respondents' attitudes towards digital coupons as a whole.

6.2 Implications

The findings carry implications for theory, for retail and marketing practice, for AI product design, and for data-protection policy. Each implication below is drawn from a specific result and weighed against current literature.

6.2.1 Practical Implications for Retailers and Marketers

For retailers, three moves follow from the findings. Because the qualitative theme of just-in-time relevance and the strength of perceived value ($\rho = .662$) both pointed to timing, coupons may be most effective when surfaced at the point of payment rather than retrieved in advance. Because social influence was jointly the strongest predictor of intention ($\beta = 0.281$) - consistent with evidence that social influence drives behavioral intention to adopt AI (Ke, 2025) - campaigns may do better to lead with social proof, namely peer reviews, success stories, and influencer demonstrations, than with feature lists.

And because exposure produced a significant positive shift in attitudes towards digital coupons (mean difference = -0.25 , $t = -8.805$, $p < .001$; H8 supported), brands partnering with an AI coupon agent may gain twice over: more redemptions of their own coupons, and a more favourable perception of digital coupons across the category - a benefit that, by its nature, accrues to every brand in the category, not only the partner.

For marketers, the demographic findings indicate a clear initial audience. Behavioural intention differed significantly by age (Kruskal-Wallis $H = 7.955$, $p = .019$), with the 25-44 cohort highest, and by digital literacy ($H = 15.038$, $p < .001$), with advanced users highest - so digitally confident shoppers aged 25 to 44 may be reached first, and the campaign then widened to less digitally active groups, for whom messaging would need to foreground ease of use, transparency of data handling, and privacy reassurance. Given that social influence was jointly the strongest predictor of intention ($\beta = 0.281$, $t = 4.477$, $p < .05$), campaigns built on functional claims alone may underperform.

6.2.2 Practical Implications for AI Product Designers

For designers, the risk findings, the strongest theme qualitatively and a significant negative predictor quantitatively ($\beta = -0.101$), which echoed the strongest theme in the qualitative interviews, point to a clear set of design requirements: clear signals about how data is handled, fine-grained permission controls, and a clearly limited scope of email access (coupons only, not banking or personal mail). These are not optional design choices but conditions for adoption. With trust and privacy identified as primary mediators of AI

adoption (Riandhi et al ., 2025), trust signals may be most usefully treated as functional features in their own right rather than as peripheral reassurance.

6.2.3 Policy and Regulatory Implications

The centrality of data-privacy concern also carries a policy implication. Perceived risk was the only significant *negative* predictor of behavioral intention ($\beta = -0.101$, $t = -2.960$, $p < .05$) and, in the qualitative data, was the most strongly grounded construct, with concern centered on data exposure - how personal data would be used (45% of participants) and the agent accessing content beyond coupons (35%). Because perceived risk depressed adoption and centered on data exposure, the viability of AI agents that read personal email may depend on alignment with India's evolving data-protection framework, including the Digital Personal Data Protection Act, 2023. The implication is that clear consent, purpose limitation, and transparency operate not only as design choices but as regulatory conditions that may determine whether such agents can be deployed at scale.

6.3 Recommendations for Future Research

Several areas of research may arise from the current findings, all of which relate to this research's limitations.

To begin with, using concept-only stimuli rather than the AI agent itself necessitates a field experiment involving consumers' participation with an AI coupon-retrieval agent. This will help assess the feasibility of bridging the intention-behavior gap in the technology adoption literature by comparing intention with actual adoption.

Secondly, the spillover effect was measured immediately after the exposure, without knowledge of its duration or persistence. Longitudinal designs are needed to determine whether perceptual rehabilitation of digital coupons persists, fades, or strengthens with additional exposure to other similar stimuli.

Thirdly, it needs to be studied why social influence, as a construct, did not emerge strongly qualitatively (weaker influence), yet showed the highest impact quantitatively (strongest effects). This finding warrants further inquiry in future research, whether social influence operates below conscious articulation, thereby adding methodological value to technology adoption research in cultures similar to India, where family opinions and social influence matter.

Fourth, the intriguing finding regarding digital literacy, where the observed pattern, a non-linear dynamic in adoption (differences between the Advanced group and others, yet no differences between the Beginner and Intermediate groups), needs closer examination.

Fifth, the current sample consisted of urban, mostly metropolitan Indian individuals, where 69.3% were identified as belonging to Technology/IT occupations. It would be important to replicate results in the non-metropolitan Indian population and other occupational sectors, as well as other emerging economies such as Southeast Asian, Latin American, and African countries.

Sixth, since the current research focused on a single AI agent (a coupon retrieval agent), it would be interesting to see whether similar effects occur with other AI-agents, and whether spillovers differ across artifacts.

