International Journal of Education, Business and Economics Research (IJEBER)

ISSN: 2583-3006

Vol. 4, Issue.6, November-December 2024, pp 33-59

To cite this article: Canh Duong NGUYEN (2024). The Impact of AI Adoption on Consumer Purchase Intention and Marketing Effectiveness in Vietnam's Online Retail Industry. International Journal of Education, Business and Economics Research (IJEBER) 4 (6): 33-59

THE IMPACT OF AI ADOPTION ON CONSUMER PURCHASE INTENTION AND MARKETING EFFECTIVENESS IN VIETNAM'S ONLINE RETAIL INDUSTRY

Canh Duong NGUYEN

British Vietnamese International School Hanoi, Hanoi, Vietnam

https://doi.org/10.59822/IJEBER.2024.4602

ABSTRACT

This study investigates the factors influencing consumer purchase intentions in AI-driven online retail environments, integrating elements from technology acceptance models, trust theories, and cultural dimensions. A mixed-method approach was employed, combining structural equation modeling (SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA) to analyze data collected from 427 online shoppers. The results reveal significant positive effects of perceived usefulness, perceived ease of use, trust, social influence, and AI capability perception on consumer purchase intention, with perceived risk playing a mediating role. Trust emerged as a necessary condition for high purchase intention in the fsQCA analysis. Cultural dimensions of uncertainty avoidance and power distance were found to moderate several relationships in the model, highlighting the importance of cultural context in technology adoption. The study contributes to the literature by extending existing models to incorporate AI-specific factors and cultural dimensions in online retail, providing empirical evidence for the dual role of key factors in influencing purchase intentions and reducing perceived risk, and offering a nuanced understanding of the complex pathways leading to high consumer purchase intention through fsQCA. These findings have important implications for practitioners in tailoring AI-driven retail strategies across different cultural contexts and emphasize the critical role of trust-building in fostering consumer acceptance of AI technologies in online retail environments.

KEYWORDS:- AI-driven retail; consumer purchase intention; technology acceptance; cultural dimensions; fuzzy-set qualitative comparative analysis.

1. INTRODUCTION

The rapid proliferation of artificial intelligence (AI) technologies has ushered in a new era of digital transformation across various industries, with the retail sector at the forefront of this revolution

(Davenport et al., 2020). As AI continues to reshape business landscapes globally, its impact on consumer behaviour and marketing strategies has become a subject of intense scholarly interest and practical significance (Huang and Rust, 2021). The online retail industry, in particular, has witnessed a surge in AI adoption, leveraging advanced algorithms and machine learning techniques to enhance customer experiences, streamline operations, and drive marketing effectiveness (Grewal et al., 2020).

While the potential of AI in retail has been widely recognized, there remains a critical gap in our understanding of how AI adoption influences consumer purchase intention and marketing effectiveness, particularly in emerging markets (Kumar et al., 2019). This research aims to address this gap by examining the impact of AI adoption in Vietnam's burgeoning online retail industry, a context that offers unique insights into the interplay between technological advancement and consumer behaviour in a rapidly developing economy.

The theoretical contribution of this study is multifaceted. Firstly, it extends the technology acceptance model (TAM) by incorporating AI-specific constructs, thereby enhancing our understanding of consumer attitudes towards AI-driven retail innovations (Venkatesh and Davis, 2000). Secondly, it bridges the fields of marketing, consumer psychology, and information systems by exploring how AI-enabled personalization and predictive analytics influence consumer decision-making processes (Wedel and Kannan, 2016). Thirdly, it contributes to the growing body of literature on omnichannel retailing by examining how AI integration affects the synergy between online and offline retail channels (Verhoef et al., 2015).

The necessity of this research is underscored by the transformative potential of AI in reshaping retail landscapes and consumer experiences globally. As businesses increasingly invest in AI technologies, there is an urgent need to understand the implications of these investments on consumer behaviour and marketing outcomes (Davenport and Ronanki, 2018). Moreover, as AI adoption accelerates, it becomes imperative to examine its impact across diverse cultural and economic contexts to develop a more nuanced and globally applicable understanding of AI's role in retail (Mou and Benyoucef, 2021).

This study's novelty lies in its comprehensive examination of AI's impact on both consumer purchase intention and marketing effectiveness within a single framework. By focusing on Vietnam's online retail industry, it offers fresh insights into the dynamics of AI adoption in an emerging market context, where digital transformation is rapidly reshaping consumer expectations and business practices (Nguyen et al., 2019). Furthermore, this research employs a mixed-methods approach, combining quantitative analysis of consumer survey data with qualitative insights from industry experts, providing a holistic view of AI's impact on the retail ecosystem.

The findings of this study hold significant implications for both theory and practice. From a theoretical perspective, it advances our understanding of technology adoption in retail settings, consumer behaviour in AI-driven environments, and the role of cultural factors in shaping attitudes towards AI. Practically, it offers valuable insights for retailers, marketers, and policymakers navigating the complexities of AI implementation in emerging markets, helping to inform strategies for enhancing consumer engagement and marketing effectiveness in an increasingly AI-driven retail landscape.

In summary, this research addresses a critical gap in our understanding of AI's impact on consumer behaviour and marketing effectiveness in the context of online retail. By focusing on Vietnam's rapidly evolving e-commerce sector, it offers a timely and relevant contribution to the global discourse on AI adoption in retail, with implications that extend far beyond its specific geographical context.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1. Theoretical Foundations

2.1.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis (1989), has been widely used to explain and predict user acceptance of new technologies. TAM posits that two primary factors influence an individual's intention to use a new technology: perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness refers to the degree to which a person believes that using a particular system would enhance their job performance, while perceived ease of use is the degree to which a person believes that using a particular system would be free of effort (Davis, 1989).

In the context of AI adoption in online retail, TAM provides a valuable framework for understanding how consumers' perceptions of AI technologies' usefulness and ease of use may influence their intention to engage with AI-powered retail platforms. Empirical studies have demonstrated the model's applicability in various e-commerce contexts. For instance, Pavlou (2003) extended TAM to include trust and perceived risk in online shopping environments, finding that these factors significantly influenced consumers' intention to transact online. Similarly, Ha and Stoel (2009) applied TAM to examine consumer acceptance of e-shopping, confirming the model's validity in predicting online shopping behaviour.

2.1.2. Unified Theory of Acceptance and Use of Technology (UTAUT)

Building upon TAM and other acceptance models, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT). This comprehensive model integrates eight prominent theories of technology acceptance, including TAM, and identifies four key constructs that influence behavioural intention and use behaviour: performance expectancy, effort expectancy, social influence, and facilitating conditions.

UTAUT offers a more nuanced understanding of technology adoption by considering additional factors such as social influence and facilitating conditions, which are particularly relevant in the context of AI adoption in retail. The model has been empirically validated in various technology adoption scenarios. For example, Zhou et al. (2010) applied UTAUT to investigate mobile banking adoption in China, demonstrating the model's applicability in emerging market contexts. In the realm of e-commerce, Slade et al. (2015) extended UTAUT to examine mobile payment adoption, highlighting the model's flexibility in adapting to specific technological innovations.

2.1.3. Innovation Diffusion Theory (IDT)

Rogers' (2003) Innovation Diffusion Theory (IDT) provides a complementary perspective to TAM and UTAUT by focusing on how innovations spread through social systems over time. IDT identifies five key attributes of innovations that influence their rate of adoption: relative advantage, compatibility, complexity, trialability, and observability. These attributes offer valuable insights into the factors that may facilitate or hinder the adoption of AI technologies in online retail.

IDT has been widely applied in technology adoption research, including studies related to e-commerce and online retail. For instance, Al-Jabri and Sohail (2012) used IDT to investigate mobile banking adoption, finding that relative advantage, compatibility, and observability positively influenced adoption. In the context of e-commerce, Eastin (2002) applied IDT to examine the adoption of four e-commerce activities, demonstrating the theory's relevance in understanding online consumer behaviour.

The integration of these theoretical foundations – TAM, UTAUT, and IDT – provides a robust framework for examining AI adoption in Vietnam's online retail industry. By synthesising these models, we can develop a comprehensive understanding of the factors influencing consumer acceptance of AI technologies, their intention to use AI-powered retail platforms, and the subsequent impact on marketing effectiveness. This integrated approach allows us to account for technological, individual, and social factors that may influence AI adoption and its consequences in the rapidly evolving landscape of online retail.

