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Exploring Customer Experience using Artificial Intelligence in Retail Businesses: A Technology Acceptance Model Approach

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Abstract

This research investigates the integration of Artificial Intelligence (AI) in the retail industry, with a focus on consumer perceptions in the UAE. Using the Technology Acceptance Model (TAM), the study explores the relationships between Perceived Usefulness (PU), Perceived Ease of Use (PEoU), Attitude Towards Use (ATT), and Intention to Use (INT) AI. The results reveal that PU positively impacts both ATT and INT, while PEoU influences ATT but does not affect PU directly. The findings suggest that enhancing the PU of AI and improving its user-friendliness can significantly boost consumer attitudes and intentions toward adopting AI technology. Key recommendations include emphasising AI's tangible benefits early on, creating more intuitive and seamless user experiences, and addressing any consumer concerns related to AI implementation. By doing so, businesses can foster a more favourable attitude toward AI, leading to higher adoption rates. These insights are crucial for companies looking to leverage AI to improve customer satisfaction and strengthen their competitive position in the market.

Keywords: Technology Acceptance Model (TAM), Artificial Intelligence (AI), Perceived Ease of Use (PEoU), Perceived Usefulness (PU), Attitude (ATT), Intention (INT)

Introduction

The retail sector is incredibly dynamic and competitive. Retailers are constantly striving to improve the customer experience, knowing that a positive shopping experience can impact customer loyalty, brand recognition, and overall profitability. Recent advancements in technology have revolutionised how businesses engage with customers, with Artificial Intelligence (AI) playing a role in enhancing customer retention and interaction. AI tools such as Chabot's, adapted recommendations, and personalised search features enable retailers to understand and meet evolving customer needs. By catering to preferences, retailers can elevate the shopping experience, giving customers an advantage in the marketplace through AI integration.

The aim of this research is to explore how intelligence (AI) tools are used to improve the shopping experience with the Technology Acceptance Model (TAM) as the conceptual model. The primary objective of this study is to examine customer's perceptions of the usefulness and ease of use of AI in environments along with their attitudes and willingness to adopt AI technologies. This research holds significance as it could offer guidance for businesses looking to integrate AI into their operations while also contributing insights to the discourse on using TAM for AI applications, in retail settings.

The paper has been divided into four parts. The literature review in Section 2 examines the overview of AI in retail and the application of the TAM for technology adoption in retail. This helps construct the hypothesis statements for the study. The research methodology in Section 3 describes the research design, data collection, and data analysis methodologies. The findings are classified into TAM components: perceived usefulness (PU), perceived ease of use (PEoU), attitude toward employing AI in retail (ATT), and behavioural intention to use AI in retail (BEH). Section 4 clarifies the discussion, evaluates these data in the context of TAM, evaluates the results, and provides recommendations appropriately.

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Literature Review

The literature review for the study has been separated into three sections. The first part gives an overview of AI, outlining its significance in business. The second part concentrates on the adoption of AI in retail, addressing current research on AI application. The last part analyses the usage of the TAM in the adoption of AI in retail, explaining AI's perceived utility (PU), perceived ease of use (PEoU), attitude towards utilising AI in retail (ATT), and behavioural intention (BI) to use AI in retail. This section also outlines the hypothesis statements for exploring the relationships regarding the adoption of AI in retail.

Overview of AI

AI refers to the simulation of human reasoning in technology that is intended to operate like humans (Russell et al., 2010). The concept of AI stretches back to the mid-20th century, when thinkers like Alan Turing and John McCarthy laid the framework for the development of intelligent computers. Turing's breakthrough work, "Computing Machinery and Intelligence" and McCarthy's coined the word "Artificial Intelligence" at the Dartmouth Conference are usually acknowledged as essential moments in AI history (McCarthy et al., 2006; Turing, 1950).

In businesses, the adoption of AI like Chabot's, targeted marketing, and sales predictions has increased efficacy and enhanced customer participation. As an example, Amazon's AI-driven recommendation algorithms given to each customer have amplified sales (Smith & Linden, 2017). Also, AI is applied to examine customer habits and preferences which helps to optimise inventory (Chui et al., 2016), and AI-powered Chabot's provides inquiring services to users (Huang & Rust, 2018) constituting a major source of innovation, yet threatening human jobs. We develop a theory of AI job replacement to address this double-edged impact. The theory specifies four intelligences required for service tasks—mechanical, analytical, intuitive, and empathetic—and lays out the way firms should decide between humans and machines for accomplishing those tasks. AI is developing in a predictable order, with mechanical mostly preceding analytical, analytical mostly preceding intuitive, and intuitive mostly preceding empathetic intelligence. The theory asserts that AI job replacement occurs fundamentally at the task level, rather than the job level, and for "lower" (easier for AI. These examples demonstrate AI's crucial significance in business.