Seventh, Value Perception was operationalized as the ratio of usefulness to risk, rather than as an independent latent variable with its own indicators. This method assumes equal influence of usefulness and risk on the value perception and was investigated separately through correlation analysis. In the future, it might be useful for the researcher to consider value perception as a second-order latent variable and to conduct the analysis using indicators of value perception.

Finally, the research does not reveal whether AI exposure changes how consumers perceive the brand issuing coupons or the corresponding physical store. Future research can explore whether brand equity, store loyalty intentions, and the propensity for word-of-mouth marketing are affected by the spillover effect.

6.4 Research Contribution

The structural model qualifies a core assumption of the Technology Acceptance Model. In TAM, perceived usefulness is the primary determinant of behavioral intention (Davis, 1989); here, however, usefulness was the weakest of the benefit-side predictors ($\beta = 0.123$), while attitude towards AI and social influence were the strongest ($\beta = 0.281$ each). On the other hand, attitudes toward AI tools in general and social influence showed the highest predictive power for behavioral intention ($\beta = 0.281$ for both). This finding suggests that, for AI agents in consumer settings, attitudes towards AI in general and social influence play a more important role than practical benefits alone. This means, in the Indian context, the functional question - will this be useful for this specific task? - arrives only after two prior judgments have been made: What does the shopper think about AI tools in general, and does their social circle endorse the AI tool?

Second, the research extended UTAUT by reframing the role of demographic moderators. Conventional UTAUT views gender, age, and experience as the primary moderating variables of the adoption behavior of any technology. This research, however, showed that fixed socioeconomic markers (gender, income, and education) did not significantly differentiate behavioral intention. Instead, capability-related factors (digital literacy and occupation) did. To some extent, age also played a factor. This means that, in the Indian retail context, what really drives adoption is familiarity-based competence rather than demographic factors. Such a finding challenges the conventional UTAUT moderator set and points toward digital literacy and category-specific exposure in technology as the more important variables in emerging-market AI adoption.

Third, the research empirically validated the Value-Based Adoption Model in a non-price-linked angle in the retail context. VAM has traditionally been applied in pricing-led contexts where value is linked to price. This research operationalized perceived value as the ratio of perceived benefit (Usefulness) to perceived cost (Risk). This research demonstrated that the derived construct yielded the strongest bivariate correlation with the observed behavioral intention (Spearman's $\rho = .662$, $p < .001$). This finding extended VAM beyond its traditional price-based framing into a benefit-risk negotiation, i.e., a value-

exchange negotiation framework. In the context of AI agents, this is more relevant to adoption, where the sacrifice consumers weigh is not financial but rather concerns about personal data exposure and trust issues.

Fourth, and most distinctively, the research extended the Stimulus-Organism-Response framework by adopting Jacoby's (2002) dual-response architecture and demonstrating empirically that an AI stimulus produces both a direct adoption intention (Response 1) and an indirect attitudinal spillover onto the adjacent task domain- in this case, perception accelerator towards digital coupons (Response 2)(Qin et al., 2025). Attitudes towards digital coupons were significantly more positive after exposure than before (mean difference = -0.25, $t = -8.805$, $p < .001$; Cohen's $d = 0.43$), confirming the spillover effect (H8 supported). Together, these showed that AI tools do more than complete a single transaction. They shape how consumers perceive the broader environment surrounding the tools and tasks they perform.

Taken together, these four contributions point in a single direction: the models inherited from organizational, largely Western, and price-based contexts systematically underspecify the drivers of consumer AI adoption in an emerging retail market. Across all four, the center of gravity shifts away from the functional, demographic, and transactional assumptions those models encode - usefulness gives way to attitude and social endorsement, fixed demographics give way to familiarity-based competence, price gives way to a benefit-risk exchange weighed in data and trust, and the single transaction gives way to attitudinal spillover onto adjacent tasks. In the Indian retail context, then, the decision to adopt an AI agent is better understood not as an isolated utility calculation but as an affective, socially anchored, and capability-gated judgment whose effects extend to the underlying tasks or processes it helps.

6.5 Conclusion

This research set out to understand the drivers of adoption for shoppers of an AI agent for retrieving digital coupons during in-store shopping in India, and to establish whether

exposure to such an agent could shift shoppers' attitudes towards the underlying digital coupons as a whole. Both aims were met, and the evidence from the findings supports each.