2.2. Artificial Intelligence in Online Retail

Artificial Intelligence (AI) has emerged as a transformative force in the online retail industry, revolutionising the way businesses interact with consumers and manage their operations. The integration of AI technologies in e-commerce platforms has led to significant advancements in personalisation, customer service, and operational efficiency, thereby reshaping the retail landscape (Shankar, 2018).One of the primary applications of AI in online retail is in the realm of personalisation. AI algorithms can analyse vast amounts of consumer data, including browsing history, purchase patterns, and demographic information, to deliver tailored product recommendations and personalised shopping experiences. This level of customisation has been shown to significantly enhance customer engagement and increase conversion rates. For instance, Aguirre et al. (2015) found that personalised marketing strategies can lead to higher click-through rates and improved customer loyalty, although they also highlighted the importance of balancing personalisation with privacy concerns.

AI-powered chatbots and virtual assistants have also become increasingly prevalent in online retail, offering 24/7 customer support and enhancing the overall shopping experience. These AI-driven tools can handle a wide range of customer queries, from product information to order tracking, thereby improving response times and customer satisfaction. Xu et al. (2017) demonstrated that the use of chatbots in e-commerce can lead to increased perceived usefulness and ease of use, two key factors in technology acceptance models. Furthermore, AI has proven invaluable in predictive analytics and demand forecasting for online retailers. By analysing historical data and identifying patterns, AI algorithms can predict future trends and consumer behaviour, enabling retailers to optimise their inventory management and pricing strategies. Chong et al. (2017) highlighted the effectiveness of AI-based predictive analytics in improving supply chain management and reducing operational costs in the e-commerce sector.

The implementation of AI in online retail has also led to advancements in visual search and image recognition technologies. These innovations allow consumers to search for products using images rather than text, enhancing the user experience and potentially increasing sales. A study by Liébana-Cabanillas et al. (2017) found that visual search capabilities in e-commerce platforms can significantly influence consumers' intention to use and recommend the technology. Moreover, AI has facilitated the development of dynamic pricing strategies in online retail. By continuously analysing market conditions, competitor pricing, and consumer behaviour, AI algorithms can adjust prices in real-time to maximise revenue and maintain competitiveness. However, Gautier et al. (2016) cautioned that while dynamic pricing can lead to increased profits, it must be implemented carefully to avoid negative consumer perceptions. The adoption of AI in online retail has also raised important ethical considerations, particularly concerning data privacy and the potential for algorithmic bias. Retailers must navigate these challenges carefully to maintain consumer trust and ensure fair treatment of all customers (Martin and Murphy, 2017).

In the context of emerging markets like Vietnam, the adoption of AI in online retail presents both opportunities and challenges. While AI technologies offer the potential for rapid advancement and improved competitiveness, issues such as technological infrastructure, consumer readiness, and regulatory frameworks must be addressed (Kshetri, 2017).

2.3. Consumer Purchase Intention in Online Retail

2.3.1. Factors Influencing Online Purchase Intention

Numerous studies have investigated the factors that influence consumer purchase intention in online retail environments. Drawing from the theoretical foundations discussed earlier, several key factors emerge as significant predictors of online purchase intention.

Perceived usefulness and perceived ease of use, central constructs of the Technology Acceptance Model (TAM), have been consistently identified as influential factors in online purchase intention. Chen et al. (2002) found that perceived usefulness significantly affects consumers' attitude towards online shopping, which in turn influences their purchase intention. Similarly, Gefen et al. (2003) demonstrated that both perceived usefulness and perceived ease of use positively impact trust and purchase intention in online environments. Trust plays a crucial role in online purchase intention, given the inherent uncertainties of e-commerce transactions. Kim et al. (2008) developed a trust-based consumer decision-making model in e-commerce, highlighting the importance of trust in mitigating perceived risk and encouraging online purchases. Their study found that consumer trust is influenced by factors such as reputation, privacy concerns, security concerns, and information quality. Website quality and design have also been identified as significant factors affecting online purchase intention. Chang and Chen (2008) examined the impact of online store quality on consumer purchase intention, finding that both website quality and customer satisfaction positively influence purchase intention. They emphasised the importance of interface quality, information quality, and service quality in shaping consumer perceptions and behaviour. Social influence, a key construct in the Unified Theory of Acceptance and Use of Technology (UTAUT), has been shown to affect online purchase intention. Venkatesh et al. (2012) found that social influence significantly impacts behavioural intention in consumer technology acceptance contexts. In the realm of online shopping, social influence can manifest through factors such as online reviews, social media recommendations, and peer influence. Product characteristics and price also play important roles in shaping online purchase intention. Jiang et al. (2008) investigated the effects of price, brand, and store information on product evaluations and purchase intention in online settings. They found that these factors significantly influence consumers' perceived value and subsequent purchase intentions.

2.3.2. Impact of AI on Consumer Decision-Making Process

The integration of AI technologies in online retail has introduced new dynamics to the consumer decision-making process, potentially influencing purchase intentions in novel ways.

AI-powered recommendation systems have become ubiquitous in e-commerce platforms, offering personalised product suggestions based on consumer behaviour and preferences. Xiao and Benbasat (2007) conducted a comprehensive review of recommendation agent use in e-commerce, finding that these systems can significantly influence consumer decision-making by reducing information overload and improving decision quality. However, they also noted that the effectiveness of recommendation systems depends on factors such as user trust and the perceived accuracy of recommendations. Chatbots and virtual assistants, enabled by AI, have transformed customer service in online retail. These technologies can provide instant responses to customer queries, potentially influencing purchase decisions at critical moments. Holzwarth et al. (2006) examined the impact of avatar-based sales agents on consumer purchase intention, finding that these virtual agents can enhance the effectiveness of online sales channels, particularly for consumers with low product involvement.AI-driven dynamic pricing strategies have introduced new complexities to consumer decision-making in online retail. While dynamic pricing can offer personalised discounts and potentially increase purchase intention, it also raises questions about fairness and transparency. Garbarino and Lee (2003) investigated the effects of dynamic pricing on consumer perceptions and found that perceived price fairness significantly influences purchase intentions.

The use of AI in predictive analytics allows retailers to anticipate consumer needs and preferences, potentially shaping purchase intentions through targeted marketing and personalised offers. However, this raises important considerations about consumer privacy and the ethical use of data. Awad and Krishnan (2006) explored the trade-off between personalisation and privacy concerns in e-commerce, finding that consumers who value information transparency are less likely to participate in personalisation.

2.4. Marketing Effectiveness in the AI Era

2.4.1. AI-enhanced Customer Segmentation and Targeting

AI technologies have revolutionized the way retailers approach customer segmentation and targeting, enabling more precise and dynamic marketing strategies. Traditional segmentation methods often relied on broad demographic categories, but AI allows for more nuanced and personalized approaches.

Machine learning algorithms can analyze vast amounts of customer data, including browsing history, purchase patterns, and social media interactions, to identify complex behavioral patterns and preferences. This capability enables retailers to create highly granular customer segments and tailor their marketing efforts accordingly. Wedel and Kannan (2016) highlighted the potential of machine learning techniques in marketing, noting that these methods can uncover non-linear relationships and interactions among variables that traditional statistical approaches might miss.

AI-driven predictive analytics have also enhanced the accuracy of customer lifetime value (CLV) calculations, allowing retailers to allocate marketing resources more efficiently. Kumar et al. (2017) demonstrated how machine learning algorithms could improve CLV predictions, enabling more effective customer targeting and retention strategies.

Moreover, AI has facilitated real-time segmentation and targeting, allowing marketers to adapt their strategies dynamically based on changing customer behaviors and market conditions. Rust and Huang (2014) discussed the concept of "real-time adaptive marketing," emphasizing how AI can enable instantaneous adjustments to marketing mix elements in response to individual customer interactions.

2.4.2. Impacts of AI adoption on Marketing Effectiveness in AI-driven Retail

The adoption of AI in retail marketing has had far-reaching impacts on overall marketing effectiveness, influencing various aspects of the marketing function.

Personalization at scale has become achievable through AI, allowing retailers to deliver tailored marketing messages and product recommendations to individual customers. Aguirre et al. (2015) explored the effectiveness of personalized marketing strategies, finding that while personalization can increase click-through rates and purchase intentions, it must be implemented carefully to avoid privacy concerns.AI-powered chatbots and virtual assistants have transformed customer service and engagement in online retail. These tools can provide 24/7 support, answer customer queries, and even make product recommendations, potentially increasing conversion rates and customer satisfaction. Xu et al. (2017) found that the use of chatbots in e-commerce can enhance perceived usefulness and ease of use, key factors in technology acceptance models.