AI in Retail

AI has changed the retail sector for customers through the use of various applications such as Chabot's, personalised recommendations, and customised searches. The research by (Adamopoulou & Moussiades, 2020) demonstrates the effect of AI-driven Chabot's on customer service. They further mentioned that Chabot provide rapid replies to customer requests, cuts wait times, and handles several queries simultaneously, which enhances the customer satisfaction. Also, (Rossmann et al., 2020; Vergaray et al., 2023) mentioned that Chabot's significantly cut operational expenditures while keeping high levels of customer service quality.

Personalised recommendations are another insinuation of AI in retail. Research by (Liu & Ding, 2022; Nagraj & Palayyan, 2024) the user experience and connection between digital platforms are exploited through semantic emotions. This provides a personalized recommendation for different user categories across the E-commerce platforms. This manuscript introduces a Syntactic Data Inquiring Scheme (SDIS states that AI can assess an enormous volume of customer data that helps to build personalised recommendations for individual customers. (Liu & Ding, 2022) the user experience and connection between digital platforms are exploited through semantic emotions. This provides a personalized recommendation for different user categories across the E-commerce platforms. This manuscript introduces a Syntactic Data Inquiring Scheme (SDIS further mentioned that the inclusion of personalised recommendations increases the customer satisfaction by making their shopping experience more pertinent and effective. Similarly, (Chandra et al., 2022; Gao & Liu, 2022) stated personalisation supports customer retention and engagement, which is also corroborated (Huang & Rust, 2021).

(Choppadandi, 2022) reveals that AI-powered search engines use machine learning algorithms to predict and offer the most relevant search returns for customer intention and prior behaviour, which assures that customers get the information that they require. (Badreddine & Hadjira, 2023; Chintalapati & Pandey, 2022) technology, and our economy, we observe artificial intelligence (AI) states that seamless and engaging purchase experience, promotes repeat visits and fostering customer loyalty. (Bawack et al., 2022; Chen et al., 2022; Chen et al., 2022) also revealed that AI-enabled search engines have helped customers to look for what they want which leads to more favourable conversion rates.

Technology Acceptance Model (TAM) and Hypothesis Statements

Customer adoption of technology determines the extent to which it is used in any business (Davis, 1989). The TAM mentions that perceived usefulness and PEoU are two important components of customers adopting technology. By perceived usefulness (PU) and perceived ease of use (PEoU), the TAM evaluates customer adoption of technology (Al-Adwan et al., 2023; Alsyouf et al., 2023) which combines a number of information technologies, is the Internet of the future. A media for immersive learning, metaverse could set future educational trends and lead to significant reform in education. Although the metaverse has the potential to improve the effectiveness of online learning experiences, metaverse-based educational implementations are still in their infancy. Additionally, what factors impact higher education students' adoption of the educational metaverse remains unclear. Consequently, the aim of this study is to explore the main factors that affect higher education students' behavioral intentions to adopt metaverse technology for education. This study has proposed an extended Technology Acceptance Model (TAM). TAM's ability to forecast the acceptance and usage of new technology has made it a vital tool for understanding how customers adopt and use technology (Billanes & Enevoldsen, 2021). The part presents TAM-based hypotheses on AI adoption in retail.

Hypothesis Statements

Perceived ease of use (PEoU) refers that adopting any technology requires minimal effort., that influences a user's desire to use the technology. When a technology is simple to use, it decreases the amount of effort required and customers adopt it (He et al., 2018; Kampa, 2023). Perceived usefulness (PU) is the notion that technology would increase productivity, and is thus a critical factor to use the technology. Research also demonstrates that PEoU influences PU, indicating that if a technology is simple to use, consumers are more inclined to find it useful as well (Jeong, 2011; Pipitwanichakarn & Wongtada, 2019; Song et al., 2023) we use the technology acceptance model (TAM). Based on the description, the hypothesis statements are:

H1: PEOU positively affects PU of adoption of AI in retail.