On the drivers, the structural model explained 73.3% of the variance in behavioral intention ($R^2 = 0.733$), and all five adoption constructs were significant: attitude towards AI and social influence were the strongest ($\beta = 0.281$ each), followed by perceived ease of use ($\beta = 0.182$), perceived usefulness ($\beta = 0.123$), and perceived risk as the sole negative predictor ($\beta = -0.101$). Perceived value, modeled as a benefit–risk ratio, showed the strongest bivariate association with intention (Spearman's $\rho = .662$, $p < .001$). Read together, these results indicate that adoption may be understood more as a value-exchange negotiation in which shoppers weigh usefulness against perceived risk (Kim et al., 2007) than as a judgement of functional utility than - a reading reinforced by current evidence that attitudes around trust and privacy are primary mediators of AI adoption (Riandhi et al., 2025), though it stands against work reporting usefulness as the dominant driver (Ibrahim et al., 2025) and so contributes to an unsettled debate. The demographic findings further qualified the picture: intention differed by capability- digital literacy ($p < .001$) and occupation ($p = .009$) - rather than by fixed markers such as gender, income, or education, consistent with evidence that AI literacy predicts behavioral intention (Ke, 2025).

On perceptual change, the second aim was met: attitudes towards digital coupons were significantly more positive after exposure than before (mean difference = -0.25, $t = -8.805$, $p < .001$; H8 supported), confirming a spillover effect (Qin et al., 2025) within the dual-response architecture proposed by Jacoby (2002). This indicates that the AI agent may operate not only as a transactional enabler but as a perceptual intermediary, easing the friction that had led shoppers to dismiss digital coupons as clutter.

The findings also surfaced gaps that bound these conclusions and set the agenda for further research. Social influence was the strongest quantitative predictor ($\beta = 0.281$) yet the weakest qualitative theme (cited by only 10% of interviewees), a divergence the data could not resolve and which may indicate that social influence operates below conscious articulation in collectivist settings. The effect of digital literacy was non-linear - advanced users differed sharply from others, while beginners and intermediates did not - without a

clear explanation. The spillover effect was measured immediately after exposure, so its durability is unknown; and, because the stimulus was concept-only, the gap between stated intention and actual behavior remains untested. These gaps frame the recommendations that follow.

To sum it up, the research suggests that AI adoption in retail is not an isolated technology decision but a value-exchange negotiation with consequences for how shoppers evaluate the tools and tasks an agent supports. For retailers and platform operators in India and comparable emerging markets, the implication is that AI agents may be most valuable when positioned as perception accelerators that simplify the retail experience, rather than as instruments of efficiency alone. It is this reframing, more than any single tool, that could shape the next phase of retail transformation.

APPENDIX A

QUALITATIVE QUESTIONNAIRE

Interview Guide

Semi-Structured Interview Protocol for Qualitative Phase

Study Title: Driving Customer Experience Through AI Agents for Digital Coupon Retrieval During In-Store Shopping in India

Interview Duration: 30-45 minutes

Mode of Conduct: Online (Google Meet)

Recording Tool: Fireflies.ai (with prior informed consent)

Consent

Thank you for agreeing to participate in this study. This interview is part of a doctoral research project exploring how consumers perceive AI-powered tools and digital coupons in the context of in-store shopping. There are no right or wrong answers - I am interested in your honest opinions and experiences. The interview will last approximately 30-45 minutes and will be audio-recorded for transcription purposes. Your responses will remain anonymous, and you may withdraw at any stage without consequence. All data will be used solely for research purposes and stored securely.

Do you consent to proceed and to have this session recorded?

☐ Yes ☐ No

Part A: Demographic and Behavioral Screening

A1. Age Group What is your age group?

- 18-24 years
- 25-34 years
- 35-50 years

- 50+ years

A2. Gender What is your gender?

- Male
- Female
- Prefer not to say

A3. Income Level (Per Annum in INR) What is your approximate annual household income?

- Less than ₹5 lakhs
- ₹5-25 lakhs
- ₹25-40 lakhs
- More than ₹40 lakhs

A4. Education Level What is your highest level of education?

- Less than graduate
- Graduate (Bachelor's degree)
- Postgraduate (Master's degree or higher)
- Others (Please specify) _____

A5. City/Tier Classification Which category best describes the city you live in?

- Metro City (Delhi, Mumbai, Bangalore, Chennai, Kolkata, Hyderabad)
- Tier 1 City (Pune, Ahmedabad, Jaipur, Lucknow, etc.)
- Tier 2/3 City (Smaller cities and towns)
- Rural Area

A6. Shopping Frequency (Offline/In-Store Shopping) How often do you shop in physical stores (excluding online shopping)?

- Daily
- A few times a week
- Once a week
- A few times a month
- Rarely

A7. Digital Coupon/Voucher Usage Do you receive discount coupons or promotional vouchers via email?

- Yes, frequently
- Yes, occasionally
- No, but I have in the past
- No, I don't receive such coupons

A8. Experience with Digital Transactions and AI Tools How comfortable are you with using AI-powered tools (e.g., chatbots, recommendation systems) for shopping?

- Very comfortable - I use them regularly
 - Somewhat comfortable - I have used them a few times
 - Neutral - I don't use them much but have no strong opinions
 - Uncomfortable - I don't trust AI tools for shopping
 - Not familiar with AI tools
-

Part B: Section 1 - Perception of AI Tools

B1. What is your overall perception of AI-powered tools (e.g., voice assistants, recommendation systems, AI chatbots)?