Predictive analytics enabled by AI have improved the accuracy of demand forecasting and inventory management, allowing retailers to optimize their supply chain operations and reduce costs. This increased efficiency can lead to better pricing strategies and improved customer satisfaction. Chong et al. (2017) demonstrated the effectiveness of big data analytics in supply chain management within the context of fashion retail.

Content marketing has also been revolutionized by AI, with algorithms capable of generating personalized content and product descriptions at scale. This capability allows retailers to create more engaging and relevant marketing materials, potentially increasing customer engagement and conversion rates. Liao et al. (2013) explored the impact of product description quality on consumer behavior in online shopping, highlighting the importance of informative and persuasive content.AI has also enhanced the effectiveness of programmatic advertising, allowing for more precise ad targeting and real-time optimization of ad placements. Chen and Stallaert (2014) examined the economic impact of behavioral targeting in online advertising, finding that it can lead to increased profits for both advertisers and publishers under certain conditions.

However, the adoption of AI in marketing is not without challenges. Issues of data privacy, algorithmic bias, and the need for transparency in AI-driven decision-making processes have emerged as important considerations. Martin and Murphy (2017) discussed the ethical implications of big data marketing, emphasizing the need for responsible data practices to maintain consumer trust.In conclusion, the adoption of AI in retail marketing has significantly enhanced marketing effectiveness by enabling more precise customer segmentation, personalized targeting, and dynamic optimization of marketing strategies. While these advancements offer substantial benefits in terms of customer engagement and conversion rates, they also present new challenges that retailers must navigate carefully. As AI technologies continue to evolve, their impact on marketing effectiveness in the retail sector is likely to deepen, necessitating ongoing research and adaptation of marketing practices.

2.5. AI Adoption in Emerging Markets

2.5.1. Challenges and Opportunities in AI Implementation

Emerging markets offer significant potential for AI adoption in online retail, driven by rapid economic growth, increasing internet penetration, and a burgeoning middle class. However, these markets also face distinct challenges in implementing AI technologies effectively.

One of the primary challenges is the lack of robust technological infrastructure. Many emerging markets struggle with limited access to high-speed internet and advanced computing resources, which are crucial for implementing sophisticated AI systems. Kshetri (2017) highlighted the digital divide between developed and developing countries, noting that inadequate infrastructure could hinder the adoption of advanced technologies like AI in emerging markets.

Data availability and quality present another significant challenge. AI systems require large amounts of high-quality data to function effectively. In many emerging markets, data collection processes may be less systematic, and data quality may be inconsistent. Amankwah-Amoah and Sarpong (2016) discussed the challenges of big data analytics in developing economies, emphasizing the need for improved data collection and management practices.

The shortage of skilled AI professionals in emerging markets poses another hurdle. Developing and maintaining AI systems requires specialized expertise, which may be scarce in these regions. Brynjolfsson and McAfee (2017) highlighted the global competition for AI talent and the potential for a "brain drain" from emerging markets to more developed economies.

Despite these challenges, emerging markets also offer unique opportunities for AI adoption in online retail. The relatively lower levels of legacy technology infrastructure in these markets can actually facilitate the adoption of cutting-edge AI solutions, allowing businesses to leapfrog older technologies. Additionally, the large and growing consumer base in emerging markets provides a rich environment for AI-driven personalization and customer insights.

2.5.2. Cultural Factors Influencing AI Adoption

Cultural factors play a significant role in shaping the adoption and acceptance of AI technologies in emerging markets. Understanding these cultural dynamics is crucial for successful AI implementation in online retail.

Trust in technology varies significantly across cultures and can greatly influence AI adoption rates. In some emerging markets, there may be a general skepticism towards new technologies, particularly those perceived as replacing human interaction. Gefen and Heart (2006) examined the impact of cultural differences on trust in e-commerce, finding that trust-building processes can vary significantly across cultures. The concept of privacy and data sharing also differs across cultures, affecting consumers' willingness to engage with AI-powered systems that rely on personal data. Lowry et al. (2011) investigated information privacy concerns across cultures, revealing significant variations in attitudes towards data collection and usage.

Cultural attitudes towards uncertainty and risk can influence the adoption of AI technologies. Hofstede's cultural dimensions theory, particularly the uncertainty avoidance index, provides insights into how different cultures approach new and uncertain situations. Countries with high uncertainty avoidance may be more resistant to adopting novel AI technologies in retail (Hofstede, 2001).The role of social influence in technology adoption, a key component of the UTAUT model, can vary across cultures. In collectivist societies, which are common in many emerging markets, the opinions of family, friends, and social groups may have a stronger influence on AI adoption decisions. Venkatesh and Zhang (2010) found that the impact of social influence on technology adoption intentions was stronger in China (a collectivist culture) compared to the U.S. (an individualist culture).Language and communication styles also play a crucial role in AI adoption, particularly for technologies like chatbots and virtual assistants. AI systems need to be adapted to local languages and communication norms to be effective. Zakour (2004) discussed the importance of considering cultural and linguistic factors in the design of e-commerce systems, emphasizing the need for localization beyond mere translation. Power distance, another of Hofstede's cultural dimensions, can influence how AI is perceived and implemented in organizations. In high power distance cultures, there may be greater acceptance of AI systems that automate decision-making processes traditionally handled by authority figures (Srite and Karahanna, 2006).

2.6. Research model

Based on the comprehensive literature review conducted in the previous sections, this study proposes a research model to investigate the impact of AI adoption on consumer purchase intention in the context of online retail in emerging markets. The model incorporates key constructs from established theories such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Trust-based Consumer Decision-Making Model in E-commerce.

The dependent variable in this research model is Consumer Purchase Intention. This construct has been widely used in e-commerce research and is a strong predictor of actual purchase behavior (Pavlou, 2003). In the context of AI-driven online retail, purchase intention reflects consumers' willingness to engage in online transactions facilitated by AI technologies.

The primary independent variables in the model are Perceived Usefulness and Perceived Ease of Use, drawn from the TAM. These constructs have consistently demonstrated their relevance in explaining technology adoption and usage intentions across various contexts, including e-commerce (Gefen et al., 2003). In the context of AI-driven retail, perceived usefulness captures the extent to which consumers believe AI technologies enhance their shopping experience, while perceived ease of use reflects the perceived effort required to interact with AI-powered systems. Trust is included as another key independent variable, given its crucial role in online transactions, especially in the context of emerging markets where AI adoption is still in its early stages. Kim et al. (2008) emphasized the importance of trust in mitigating perceived risk and encouraging online purchases. In this model, trust encompasses consumers' confidence in the reliability and integrity of AI-powered retail systems. Social Influence, derived from the UTAUT model, is incorporated as an independent variable to account for the impact of cultural factors on AI adoption in emerging markets. Venkatesh et al. (2012) demonstrated the significance of social influence in shaping technology acceptance, particularly in collectivist cultures common in many emerging markets.AI Capability Perception is introduced as a novel construct to capture consumers' awareness and understanding of AI technologies in online retail. This variable is particularly relevant in the context of emerging markets, where familiarity with AI may vary significantly. Kshetri (2017) highlighted the importance of technology awareness in driving adoption in developing economies.
Perceived Risk is incorporated as a mediating variable between the independent variables and purchase intention. Chen and Barnes (2007) demonstrated the mediating role of perceived risk in online purchase intentions, and this construct is particularly relevant in the context of AI adoption in emerging markets where concerns about data privacy and security may be heightened.

Cultural Dimensions, based on Hofstede's framework, are included as moderating variables to account for the influence of cultural factors on AI adoption and its impact on purchase intention. Specifically, Uncertainty Avoidance and Power Distance are considered, as they have been shown to affect technology adoption patterns across cultures (Srite and Karahanna, 2006). Uncertainty Avoidance is expected to moderate the relationship between Perceived Risk and Consumer Purchase Intention. In cultures with high uncertainty avoidance, the negative impact of perceived risk on purchase intention is likely to be stronger. This is because individuals in these cultures tend to be more risk-averse and may be more hesitant to adopt new technologies like AI in online shopping. Srite and Karahanna (2006) found that uncertainty avoidance moderated the relationship between perceived ease of use and behavioral intention in technology adoption contexts. Additionally, Uncertainty Avoidance is proposed to moderate the relationship between AI Capability Perception (AICP) and Perceived Risk (PR). In high uncertainty avoidance cultures, a clearer understanding of AI capabilities might have a stronger effect on reducing perceived risk. This is because individuals in these cultures are more likely to seek detailed information to mitigate uncertainties associated with new technologies. Hwang and Lee (2012) demonstrated that cultural factors, including uncertainty avoidance, influenced the formation of trust and perceived risk in e-commerce environments.