H2: PU positively affects ATT towards the adoption of AI in retail.

H3: PEOU positively affects ATT towards the adoption of AI in retail.

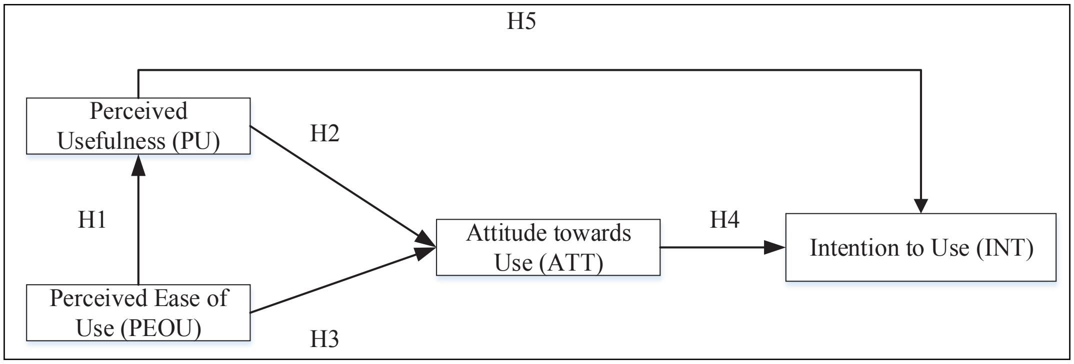
In TAM, attitude (ATT) also plays a significant part in establishing a user's desire to use technology (Quoquab & Mohammad, 2020; Weinlich & Semerádová, 2022) and is a mediator in the TAM model (Netzer et al., 2018; Pan, 2020; Zhang & Sun, 2009). The hypotheses statement can be stated as:

H4: ATT positively affects BI for the adoption of AI in retail.

Numerous studies also repeatedly suggest the significant influence of PU on BI (Islam et al., 2023; Peng & Yan, 2022; Songkram et al., 2023; Tseng et al., 2022) the need for greater technological proficiency that underpins online purchasing presents a significant challenge for entrepreneurs, managers, and consumers. This paper employed TAM (Technology Acceptance Model). Therefore,

H5: PU positively affects BI towards the adoption of AI in retail.

In this study, we present the model illustrated in Fig. 1.



Source: Author.

Fig. 1: Proposed Conceptual Framework

Research Methodology

Research Design

In this study, a quantitative research technique is employed to examine the relationships between perceived usefulness (PU), perceived ease of use (PEOU), attitude towards usage (ATT), and intention to use (INT) AI in retail. A sample size of 200 customers who decided to use any type of AI while purchasing was considered. Data is acquired via standardised questionnaires on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), combining validated measurements for each dimension. Statistical investigations, including reliability and validity tests along with two-tailed t-tests, are done to examine the expected relationships. This technique delivers complete insight into the aspects driving AI adoption in retail, enabling to build methods to improve customer acceptance and usage of AI.

Data Collection

This research focuses on customers who are accustomed to any type of AI in purchasing. Participants who fulfilled the requirements were chosen for data collection and thus stratified sample approach was adopted. Participants were told about the study, and their experience with using AI for purchase was evaluated. The anonymous online survey generated 200 replies, which were complete and incorporated in the study.

Data Analysis

The measurement model includes reliability and validity tests to ensure the measuring scales were durable. For reliability, Cronbach Alpha is performed and for validity, Heterotrait-Monotrait Ratio (HTMT) are performed. Additionally, two-tailed t-tests were performed to assess the expected relationships between perceived utility (PU), perceived ease of use (PEoU), attitude towards usage (ATT), and intention to use (INT). This extensive approach to data analysis provides an understandable overview of the aspects driving AI adoption in retail, offering important insights for enhancing customer acceptance and usage of AI.

Measurement Model

The present research tested the measurement model by performing reliability and validity tests. Results are given in Tables 1 and 2. For reliability test, factors such as composite reliability (CR) above 0.7 and average variance extracted (AVE) above 0.5 were chosen. As shown in Table 1, all reliability measures meet these standards, showing good consistency. Convergent validity was supported by AVE values topping 0.5 for all groups, as seen in Table 1. Discriminant validity, measured using HTMT values below 0.9, is proven in Table 2, meeting the needed requirements. In summary, the model shows both good reliability and validity.