B2. How frequently do you use AI-powered tools in daily life?

B3. What drives or hinders your usage?

Part C: Section 2 - Perception of Digital Coupons/Vouchers

C1. What is your overall perception of digital coupons that you receive in emails?

C2. How frequently do you redeem coupons?

C3. Where do you typically redeem coupons more - online or offline? Why?

C4. Probe - What drives or hinders your usage?

C5. Probe - What could help you redeem your coupons more?

Part D: Section 3 - Perception of Risk in AI Agents

D1. What concerns, if any, do you have about using AI-powered tools?

D2. Can you describe a situation where you felt uncomfortable or hesitant about using an AI-driven tool?

[STIMULUS EXPOSURE]

The interviewer introduces the concept of the AI Agent for coupon retrieval and redemption using the following description and three Standardized mock-up screens.

Concept Description (read aloud to participant):

Imagine a smart assistant that helps you find and use the best available digital coupons while shopping in-store. This AI-powered coupon agent automatically scans your email for relevant discount vouchers, applies the most suitable ones, and suggests the best deals in real time.

For example, if you are shopping at a clothing store, the AI agent can check your email for brand-specific discount coupons, recommend the best offer available, and even remind you to redeem it before checkout. It ensures you never miss a savings opportunity and simplifies the process of using digital coupons effortlessly.

Mock-up Screens Shown

Concept Screen 1



The agent is connected to the user's email account provided at checkout at various stores (online/offline). When the user logs in to the agent through a user interface as illustrated, he/she can input what he/she is shopping for. In this example, the user has selected 'Apparel.'

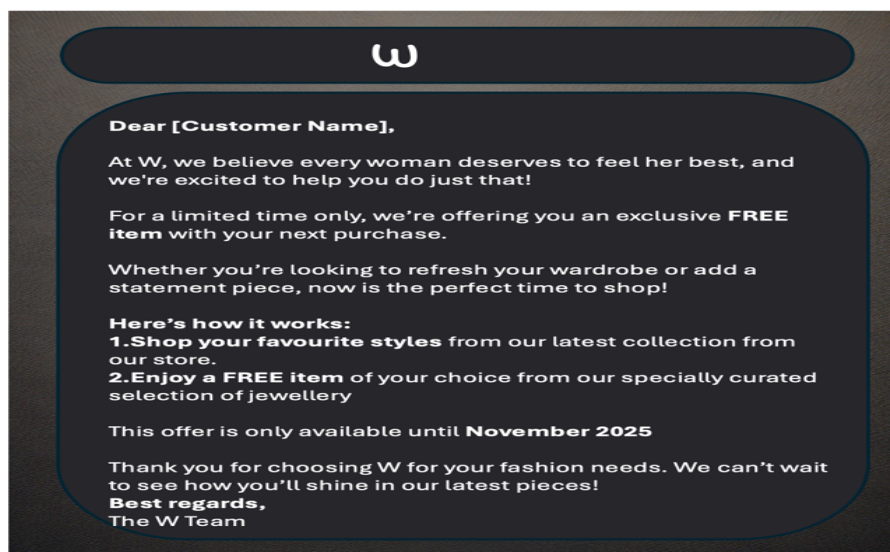
Concept Screen 2



Sender	Subject line
W	Double the Joy: Free Item with Your Purchase!
Reliance Trends	Hurry! Mega Discounts on Electronics Await!
Zara	Save Big: Up to 70% Off on Bestsellers – For You!
Shoppers Stop	Here's Your Exclusive Coupon – Don't Miss Out!
Kalyan Sarees	Your Personalized Discount Voucher Is Here!

The agent scans the user's emails for relevant digital messages or offers and loads them in an easy-to-read and retrieve interface. In this example, the user can see at least five offers received recently.

Concept Screen 3



The user can click on the offer, make their purchases (impulse/planned), and redeem the offers easily at checkout at the stores.

Part E: Section 4 - Future Intentions and Recommendations (Post-Stimulus)

E1. Based on this concept, would you consider using an AI agent to find and redeem coupons in-store in the future? Why do you say that?

E2. What risks or concerns would you have with such an agent?

E3. What improvements or safeguards would make you more comfortable using AI-powered shopping tools?

Closing

Thank you for your time and your candid responses. Your insights are invaluable to this research. If you have any further thoughts after this session, please feel free to share them via email. All data from this interview will remain anonymous and confidential

APPENDIX B

QUANTITATIVE QUESTIONNAIRE

Structured Online Survey Administered via SurveyMonkey

Study Title: Driving Customer Experience Through AI Agents for Digital Coupon Retrieval During In-Store Shopping in India

SECTION 1: DEMOGRAPHICS AND SCREENING

Q1. What age group do you belong to?