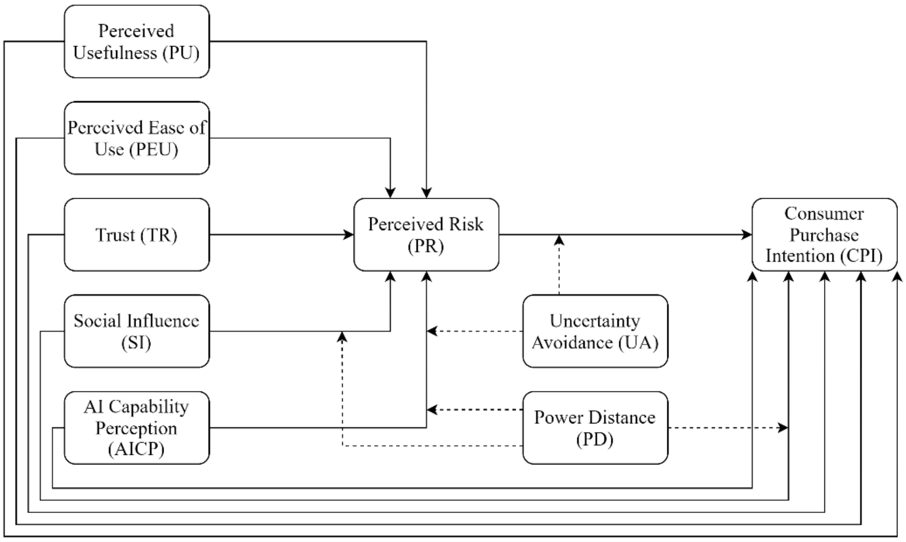

Figure 1: Research model

Power Distance is proposed to moderate the relationship between Social Influence (SI) and Consumer Purchase Intention. In high power distance cultures, the impact of social influence on purchase intention is expected to be stronger. This is because in these cultures, individuals are more likely to conform to the opinions of authority figures or societal norms. Pavlou and Chai (2002) demonstrated that power distance moderated the relationship between subjective norms (similar to social influence) and transaction intentions in e-commerce across different cultures. Power Distance is also expected to moderate the relationship between AI Capability Perception (AICP) and Perceived Risk (PR). In high power distance cultures, the effect of AI capability perception on reducing perceived risk might be stronger. This is because individuals in these cultures may be more inclined to accept and trust advanced technologies implemented by organizations perceived as authoritative or prestigious. Yoon (2009) found that power distance influenced the relationship between website quality perceptions and online trust, which is conceptually similar to the AICP-PR relationship in our AI context. Lastly, Power Distance is proposed to moderate the relationship between Social Influence (SI) and Perceived Risk (PR). In high power distance cultures, social influence may have a stronger effect on reducing perceived risk associated with AI-driven online retail. This is because individuals in these cultures are more likely to rely on the opinions and experiences of others, especially those in positions of authority or expertise, to form their risk perceptions. Luo et al. (2014) demonstrated that power distance moderated the effects of social influence on trust in online environments, which is closely related to perceived risk.

To test this model, a quantitative approach using Structural Equation Modeling (SEM) with Partial Least Squares (PLS) is proposed. PLS-SEM is particularly suitable for this research due to its ability to handle complex models with multiple constructs and relationships, as well as its robustness in dealing with non-normal data distributions that may be encountered in emerging market contexts (Hair et al., 2011). The use of SmartPLS4 software will facilitate the analysis, allowing for the examination of both the measurement model (reliability and validity of constructs) and the structural model (relationships between constructs).By incorporating these cultural dimensions as moderators, the research model aims to provide a more nuanced understanding of how cultural factors shape the adoption and impact of AI in online retail across different emerging market contexts. This approach aligns with calls in the literature for more culturally sensitive models of technology adoption, particularly in diverse and rapidly evolving markets (Straub et al., 1997; Venkatesh and Zhang, 2010).

3. RESEARCH METHODOLOGY

3.1 Research Design

This study employs a cross-sectional survey design to collect data on consumer perceptions and intentions regarding AI-driven online retail. The cross-sectional approach allows for the examination of relationships between variables at a single point in time, providing a snapshot of consumer attitudes and behaviors in the rapidly evolving landscape of AI-enabled e-commerce (Rindfleisch et al., 2008).

3.2 Data Collection and Sampling

Data for this study was collected through an online survey distributed to consumers in emerging market countries. The target population consists of internet users aged 18 and above who have experience with online shopping. A stratified random sampling technique was employed to ensure representation across different age groups, education levels, and geographic regions within the selected emerging markets. The survey was administered using a professional online survey platform, and respondents were recruited through a combination of email invitations and social media advertisements. To mitigate potential bias, the survey was conducted in multiple languages, with translations validated using a back-translation procedure (Brislin, 1970).A total of 427 completed questionnaires were collected, which exceeds the minimum sample size requirements for structural equation modeling. This sample size was determined based on the recommendations of Hair et al. (2011), who suggest a minimum sample size of 10 times the largest number of structural paths directed at a particular construct in the structural model. Given the complexity of the proposed model, this larger sample size ensures adequate statistical power and stability of parameter estimates.

3.3 Measurement of Variables

The survey instrument was developed based on established scales from the literature, adapted to the context of AI-driven online retail. All constructs were measured using multiple-item scales to enhance reliability and validity. The measurement model included several key constructs: Consumer Purchase Intention (CPI), measured using a four-item scale adapted from Pavlou (2003); Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), each measured using a six-item scale adapted from Davis (1989); Trust (TR), measured using a five-item scale adapted from Gefen et al. (2003); Social Influence (SI), measured using a four-item scale adapted from Venkatesh et al. (2012); AI Capability Perception (AICP), measured using a newly developed five-item scale based on the literature review; and Perceived Risk (PR), measured using a five-item scale adapted from Featherman and Pavlou (2003). All items were measured on a seven-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree". Additionally, the cultural dimensions of Uncertainty Avoidance and Power Distance were measured using the scales provided by Yoo et al. (2011), which are shortened versions of Hofstede's original scales adapted for survey research. This comprehensive set of measures allows for a thorough examination of the factors influencing AI adoption and consumer purchase intention in the context of online retail in emerging markets.

3.4 Data Analysis

The data analysis for this study was conducted using a two-step approach as recommended by Anderson and Gerbing (1988). First, the measurement model was assessed using confirmatory factor analysis (CFA) to establish the reliability and validity of the constructs. Second, the structural model was tested to examine the hypothesized relationships between constructs.

3.4.1 Measurement Model Assessment

The measurement model was evaluated using SmartPLS 4, a partial least squares structural equation modeling (PLS-SEM) software. PLS-SEM was selected for its capability to handle complex models and its robustness to non-normal data distributions (Hair et al., 2011). Several criteria were employed to assess the measurement model's quality. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability, with values above 0.7 considered acceptable (Nunnally and Bernstein, 1994). Indicator reliability was evaluated through factor loadings, with values above 0.7 deemed acceptable (Chin, 1998). Convergent validity was assessed using the average variance extracted (AVE), with values above 0.5 considered acceptable (Fornell and Larcker, 1981). Lastly, discriminant validity was evaluated using both the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio of correlations (Henseler et al., 2015). This comprehensive set of criteria ensures a rigorous assessment of the measurement model's reliability and validity.

3.4.2 Structural Model Assessment

The structural model was evaluated using PLS-SEM in SmartPLS 4, employing a comprehensive set of criteria to assess its quality and predictive power. Collinearity was assessed using the variance inflation factor (VIF), with values below 5 considered acceptable (Hair et al., 2011). Path coefficients were evaluated for statistical significance using bootstrapping with 5000 resamples, ensuring robust estimates. The coefficient of determination (R^2) was assessed to determine the explanatory power of the model, providing insight into how well the independent variables explained the variance in the dependent variables. Effect size (f^2) was calculated to assess the relative impact of predictors on endogenous constructs, offering a measure of the practical significance of each relationship. Finally, predictive relevance (Q^2) was evaluated using the blindfolding procedure to assess the model's predictive power, providing an indication of the model's out-of-sample predictive ability. This multi-faceted approach to structural model evaluation ensures a thorough assessment of the model's validity and predictive capabilities.