Table 1: Reliability Test Outcomes

Variables	*Cronbach Alpha*
PEoU→ PU	0.79
PU→ATT	0.83
PEoU→ATT	0.79
ATT→INT	0.70
PU→INT	0.96

Table 2: Validity Test Outcomes

Variables	*PEoU→ PU*	*PU→ATT*	*PEoU→ATT*	*ATT→INT*	*PU→INT*
PEoU→ PU	X				
PU→ATT	0.56	X			
PEoU→ATT	0.07	0.07	X		
ATT→INT	0.02	0.04	0.03	X	
PU→INT	0.16	0.16	0.56	0.03	X

Structural Model

The evaluation of path coefficients is given in Fig. 2 and Table 3. Out of the five research hypotheses proposed for the study, three have been accepted. As indicated in Fig. 3, the relationships PEoU → PU ($\beta = 0.01$, $t = 0.43$, $p < 0.05$) and ATT → INT ($\beta = -0.03$, $t = 2.56$, $p < 0.05$) did not meet the acceptance criteria. However, the analysis assures the validity of three research hypotheses: PU → ATT ($\beta = 0.38$, $t = 8.82$, $p < 0.05$), PEoU → ATT ($\beta = 0.13$, $t = 2.56$, $p < 0.05$), and PU → INT ($\beta = 0.12$, $t = 2.56$, $p < 0.05$). This exerts a significant influence of AI in the retail in the UAE. Consequently, H2, H3, and H5 are accepted and H1 and H4 are not validated.

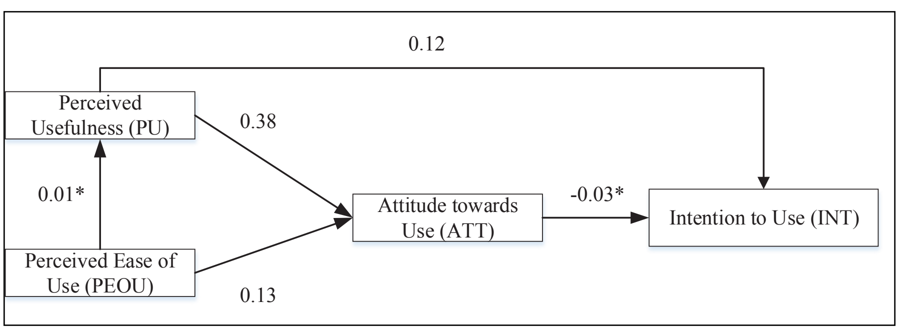


Fig. 2: Model Evaluation Result

Table 3: Path Coefficient Outcomes

Hypotheses	*Path*	*β*	*T-Value*	*P-Value*	*Supported*
H1	PEoU→ PU	0.01	0.43	6.66e-01	No
H2	PU→ATT	0.38	8.82	3.87e-17	Yes
H3	PEoU→ATT	0.13	2.76	5.98e-03	Yes
H4	ATT→INT	-0.03	-1	3.17e-01	No
H5	PU→INT	0.12	2.56	1.06e-02	Yes

Conclusion and Recommendations

According to the detailed analysis, Perceived Usefulness (PU) has a positive impact on both Attitude Towards Use (ATT) and Intention to Use (INT) AI technologies in the UAE retail sector. The research found that, whereas Perceived Ease of Use (PEoU) influences ATT, its direct effect on PU was not confirmed. These results imply that retail organisations in the UAE should work on strengthening the perceived usefulness of AI to boost attitudes and intentions to use AI. Additionally, making AI technology more user-friendly and addressing any concerns will help to increase adoption. By deliberately focusing on these areas, businesses may use AI to build a more efficient, customised, and competitive market. Overall, the analysis emphasises the role of PU and ATT in boosting AI adoption and provides insights for businesses looking to effectively incorporate AI technology into their business models.

Based on the analysis of the data, the following recommendations can be made to enhance AI adoption in the retail sector:

- *Improve Perceived Utility (PU):* Consistently express AI advantages such as customised purchasing, quick service, and data-driven choices for the implication of AI in retail.
- *Optimise the perceived ease of use (PEoU):* The businesses should invest in intuitive AI interfaces to increase consumer confidence.
- *Enhance the ATT:* Resolve privacy issues with open communication.
- *Tailor AI applications:* Adapt AI tools for customised recommendations to improve PU and PEoU.

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