- 18-24 years
- 25-44 years
- 45+ years

Q2. What is your gender?

- Male
- Female

Q3. What is your approximate ANNUAL household income?

- Less than ₹5 lakhs
- ₹5-25 lakhs
- ₹25-40 lakhs
- More than ₹40 lakhs

Q4. What is your highest level of education?

- Less than graduate
- Graduate (Bachelor's degree)
- Postgraduate (Master's degree or higher)
- Others

Q5. How would you rate your digital literacy / Comfort in using digital tools & technology like apps on your phone?

- Beginner
- Intermediate
- Advanced

Q6. What field of work are you in / occupation?

- Technology / IT
- Others

Q7. How often do you shop in physical stores or traditional stores (excluding online shopping)?

- Daily
- A few times a week
- Once a week
- A few times a month
- Rarely

Q8. Do you receive discount coupons or promotional vouchers via emails from brands as part of their marketing/promotions emails?

- Yes, frequently
- Yes, occasionally
- No, but I have in the past
- No, I have never received such coupons

Q9. How frequently do you REDEEM digital coupons?

- Every time I shop
- Often
- Occasionally
- Rarely
- Never

Q10. What are the main reasons you rarely or never use digital coupons? (Select all that apply)

- Forget to use digital coupons
- Process of redeeming digital coupons cumbersome
- Consider them spam emails
- Irrelevant promotional offers
- Other (please specify)
- None of the above

Q11. Do you use AI tools in your day-to-day tasks?

- Yes
- No

Q12. What are the main reasons you rarely or never use AI tools?

- Privacy concerns
- Fear of AI errors
- Lack of trust in AI / AI lacks transparency
- AI can be biased towards promoting shopping
- Prefer human interaction over AI bots
- Other (please specify)
- None of the above

SECTION 2: PERCEPTION AND USAGE OF AI TOOLS

Please indicate your level of agreement with each statement using the scale below:

Scale: Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree

Code	Statement
Per1	I feel comfortable using AI-powered technologies in my daily life.
Per2	I enjoy experimenting with new AI-powered tools and applications.
Per3	I feel confident in my ability to interact with AI-driven systems.
Per4	AI technologies enhance my daily experiences and activities.
Per5	AI-powered tools help improve efficiency and save time.
Per6	I trust AI agents to provide accurate and reliable information.
Per7	I feel comfortable sharing personal information with AI-powered services.
Per8	I trust AI tools in my professional work only.

Q13. How would you DESCRIBE YOUR PERCEPTION of AI tools? (Open-ended)

Q14. ATTENTION CHECK: For quality control, please select which of the following activities would not typically require physical movement?

- Bowling
- Cycling
- Reading Instructions
- Walking

SECTION 3: PERCEPTION AND USAGE OF DIGITAL COUPONS/VOUCHERS RECEIVED THROUGH EMAIL

Please indicate your level of agreement with each statement using the scale below:

Scale: Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree

Code	Statement
Attd1	I frequently use digital coupons when shopping.
Attd2	Digital coupons make my shopping experience more convenient.
Attd3	I actively search for digital coupons before making a purchase.
Attd4	Digital coupons influence where I choose to shop.
Attd5	I trust digital coupon emails and find them relevant, rather than spam.
Attd6	I prefer receiving fewer but more personalized digital coupon emails.
Attd7	I am more likely to buy a product if I receive a digital coupon for it in my email.

Q15. How would you describe your attitude towards Digital Coupons or vouchers that you receive in emails as marketing messages? (Open-ended)

SECTION 4: STIMULUS EXPOSURE - INTRODUCTION TO AI AGENT CONCEPT

The following concept description and three mock-up screens are presented to all respondents:

Concept Description:

Imagine having a personal shopping assistant that helps you save money effortlessly. This AI-powered tool or an AI Agent is designed to find and apply the best digital coupons from your email inbox, making it easier to enjoy discounts when shopping in-store.

Here is how it works:

During a physical shopping experience in a store, when you open the AI agent on your phone:

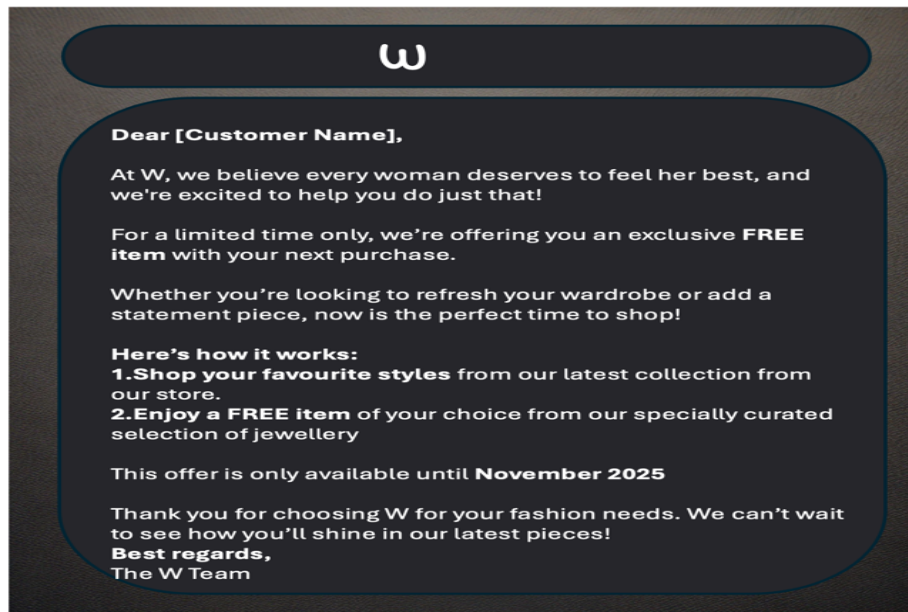
Image 1: The AI agent asks what you are shopping for.



Image 2: The AI agent scans your connected email account for relevant discount vouchers, selects the most suitable ones, and shows you the best deals in real-time. For instance, if you're shopping at a clothing store, it can identify brand-specific coupons and recommend the best available offers, maybe at a competitor!

Here are your email vouchers!	
Sender	Subject line
W	Double the Joy: Free Item with Your Purchase!
Reliance Trends	Hurry! Mega Discounts on Electronics Await!
Zara	Save Big: Up to 70% Off on Bestsellers – For You!
Shoppers Stop	Here's Your Exclusive Coupon – Don't Miss Out!
Kalyan Sarees	Your Personalized Discount Voucher Is Here!

Image 3: You can click on the voucher line and see the actual coupon so that you can redeem them easily at the physical store checkout.



This way, you'll never miss a chance to save and can enjoy a seamless shopping experience.

We're interested in hearing your thoughts and experiences about using such an AI-powered tool. Your feedback will help us understand how useful and trustworthy this technology can be for shoppers like you.

SECTION 5: USEFULNESS OF AI AGENT FOR COUPON REDEMPTION

Please indicate your level of agreement with each statement using the scale below:

Scale: Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree

Code	Statement
Benf1	The AI Agent improves the efficiency of retrieving digital coupons.
Benf2	The AI Agent helps me find better discounts and promotions compared to my usual methods.
Benf3	Using the AI Agent can increase my total savings when shopping.
Benf4	The AI Agent helps me discover personalized coupon offers that I wouldn't normally find.
Benf5	The AI Agent improves my overall shopping experience by offering valuable deals.
Benf6	The AI Agent helps me plan my shopping by suggesting relevant discounts in advance.
Benf7	I am more likely to shop at a store that offers AI-driven coupon recommendations.

Q16. How useful and beneficial do you perceive the AI agent to help you redeem coupons during shopping? (Open-ended)

SECTION 6: EASE AND INTUITIVENESS OF AI AGENT

Please indicate your level of agreement with each statement using the scale below:

Scale: Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree

Code	Statement
Ease1	The AI agent looks easy to navigate and interact with.
Ease2	The AI agent appears to be intuitive and user-friendly for retrieving digital coupons.

Ease3	It looks like I can quickly learn how to use the AI agent without assistance.
Ease4	The AI agent will reduce the time I spend searching for discounts in my emails.
Ease5	I feel comfortable using the AI agent even if I am not tech-savvy.
Ease6	The AI agent will make my shopping experience easier.
Ease7	The AI agent provides clear instructions and guidance for first-time users.

Q17. How easy and intuitive do you perceive the AI agent to help you redeem coupons during shopping? (*Open-ended*)

SECTION 7: SOCIAL INFLUENCE ON AI AGENT USAGE

Please indicate your level of agreement with each statement using the scale below:

Scale: Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree

Code	Statement
SID1	I would use if people whose opinions I value (friends, family, colleagues) would approve of me using the AI Agent.
SID2	I am more likely to use the AI Agent if my friends or family members are using it.
SID3	If other shoppers in the store are using the AI Agent, I would be more inclined to try it.
SID4	Positive online reviews or ratings would increase my likelihood of using the AI Agent.
SID5	Retailer promotions (e.g., staff recommendations, ads) would encourage me to use the AI Agent.
SID6	Seeing social media influencers or well-known personalities endorse the AI Agent would make me more likely to use it.
SID7	Hearing success stories from other users (e.g., how much they saved) would make me more interested in trying the AI Agent.

SID8 If the AI Agent becomes widely adopted, I would feel more comfortable using it.