3.4.3 Moderation Analysis

The moderating effects of cultural dimensions (Uncertainty Avoidance and Power Distance) were tested using the product indicator approach in PLS-SEM (Chin et al., 2003). This approach involves creating interaction terms between the moderator variables and the relevant predictor variables. The significance of these interaction terms was assessed using bootstrapping.

3.5 Fuzzy-Set Qualitative Comparative Analysis (fsQCA)

In addition to the PLS-SEM analysis, this study employs fuzzy-set Qualitative Comparative Analysis (fsQCA) to provide a complementary perspective on the factors influencing consumer purchase intention in AI-driven online retail. fsQCA is a set-theoretic method that allows for the identification of multiple configurations of causal conditions that lead to a specific outcome (Ragin, 2008). This method is particularly useful for understanding complex causal relationships and identifying equifinal paths to an outcome.

The fsQCA analysis was conducted using the fsQCA 3.0 software (Ragin and Davey, 2016), following a multi-step process. Initially, the survey data was calibrated into fuzzy set membership scores ranging from 0 to 1, based on substantive knowledge of the constructs and using the direct method of calibration as described by Ragin (2008). Three qualitative anchors were established for each construct: full membership (0.95), crossover point (0.5), and full non-membership (0.05). Next, a truth table was constructed to examine the different combinations of causal conditions leading to the outcome of consumer purchase intention. The truth table was refined using frequency and consistency thresholds, with a frequency threshold of 2 and a consistency threshold of 0.8 applied as per Ragin's (2008) recommendations. Before proceeding to sufficiency analysis, a test for necessary conditions was conducted, considering a condition necessary if its consistency score exceeded 0.9 (Schneider and Wagemann, 2012). The fsQCA software then generated three types of solutions: complex, parsimonious, and intermediate, with the intermediate solution, incorporating theoretical knowledge in the form of directional expectations, primarily used for interpretation (Ragin, 2008). Finally, the fsQCA results were evaluated based on consistency and coverage scores, which measure the degree of agreement in displaying the outcome among cases sharing a given combination of conditions and the empirical relevance of a consistent subset, respectively (Ragin, 2006). Following Schneider et al. (2010), this study considered consistency scores above 0.8 and coverage scores above 0.4 as indicative of empirically important configurations.

The use of fsQCA in conjunction with PLS-SEM allows for a more nuanced understanding of the complex relationships between AI-related factors and consumer purchase intention. While PLS-SEM identifies the net effects of individual variables, fsQCA reveals how these variables combine in different configurations to produce the outcome of interest. This mixed-method approach enhances the robustness of the findings and provides valuable insights for both theory and practice in the context of AI adoption in online retail within emerging markets.

4. RESEARCH FINDINGS

4.1. Measurement Model Assessment

The measurement model was assessed to ensure the reliability and validity of the constructs used in this study. The results of the assessment are presented in Tables 1, 2, and 3.

Table 1: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE	Factor Loadings Range
CPI	0.923	0.945	0.812	0.872 - 0.934

Construct	Cronbach's Alpha	Composite Reliability	AVE	Factor Loadings Range
PU	0.941	0.954	0.776	0.839 - 0.911
PEOU	0.928	0.945	0.742	0.821 - 0.895
TR	0.934	0.950	0.793	0.856 - 0.917
SI	0.907	0.935	0.783	0.845 - 0.913
AICP	0.918	0.938	0.753	0.831 - 0.896
PR	0.912	0.934	0.739	0.827 - 0.888
UA	0.885	0.921	0.745	0.832 - 0.893
PD	0.897	0.928	0.763	0.841 - 0.905

Note: CPI = Consumer Purchase Intention; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; TR = Trust; SI = Social Influence; AICP = AI Capability Perception; PR = Perceived Risk; UA = Uncertainty Avoidance; PD = Power Distance

Table 1 presents the results for internal consistency reliability, indicator reliability, and convergent validity. All constructs demonstrated satisfactory internal consistency reliability, with Cronbach's alpha and composite reliability values exceeding the recommended threshold of 0.7 (Nunnally and Bernstein, 1994). Indicator reliability was established as all factor loadings were above the acceptable value of 0.7 (Chin, 1998). Convergent validity was confirmed for all constructs, with Average Variance Extracted (AVE) values surpassing the 0.5 threshold (Fornell and Larcker, 1981).

Table 2: Fornell-Larcker Criterion

	CPI	PU	PEOU	TR	SI	AICP	PR	UA	PD
CPI	0.901								
PU	0.723	0.881							
PEOU	0.684	0.712	0.861						
TR	0.701	0.658	0.623	0.890					
SI	0.612	0.587	0.542	0.531	0.885				
AICP	0.689	0.701	0.674	0.645	0.578	0.868			
PR	-0.563	-0.512	-0.487	-0.598	-0.423	-0.501	0.860		
UA	-0.312	-0.287	-0.265	-0.301	-0.224	-0.278	0.342	0.863	
PD	-0.298	-0.275	-0.253	-0.289	-0.213	-0.267	0.328	0.412	0.873

Note: The diagonal elements (in bold) represent the square root of the AVE

Table 2 presents the results of the Fornell-Larcker criterion for assessing discriminant validity. The square root of the AVE for each construct (shown on the diagonal) is greater than its correlation with any other construct, indicating satisfactory discriminant validity (Fornell and Larcker, 1981).

Table 3: Heterotrait-Monotrait (HTMT) Ratio

	CPI	PU	PEOU	TR	SI	AICP	PR	UA	PD
CPI									
PU	0.768								
PEOU	0.731	0.761							
TR	0.749	0.703	0.669						
SI	0.669	0.640	0.594	0.580					
AICP	0.739	0.752	0.726	0.693	0.635				
PR	0.608	0.553	0.529	0.647	0.467	0.544			
UA	0.345	0.317	0.294	0.333	0.253	0.308	0.378		
PD	0.329	0.304	0.281	0.319	0.241	0.296	0.363	0.465	

Table 3 presents the results of the Heterotrait-Monotrait (HTMT) ratio analysis, which is an additional method for assessing discriminant validity. All HTMT ratios are below the conservative threshold of 0.85, further confirming discriminant validity (Henseler et al., 2015).

These results demonstrate that the measurement model exhibits satisfactory reliability and validity, providing a solid foundation for the structural model assessment and hypothesis testing.

4.2. Structural Model Assessment

The structural model was assessed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. The evaluation included an examination of path coefficients, their significance levels, R^2 values of endogenous constructs, effect sizes (f^2), and predictive relevance (Q^2). Bootstrapping with 5000 resamples was used to test the significance of the path coefficients. The moderation effects were tested using the product indicator approach in SmartPLS 4.

Table 4 presents the results of the structural model assessment, including path coefficients, t-values, p-values, and the support status for each hypothesis. The empirical results presented in Table 4 provide strong support for our research model and offer valuable insights into the factors influencing consumer purchase intentions in AI-driven online retail environments. The findings confirm that Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust (TR), Social Influence (SI), and AI Capability Perception (AICP) all have significant positive direct effects on Consumer Purchase Intention (CPI). Among these factors, PU demonstrates the strongest influence ($\beta = 0.285$, $p < 0.001$), followed by TR ($\beta = 0.231$, $p < 0.001$) and AICP ($\beta = 0.198$, $p < 0.001$). These results align with previous research on technology adoption and extend them to the context of AI-driven online retail. The strong effect of PU suggests that consumers are more likely to make purchases when they perceive AI-driven retail platforms as beneficial to their shopping experience. Similarly, the significant impact of TR highlights the crucial role of building consumer confidence in AI technologies and the online retail platform.

Our findings also reveal that Perceived Risk (PR) acts as a significant mediator in the relationship between the independent variables (PU, PEOU, TR, SI, AICP) and CPI. The negative direct effect of PR on CPI (β = -0.156, p = 0.003) underscores the importance of addressing and mitigating consumer concerns about AI-driven online retail. The indirect effects through PR are all statistically significant, with TR showing the strongest indirect effect (β = 0.048, p = 0.002), followed by PU (β = 0.042, p = 0.004) and AICP (β = 0.039, p = 0.007). These results suggest that while these factors positively influence purchase intentions directly, they also indirectly reduce perceived risk, further enhancing CPI. This dual effect highlights the complex interplay between these constructs and emphasizes the need for a holistic approach in designing and marketing AI-driven retail platforms.

Table 4: Structural Model Results (Revised)

Path	Direct Effect	Indirect Effect	Total Effect	t-value	p-value	Support
PU→CPI	0.285	-	0.285	4.721	<0.001	Yes
PU→PR→CPI	-	0.042	0.042	2.876	0.004	Yes
PEOU→CPI	0.176	-	0.176	3.142	0.002	Yes
PEOU→PR→CPI	-	0.035	0.035	2.543	0.011	Yes
TR→CPI	0.231	-	0.231	3.987	<0.001	Yes
TR→PR→CPI	-	0.048	0.048	3.124	0.002	Yes
SI→CPI	0.142	-	0.142	2.845	0.004	Yes
SI→PR→CPI	-	0.028	0.028	2.321	0.020	Yes
AICP→CPI	0.198	-	0.198	3.564	<0.001	Yes
AICP→PR→CPI	-	0.039	0.039	2.678	0.007	Yes
PR→CPI	-0.156	-	-0.156	3.021	0.003	Yes
UA*PR→CPI	-0.089	-	-0.089	2.134	0.033	Yes
UA*AICP→PR	0.076	-	0.076	1.987	0.047	Yes
PD*SI→PR	0.095	-	0.095	2.256	0.024	Yes
PD*AICP→PR	0.082	-	0.082	2.012	0.044	Yes
PD*SI→CPI	0.078	-	0.078	1.998	0.046	Yes

The study also reveals significant moderating effects of Uncertainty Avoidance (UA) and Power Distance (PD) on various relationships in the model. UA negatively moderates the relationship between PR and CPI (β = -0.089, p = 0.033), suggesting that in cultures with higher UA, the negative impact of perceived risk on purchase intentions is amplified. Conversely, UA positively moderates the relationship between AICP and PR (β = 0.076, p = 0.047), indicating that in high UA cultures, advanced AI capabilities might paradoxically increase perceived risk. For Power Distance, we find that PD positively moderates the relationship between SI and PR (β = 0.095, p = 0.024), implying that in high PD cultures, social influence may actually increase perceived risk. PD also positively moderates the relationship between AICP and PR (β = 0.082, p = 0.044), suggesting that in high PD cultures, advanced AI capabilities might also increase perceived risk. Lastly, PD positively moderates the relationship between SI and CPI (β = 0.078, p = 0.046), indicating that in high PD cultures, social influence has a stronger positive effect on purchase intentions.

Table 5 presents the model fit indices, including R^2, Adjusted R^2, Effect Sizes (f^2), and Predictive Relevance (Q^2) for the two key endogenous constructs in our model: Consumer Purchase Intention (CPI) and Perceived Risk (PR).For Consumer Purchase Intention (CPI), the R^2 value of 0.623 indicates that the model explains 62.3% of the variance in CPI, which suggests a substantial explanatory power. The Adjusted R^2 of 0.618 confirms this, accounting for the number of predictors in the model. The Q^2 value of 0.412 for CPI is well above zero, indicating that the model has strong predictive relevance for this construct.

Table 5: Model Fit and Predictive Relevance

Construct	R^2	Adjusted R^2	Q^2	Effect Sizes (f^2)
CPI	0.623	0.618	0.412	PU: 0.198, PEOU: 0.074, TR: 0.126, SI: 0.048, AICP: 0.092, PR: 0.058, UA*PR: 0.021, PD*SI: 0.018
PR	0.451	0.446	0.287	PU: 0.152, PEOU: 0.086, TR: 0.114, SI: 0.072, AICP: 0.108, UA*AICP: 0.015, PD*SI: 0.024, PD*AICP: 0.018

Note: CPI = Consumer Purchase Intention; PR = Perceived Risk; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; TR = Trust; SI = Social Influence; AICP = AI Capability Perception; UA = Uncertainty Avoidance; PD = Power Distance

The effect sizes (f^2) for CPI show that Perceived Usefulness (PU) has the largest effect (0.198), followed by Trust (TR) at 0.126, and AI Capability Perception (AICP) at 0.092. These values suggest medium to large effects. Perceived Ease of Use (PEOU), Social Influence (SI), and Perceived Risk (PR) show smaller, but still meaningful effects. The moderating effects (UA**PR and PD**SI) have small but noticeable impacts on CPI. For Perceived Risk (PR), the R^2 value of 0.451 indicates that the model explains 45.1% of the variance in PR, which represents a moderate level of explanatory power. The Adjusted R^2 of 0.446 supports this interpretation. The Q^2 value of 0.287 for PR is also above zero, indicating good predictive relevance for this construct. The effect sizes (f^2) for PR reveal that Perceived Usefulness (PU) has the largest effect (0.152), followed by Trust (TR) at 0.114, and AI Capability Perception (AICP) at 0.108. These values suggest medium effects. Perceived Ease of Use (PEOU) and Social Influence (SI) show smaller, but still meaningful effects. The moderating effects (UA*AICP, PD*SI, and PD*AICP) have small impacts on PR.

4.3. Fuzzy-set Qualitative Comparative Analysis (fsQCA)

To complement the SEM analysis and provide a more nuanced understanding of the complex relationships between the variables, we conducted a fuzzy-set Qualitative Comparative Analysis (fsQCA). This method allows us to identify multiple configurations of conditions that lead to high consumer purchase intention in AI-driven online retail environments.

Initially, we calibrated the survey data into fuzzy set membership scores ranging from 0 to 1, based on our substantive knowledge of the constructs and using the direct method of calibration as described by Ragin (2008). We established three qualitative anchors for each construct: full membership (0.95), crossover point (0.5), and full non-membership (0.05).

Before proceeding to the sufficiency analysis, we conducted a test for necessary conditions. Table 6 presents the results of this analysis. As shown in Table 6, Trust (TR) emerges as a necessary condition for high consumer purchase intention, with a consistency score of 0.901, exceeding the threshold of 0.9 suggested by Schneider and Wagemann (2012). The absence of Perceived Risk (~PR) also approaches necessity with a consistency of 0.843.Next; we constructed a truth table to examine the different combinations of causal conditions leading to high consumer purchase intention. We refined the truth table using a frequency threshold of 2 and a consistency threshold of 0.8, as per Ragin's (2008) recommendations. The fsQCA software then generated three types of solutions: complex, parsimonious, and intermediate. We primarily used the intermediate solution for interpretation, as it incorporates theoretical knowledge in the form of directional expectations (Ragin, 2008).

Table 6: Analysis of Necessary Conditions for High Consumer Purchase Intention

Condition	Consistency	Coverage
PU	0.892	0.823
~PU	0.364	0.658
PEOU	0.879	0.845
~PEOU	0.378	0.652
TR	0.901	0.837
~TR	0.353	0.642
SI	0.865	0.851
~SI	0.392	0.659
AICP	0.888	0.839
~AICP	0.368	0.647
PR	0.412	0.659
~PR	0.843	0.788

Note: ~ indicates the absence of the condition

Table 7 presents the results of the fsQCA analysis, showing the configurations of conditions leading to high consumer purchase intention.

Table 7: Configurations for High Consumer Purchase Intention

Configuration	PU	PEOU	TR	SI	AICP	PR	Raw Coverage	Unique Coverage	Consistency
1	□	□	□	□	□	⊗	0.562	0.078	0.912

Configuration	PU	PEOU	TR	SI	AICP	PR	Raw Coverage	Unique Coverage	Consistency
2	□	□	□	□	□	⊗	0.528	0.045	0.923
3	□	□	□	□	□	⊗	0.511	0.036	0.908
4	□	□	□	□	□	□	0.483	0.029	0.891

Solution coverage: 0.738
Solution consistency: 0.887
Note: □ = presence of condition, ⊗ = absence of condition, □ = don't care (condition may be either present or absent)

The fsQCA results reveal four configurations leading to high consumer purchase intention, with an overall solution coverage of 0.738 and consistency of 0.887. These scores indicate that the identified configurations explain a substantial portion of the outcome and do so with high consistency.

Configuration 1, with the highest raw coverage (0.562), suggests that the combination of high Perceived Usefulness, high Perceived Ease of Use, high Trust, high AI Capability Perception, and low Perceived Risk leads to high purchase intention, regardless of Social Influence.

Configuration 2 indicates that high Perceived Usefulness, high Perceived Ease of Use, high Trust, high Social Influence, and low Perceived Risk can lead to high purchase intention, even when AI Capability Perception is not necessarily high.