Q18. How do you think social factors influence your decision to use an AI-powered Agent to help you redeem coupons during shopping? (Open-ended)

SECTION 8: RISK PERCEPTION OF AI AGENT

Please indicate your level of agreement with each statement using the scale below:

Scale: Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree

Code	Statement
Risk1	I am concerned about how my personal data will be used when using the AI Agent.
Risk2	I worry that the AI Agent might collect too much personal information.
Risk3	I am hesitant to use the AI Agent because of potential security risks (e.g., hacking, data leaks).
Risk4	I fear that using the AI Agent might lead to unwanted marketing messages or spam.
Risk5	I worry that relying on the AI Agent for discounts might make me miss out on better deals elsewhere.
Risk6	I am uncomfortable with the possibility that the AI agent may access other information on my phone.
Risk7	I am concerned that the AI Agent might not always handle my personal data accurately or securely.

Q19. How do you think concerns regarding privacy, security, and trust influence your decision to use an AI-powered Agent to help you redeem coupons during shopping? (Open-ended)

SECTION 9: ATTITUDE TOWARDS DIGITAL COUPONS AFTER AI AGENT EXPOSURE

Now that you have seen the AI agent and how it can help you, please indicate your level of agreement with each statement using the scale below:

Scale: Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree

Code	Statement
AttAft1	I will frequently use digital coupons when shopping.
AttAft2	Digital coupons will make my shopping experience more convenient.
AttAft3	I will actively search for digital coupons before making a purchase.
AttAft4	Digital coupons will influence where I choose to shop.
AttAft5	I trust digital coupon emails more and will find them relevant, rather than perceiving them as spam.
AttAft6	I would still prefer receiving fewer but more personalized digital coupon emails.
AttAft7	I am now more likely to buy a product if I receive a digital coupon for it in my email.

SECTION 10: BEHAVIORAL INTENTION

Q20. Now that you have seen the AI agent and how it can help you, Please indicate your level of agreement with each statement using the scale below:

(This is repeated as the header for Section 9 above in the PDF - the actual behavioral intention item is Q21 below.)

Q21. Having seen the AI Agent, how likely are you to use the above introduced AI agent for your shopping experiences?

- Not at all likely
- - Unlikely
- - Neutral
- - Likely
- - Very likely

APPENDIX C

KEY SEM AND T-TEST RESULTS

Table C1

Measurement Model - Standardized Factor Loadings, Composite Reliability, and Average Variance Extracted

Sr.	Construct	Item	Standardized Loading	Composite Reliability (CR)	AVE
1	Attitude towards AI Tools	Per1	0.951	0.959	0.854
		Per3	0.932		
		Per4	0.924		
		Per6	0.889		
2	Usefulness of AI Agent	Benf3	0.937	0.941	0.8
		Benf4	0.887		
		Benf6	0.891		
		Benf7	0.861		
3	Ease and Intuitiveness	Ease3	0.889	0.93	0.817
		Ease5	0.885		
		Ease7	0.936		
4	Social Influence	SID5	0.881	0.932	0.821
		SID6	0.911		
		SID7	0.925		
5	Risk Perception	Risk2	0.854	0.946	0.815
		Risk4	0.908		
		Risk6	0.935		
		Risk7	0.913		

Note: All loadings exceed the 0.70 threshold. $CR \geq 0.70$ and $AVE \geq 0.50$ confirmed for all constructs.

Table C2

Cronbach's Alpha by Construct

Construct	No. of Items	Cronbach's α
Attitude towards AI Tools	4	0.960
Usefulness of AI Agent for Coupon Redemption	4	0.941
Ease and Intuitiveness of AI Agent	3	0.930
Social Influence on AI Agent Usage	3	0.933
Risk Perception of AI Tool	4	0.946

Note: All values exceed the recommended threshold of 0.70 (Hajjar, 2018; Olaniyi, 2019). Output generated from IBM SPSS Statistics

Table C3

Discriminant Validity Matrix (Fornell-Larcker Criterion)

	Attitude	Usefulness	Ease	Risk	Social
Attitude towards AI Tools	0.924				
Usefulness of AI Agent	0.781	0.894			
Ease and Intuitiveness	0.757	0.676	0.904		
Risk Perception	-0.560	-0.532	-0.441	0.903	
Social Influence	0.835	0.785	0.733	-0.561	0.906

Note: Diagonal values (bold) represent $\sqrt{AVE}$ for each construct. Off-diagonal values are inter-construct correlations. Discriminant validity is established when diagonal values exceed all corresponding off-diagonal values in the same row and column (Anderson and Gerbing, 1988). Output generated from IBM SPSS AMOS

Table C4

Model Fit Indices - Measurement Model

Fit Index	Recommended Threshold	Obtained Value	Source
CMIN/df	≤ 2	1.785	Ullman (2006); Schumacker and Lomax (2004)
GFI	> 0.90	0.944	Hair et al. (2010)
CFI	> 0.90	0.988	Bentler (1990)
TLI	> 0.90	0.986	Bentler (1990)
SRMR	< 0.08	0.021	Hu and Bentler (1998)
RMSEA	< 0.06	0.044	Hu and Bentler (1998)