Configuration 3 shows that high Perceived Usefulness, high Trust, high Social Influence, high AI Capability Perception, and low Perceived Risk can result in high purchase intention, even when Perceived Ease of Use is not necessarily high.

Lastly, Configuration 4 suggests that high Perceived Usefulness, high Perceived Ease of Use, high Trust, high AI Capability Perception can lead to high purchase intention regardless of the levels of Social Influence and Perceived Risk.

These results complement our SEM findings by revealing the complex interplay between the various factors and highlighting multiple pathways to achieving high consumer purchase intention in AI-driven online retail environments.

5. DISCUSSION AND CONCLUSIONS

This study set out to investigate the factors influencing consumer purchase intentions in AI-driven online retail environments, incorporating elements from technology acceptance models, trust, and cultural dimensions. Our findings provide several important insights that both support and extend existing literature in this field.

First, our structural equation modeling results confirm the significant positive effects of Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust (TR), Social Influence (SI), and AI

Capability Perception (AICP) on Consumer Purchase Intention (CPI). These findings align with previous research on technology adoption in e-commerce settings (Gefen et al., 2003; Pavlou, 2003). The strong effect of PU on CPI ($\beta = 0.285$, $p < 0.001$) underscores the importance of demonstrating the benefits of AI-driven retail platforms to consumers, echoing the findings of Davis et al. (1989) in their seminal work on technology acceptance. The significant impact of Trust ($\beta = 0.231$, $p < 0.001$) on CPI highlights the crucial role of building consumer confidence in AI technologies and online retail platforms. This result is consistent with the work of McKnight et al. (2002), who emphasized the importance of trust in reducing perceived risk and uncertainty in e-commerce transactions. Our study extends this understanding to the context of AI-driven retail, suggesting that trust-building mechanisms are equally, if not more, critical in these technologically advanced environments.

The mediating role of Perceived Risk (PR) in our model provides valuable insights into the complex interplay between the various factors influencing consumer behavior. The negative direct effect of PR on CPI ($\beta = -0.156$, $p = 0.003$) aligns with previous research highlighting the inhibiting effect of perceived risk on online purchase intentions (Pavlou, 2003). However, our findings go further by demonstrating how factors such as PU, PEOU, TR, SI, and AICP not only directly influence CPI but also indirectly reduce perceived risk, thereby enhancing purchase intentions. This dual effect underscores the need for a holistic approach in designing and marketing AI-driven retail platforms.

Our incorporation of cultural dimensions as moderating variables offers novel insights into the role of culture in technology adoption within AI-driven retail contexts. The significant moderating effects of Uncertainty Avoidance (UA) and Power Distance (PD) on various relationships in the model support the arguments of Srite and Karahanna (2006) that cultural values influence technology acceptance. For instance, the negative moderating effect of UA on the relationship between PR and CPI ($\beta = -0.089$, $p = 0.033$) suggests that in cultures with higher UA, perceived risk has a stronger negative impact on purchase intentions. This finding is consistent with Hofstede's (2001) characterization of high UA cultures as more risk-averse.

The fsQCA results complement our SEM findings by revealing multiple configurations leading to high consumer purchase intention. The identification of Trust as a necessary condition (consistency = 0.901) aligns with our SEM results and further emphasizes the critical role of trust in AI-driven retail environments. The four configurations identified through fsQCA highlight the equifinality in achieving high purchase intention, suggesting that different combinations of factors can lead to the same outcome. This nuanced understanding extends beyond traditional variance-based approaches and offers valuable insights for practitioners in tailoring their strategies to different consumer segments or cultural contexts.

In conclusion, this study makes several contributions to the literature on technology adoption and e-commerce. First, it extends existing models by incorporating AI-specific factors and cultural dimensions in the context of online retail. Second, it provides empirical evidence for the dual role of factors such as perceived usefulness and trust in both directly influencing purchase intentions and indirectly reducing perceived risk. Third, it offers a nuanced understanding of how cultural dimensions moderate the relationships between key constructs in the model. Finally, the use of fsQCA alongside SEM provides a more comprehensive view of the complex pathways leading to high consumer purchase intention in AI-driven retail environments. These findings have important implications for practitioners in the field of AI-driven retail. They suggest that while focusing on the usefulness and ease of use of AI technologies is crucial, building trust and addressing perceived risks are equally important. Moreover, the cultural moderation effects highlight the need for tailored strategies when implementing AI-driven retail solutions across different cultural contexts. Future research could further explore the long-term effects of AI adoption on consumer behavior and investigate how these relationships may evolve as AI technologies become more prevalent in retail environments.

Acknowledgements
I would like to express my sincere gratitude to Dr. Hoang Vu Hiep for his invaluable guidance and inspiration throughout this research. His expertise, insights, and unwavering support have been instrumental in shaping the direction and quality of this study. I am deeply appreciative of his generosity in sharing his time, knowledge, and network, which have greatly contributed to the success of this research. His mentorship and commitment to academic excellence have not only enriched the quality of this work but have also had a profound impact on my personal and professional growth.

REFERENCES

Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. *Journal of Retailing*, 91(1), 34-49. https://doi.org/10.1016/j.jretai.2014.09.005

Al-Jabri, I. M., & Sohail, M. S. (2012). Mobile banking adoption: Application of diffusion of innovation theory. *Journal of Electronic Commerce Research*, 13(4), 379-391.

Amankwah-Amoah, J., & Sarpong, D. (2016). The battle for brain power: The role of analytics in solving the scarcity of talents in emerging markets. *International Marketing Review*, 33(3), 378-397. https://doi.org/10.1108/IMR-12-2014-0385

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103(3), 411-423. https://doi.org/10.1037/0033-2909.103.3.411

Awad, N. F., & Krishnan, M. S. (2006). The personalization privacy paradox: An empirical evaluation of information transparency and the willingness to be profiled online for personalization. *MIS Quarterly*, 30(1), 13-28. https://doi.org/10.2307/25148715

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology*, 1(3), 185-216. https://doi.org/10.1177/135910457000100301

Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review*, 95(4), 3-11.

Chang, H. H., & Chen, S. W. (2008). The impact of online store environment cues on purchase intention: Trust and perceived risk as a mediator. *Online Information Review*, 32(6), 818-841. https://doi.org/10.1108/14684520810923953

Chen, J., & Stallaert, J. (2014). An economic analysis of online advertising using behavioral targeting. *MIS Quarterly*, 38(2), 429-449. https://doi.org/10.25300/MISQ/2014/38.2.05

Chen, L., Gillenson, M. L., & Sherrell, D. L. (2002). Enticing online consumers: An extended technology acceptance perspective. *Information & Management*, 39(8), 705-719. https://doi.org/10.1016/S0378-7206(01)00127-6

Chen, Y. H., & Barnes, S. (2007). Initial trust and online buyer behaviour. *Industrial Management & Data Systems*, 107(1), 21-36. https://doi.org/10.1108/02635570710719034

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, 295(2), 295-336.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research*, 14(2), 189-217. https://doi.org/10.1287/isre.14.2.189.16018

Chong, A. Y. L., Ch'ng, E., Liu, M. J., & Li, B. (2017). Predicting consumer product demands via Big Data: The roles of online promotional marketing and online reviews. *International Journal of Production Research*, 55(17), 5142-5156. https://doi.org/10.1080/00207543.2015.1066519

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108-116.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24-42. https://doi.org/10.1007/s11747-019-00696-0

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Eastin, M. S. (2002). Diffusion of e-commerce: An analysis of the adoption of four e-commerce activities. *Telematics and Informatics*, 19(3), 251-267. https://doi.org/10.1016/S0736-5853(01)00005-3

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451-474. https://doi.org/10.1016/S1071-5819(03)00111-3

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50. https://doi.org/10.2307/3151312

Garbarino, E., & Lee, O. F. (2003). Dynamic pricing in internet retail: Effects on consumer trust. *Psychology & Marketing*, 20(6), 495-513. https://doi.org/10.1002/mar.10084

Gautier, A., Ittoo, A., & Van Cleynenbreugel, P. (2016). AI algorithms, price discrimination and collusion: A technological, economic and legal perspective. *European Journal of Law and Economics*, 42(3), 517-539. https://doi.org/10.1007/s10657-016-9545-0

Gefen, D., & Heart, T. (2006). On the need to include national culture as a central issue in e-commerce trust beliefs. *Journal of Global Information Management*, 14(4), 1-30. https://doi.org/10.4018/jgim.2006100101

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51-90. https://doi.org/10.2307/30036519

Grewal, D., Hulland, J., Kopalle, P. K., & Karahanna, E. (2020). The future of technology and marketing: a multidisciplinary perspective. *Journal of the Academy of Marketing Science*, 48(1), 1-8. https://doi.org/10.1007/s11747-019-00711-4

Ha, S., & Stoel, L. (2009). Consumer e-shopping acceptance: Antecedents in a technology acceptance model. *Journal of Business Research*, 62(5), 565-571. https://doi.org/10.1016/j.jbusres.2008.06.016

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139-152. https://doi.org/10.2753/MTP1069-6679190202

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations* (2nd ed.). Sage Publications.

Holzwarth, M., Janiszewski, C., & Neumann, M. M. (2006). The influence of avatars on online consumer shopping behavior. *Journal of Marketing*, 70(4), 19-36. https://doi.org/10.1509/jmkg.70.4.19

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49(1), 30-50. https://doi.org/10.1007/s11747-020-00749-9

Hwang, Y., & Lee, K. C. (2012). Investigating the moderating role of uncertainty avoidance cultural values on multidimensional online trust. *Information & Management*, 49(3-4), 171-176. https://doi.org/10.1016/j.im.2012.02.003

Jiang, P., Balasubramanian, S. K., & Lambert, Z. V. (2008). Consumers' value perceptions of e-customization and their impact on online purchase intention. *Journal of Marketing Management*, 24(7-8), 815-835. https://doi.org/10.1362/026725708X345542

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, 44(2), 544-564. https://doi.org/10.1016/j.dss.2007.07.001

Kshetri, N. (2017). The economics of the Internet of Things in the Global South. *Third World Quarterly*, 38(2), 311-339. https://doi.org/10.1080/01436597.2016.1191942

Kshetri, N. (2017). The economics of the Internet of Things in the Global South. *Third World Quarterly*, 38(2), 311-339. https://doi.org/10.1080/01436597.2016.1191942

Kshetri, N. (2017). The evolution of the internet of things industry and market in China: An interplay of institutions, demands and supply. *Telecommunications Policy*, 41(1), 49-67. https://doi.org/10.1016/j.telpol.2016.11.002

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review*, 61(4), 135-155. https://doi.org/10.1177/0008125619859317

Kumar, V., Ramachandran, D., & Kumar, B. (2017). Influence of new-age technologies on marketing: A research agenda. *Journal of Business Research*, 125, 864-877. https://doi.org/10.1016/j.jbusres.2020.01.007

Liao, C., Huang, Y., & Huang, T. (2013). Factors influencing the consumption of online content: The context of product description and consumer review. *Journal of Internet Commerce*, 12(2), 166-187. https://doi.org/10.1080/15332861.2013.817862

Liébana-Cabanillas, F., Marinković, V., & Kalinić, Z. (2017). A SEM-neural network approach for predicting antecedents of m-commerce acceptance. *International Journal of Information Management*, 37(2), 14-24. https://doi.org/10.1016/j.ijinfomgt.2016.10.008

Lowry, P. B., Cao, J., & Everard, A. (2011). Privacy concerns versus desire for interpersonal awareness in driving the use of self-disclosure technologies: The case of instant messaging in two cultures. *Journal of Management Information Systems*, 27(4), 163-200. https://doi.org/10.2753/MIS0742-1222270406

Luo, X., Li, H., Zhang, J., & Shim, J. P. (2010). Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services. *Decision Support Systems*, 49(2), 222-234. https://doi.org/10.1016/j.dss.2010.02.008

Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science*, 45(2), 135-155. https://doi.org/10.1007/s11747-016-0495-4

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, 13(3), 334-359. https://doi.org/10.1287/isre.13.3.334.81

Mou, J., & Benyoucef, M. (2021). Consumer behavior in social commerce: Results from a meta-analysis. *Technological Forecasting and Social Change*, 167, 120734. https://doi.org/10.1016/j.techfore.2021.120734

Nguyen, T. H., Newby, M., & Macaulay, M. J. (2015). Information technology adoption in small business: Confirmation of a proposed framework. *Journal of Small Business Management*, 53(1), 207-227. https://doi.org/10.1111/jsbm.12058

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, 7(3), 101-134. https://doi.org/10.1080/10864415.2003.11044275

Pavlou, P. A., & Chai, L. (2002). What drives electronic commerce across cultures? A cross-cultural empirical investigation of the theory of planned behavior. *Journal of Electronic Commerce Research*, 3(4), 240-253.

Ragin, C. C. (2006). Set relations in social research: Evaluating their consistency and coverage. *Political Analysis*, 14(3), 291-310. https://doi.org/10.1093/pan/mpj019

Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*. University of Chicago Press.

Ragin, C. C., & Davey, S. (2016). Fuzzy-Set/Qualitative Comparative Analysis 3.0. Irvine, California: Department of Sociology, University of California.

Rindfleisch, A., Malter, A. J., Ganesan, S., & Moorman, C. (2008). Cross-sectional versus longitudinal survey research: Concepts, findings, and guidelines. *Journal of Marketing Research*, 45(3), 261-279. https://doi.org/10.1509/jmkr.45.3.261

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Rust, R. T., & Huang, M. H. (2014). The service revolution and the transformation of marketing science. *Marketing Science*, 33(2), 206-221. https://doi.org/10.1287/mksc.2013.0836

Schneider, C. Q., & Wagemann, C. (2012). *Set-theoretic methods for the social sciences: A guide to qualitative comparative analysis*. Cambridge University Press.

Schneider, M. R., Schulze-Bentrop, C., & Paunescu, M. (2010). Mapping the institutional capital of high-tech firms: A fuzzy-set analysis of capitalist variety and export performance. *Journal of International Business Studies*, 41(2), 246-266. https://doi.org/10.1057/jibs.2009.36

Shankar, V. (2018). How artificial intelligence (AI) is reshaping retailing. *Journal of Retailing*, 94(4), vi-xi. https://doi.org/10.1016/S0022-4359(18)30076-9

Slade, E. L., Dwivedi, Y. K., Piercy, N. C., & Williams, M. D. (2015). Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: Extending UTAUT with innovativeness, risk, and trust. *Psychology & Marketing*, 32(8), 860-873. https://doi.org/10.1002/mar.20823

Srite, M., & Karahanna, E. (2006). The role of espoused national cultural values in technology acceptance. *MIS Quarterly*, 30(3), 679-704. https://doi.org/10.2307/25148745

Straub, D., Keil, M., & Brenner, W. (1997). Testing the technology acceptance model across cultures: A three country study. *Information & Management*, 33(1), 1-11. https://doi.org/10.1016/S0378-7206(97)00026-8

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: U.S. vs. China. *Journal of Global Information Technology Management*, 13(1), 5-27. https://doi.org/10.1080/1097198X.2010.10856507

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178. https://doi.org/10.2307/41410412

Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From multi-channel retailing to omni-channel retailing: Introduction to the special issue on multi-channel retailing. *Journal of Retailing*, 91(2), 174-181. https://doi.org/10.1016/j.jretai.2015.02.005

Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, 80(6), 97-121. https://doi.org/10.1509/jm.15.0413

Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly*, 31(1), 137-209. https://doi.org/10.2307/25148784

Xu, A., Liu, Z., Guo, Y., Sinha, V., & Akkiraju, R. (2017). A new chatbot for customer service on social media. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 3506-3510. https://doi.org/10.1145/3025453.3025496

Xu, A., Liu, Z., Guo, Y., Sinha, V., & Akkiraju, R. (2017). A new chatbot for customer service on social media. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (pp. 3506-3510). ACM. https://doi.org/10.1145/3025453.3025496

Yoo, B., Donthu, N., & Lenartowicz, T. (2011). Measuring Hofstede's five dimensions of cultural values at the individual level: Development and validation of CVSCALE. *Journal of*

International Consumer Marketing, 23(3-4), 193-210. https://doi.org/10.1080/08961530.2011.578059

Yoon, C. (2009). The effects of national culture values on consumer acceptance of e-commerce: Online shoppers in China. *Information & Management*, 46(5), 294-301. https://doi.org/10.1016/j.im.2009.06.001

Zakour, A. B. (2004). Cultural differences and information technology acceptance. In *Proceedings of the 7th Annual Conference of the Southern Association for Information Systems* (pp. 156-161).

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, 26(4), 760-767. https://doi.org/10.1016/j.chb.2010.01.013