*Note: All indices meet or exceed recommended thresholds, confirming adequate model fit.
Output generated from IBM SPSS AMOS*

Table C5

Structural Model - Path Coefficients (H1, H3-H6)

Hypothesized Path	β (Standardized)	t-value	p-value	Decision
Attitude towards AI Tools $\rightarrow$ BI (H1)	0.281	4.511	$< .05$	Reject H_0
Usefulness $\rightarrow$ BI (H3)	0.123	2.407	$< .05$	Reject H_0
Ease of Use $\rightarrow$ BI (H4)	0.182	3.922	$< .05$	Reject H_0
Social Influence $\rightarrow$ BI (H5)	0.281	4.477	$< .05$	Reject H_0
Risk Perception $\rightarrow$ BI (H6)	-0.101	-2.960	$< .05$	Reject H_0

*Note: $R^2 = 0.733$. Dependent variable: Behavioral Intention to use the AI agent. $N = 410$.
Output generated from IBM SPSS AMOS*

Table C6

Correlation Analysis - Perceived Value and Behavioral Intention (H7)

Test Applied	Correlation Coefficient	Sig. Value
Pearson Correlation	.511	< .001
Spearman's rho	.662	< .001

Note: Perceived Value operationalized as the ratio of Perceived Benefit (Usefulness) to Perceived Cost (Risk). Both coefficients significant at the 0.001 level. Output generated from IBM SPSS Statistics

Table C7

Paired-Sample t-Test - Attitude Toward Digital Coupons Pre vs. Post Exposure (H8)

Pair	Mean Difference	SD	SE Mean	95% CI Lower	95% CI Upper	t	df	Sig. (2-tailed)
Pre - Post	-0.25	0.576	0.028	-0.306	-0.195	-8.805	409	< .001

Note: Difference calculated as Mean Attitude Before - Mean Attitude After. Negative difference indicates improvement in attitude post-exposure. Output generated from IBM SPSS Statistics

Cohen's $d = \text{Mean Difference} \div \text{SD of difference scores} = 0.25 \div 0.576 = 0.434 \rightarrow$ reported as 0.43

Cohen's $d = 0.43$ (small-to-medium effect).

Table C8

Pre- and Post-Exposure Measurement Properties - Attitude Toward Digital Coupons

Time Point	Factor Loading Range	Composite Reliability	Cronbach's α	AVE
Before Exposure	0.736 - 0.830	0.907	0.906	0.619
After Exposure	0.682 - 0.806	0.887	0.886	0.567

Note: All values exceed minimum threshold criteria ($CR \geq 0.70$, $\alpha \geq 0.70$, $AVE \geq 0.50$), confirming reliable and valid measurement at both time points. Output generated from IBM SPSS AMOS

Table C9

Hypothesis Testing Summary for Demographic Variables (H2)

Variable	Test	Test Statistic	p-value	Decision
Gender	Mann-Whitney U	20,104.000	.747	Fail to Reject H ₀
Occupation	Mann-Whitney U	15,153.000	.009	Reject H ₀
Age	Kruskal-Wallis H	7.955	.019	Reject H ₀
Annual Income	Kruskal-Wallis H	2.819	.420	Fail to Reject H ₀
Education	Kruskal-Wallis H	3.334	.343	Fail to Reject H ₀
Digital Literacy	Kruskal-Wallis H	15.038	< .001	Reject H ₀

Note: Non-parametric tests applied following normality violations (Kolmogorov-Smirnov and Shapiro-Wilk $p < .05$ across all categories). Output generated from IBM SPSS Statistics

Table C10

Consolidated Hypothesis Testing Results

H	Hypothesis Statement	Supported?	Key Statistic
H1	Attitude toward AI → BI	Yes	$\beta = 0.281, p < .05$
H2	Demographics → BI	Yes for 3	3 of 6 significant (Occupation $p = .009$; Age $p = .019$; Digital Literacy $p < .001$)
H3	Perceived Usefulness → BI	Yes	$\beta = 0.123, p < .05$
H4	Perceived Ease of Use → BI	Yes	$\beta = 0.182, p < .05$
H5	Social Influence → BI	Yes	$\beta = 0.281, p < .05$
H6	Perceived Risk → BI	Yes	$\beta = -0.101, p < .05$
H7	Perceived Value → BI	Yes	$\rho = .662, p < .001$
H8	AI exposure → Attitude shift	Yes	$t = -8.805, p < .001, d = 0.43$

Note: $R^2 = 0.733$ for the structural model. $N = 410$. All statistics extracted from SPSS v26 and AMOS v21 outputs.

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