Key Factors Affecting AI Adoption Rate in Retail Business (Multiple Theory Perspectives)

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Abstract

This study aims to identify and analyze the key factors that influence the adoption intention of *Artificial Intelligence* (AI) in retail businesses in Surakarta City. With the rapid development of technology, AI adoption has become an urgency for retail businesses to improve operational efficiency and customer experience. The research method used was quantitative with a survey approach, involving 135 randomly selected retail businesses. Data were collected through a questionnaire with a 5-point Likert scale and analyzed using *Partial Least Squares Structural Equation Modeling* (PLS-SEM). The results showed that*perceived ease of use*,*environmental* factors and*effort expectancy* had a positive and significant influence on AI adoption intention, while perceived*usefulness* and*performanceexpectancy* showed no significant influence. The limitations of this study lie in the limited geographical scope and small sample size. Future research is expected to expand geographic coverage and use a larger sample to increase the generalizability of the findings. In addition, future research can explore other factors that may influence AI adoption in different contexts.

Keywords: *Adoption of AI, TAM, TEO Framework, TTF, ATAUT*

INTRODUCTION

The development of technology that grows so fast, requires organizations to be able to adapt to existing developments. The level of digital transformation in an organization significantly affects the intention to adopt *Artificial Intelligence* (AI). Many factors that influence organizations to adopt AI, such as relative advantage, top management support, cost-effectiveness, competitive pressure, vendor support, compatibility, AI strategic alignment, resource availability (Horani, 2023), and the presence of interdependent tasks in the organization (Agrawal et al., 2024) play an important role in shaping AI adoption decisions. In addition, individual employees' intention to use AI is influenced by organizational culture, customs, job insecurity, perceived self-image, and perceived usefulness (Nicholas R. J. Frick, 2021). In addition, the importance of technological and organizational factors at various stages of adoption, with environmental factors generally being less critical, impacts the successful adoption of AI in public organizations (Neumann et al., 2024). Therefore, a high degree of digital transformation can create an environment conducive to embracing AI technologies, provided that various internal and external factors are carefully considered and managed (Dabbous & Barakat, Karine Aoun Sayegh, 2021).

AI adoption in retail business refers to the integration and utilization of artificial intelligence technology within the retail sector to improve various operations such as customer behavior analysis, remote view estimation, and conversational commerce through *chatbots*. Studies highlight the importance of AI in retail, showing its benefits in analyzing customer behavior (Keegan et al., 2022a), improving marketing strategies (Upadhyay, Nitin, Upadhyay et al., 2022), and enhancing customer interactions through chatbot messengers (Akgül et al., 2018). AI adoption in retail involves utilizing technologies such as deep learning for remote view estimation in analyzing customer behavior, implementing AI-powered marketing strategies for business growth, and leveraging chatbots for conversational commerce to improve customer experience and drive sales, ultimately revolutionizing the retail industry through innovative technology applications (Senarath et al., 2022) (Mehta et al., 2022).

The urgency of AI adoption in retail businesses is critical due to its potential to improve various aspects of operations. AI technologies, such as deep reinforcement learning for real-time pricing (Liang et al., 2023), chatbots for conversational commerce (Keegan et al., 2022b), and personalized AI experiences for consumers on online shopping platforms (Mehta et al., 2022), offer significant advantages. However, organizations face challenges in leveraging AI effectively, requiring a coherent understanding of its value-generating mechanisms (Bunod et al., 2022). The adoption of AI in retail can optimize pricing strategies, improve customer interactions, enhance consumer trust, and increase purchase intent. Therefore, embracing AI in retail businesses is essential to stay competitive, improve customer experience, and drive profitability in a rapidly evolving digital landscape (Yin & Qiu, 2021).

AI adoption in the retail business sector is an important aspect of modern business strategy (Santos et al., 2020). Research on information technology governance in retail companies highlights the importance of AI implementation, particularly in the Acquire and Implement (AI) domain, to improve operational efficiency and goal achievement (Pranoto, 2022). Furthermore, the development of software applications for asset procurement emphasizes the utilization of technology, such as AI, to streamline processes and improve business management (Nadhir & Karismariyanti, 2015). Understanding the impact of the modern retail marketing mix on customer satisfaction and loyalty underscores the importance of AI integration in creating positive shopping experiences and fostering customer loyalty in the retail industry (Tunfadilah, 2023). Overall, the adoption of AI in retail businesses is essential to optimize operations, improve customer satisfaction, and drive business growth (Vasconcellos et al., 2020).

AI is revolutionizing retail business operations by improving efficiency, customer experience, and decision-making processes. Through the fusion of AI and IoT technologies, retailers can design innovative customer experiences (R. & Devi, 2022). AI in retail analytics plays an important role in measuring conversion rates, optimizing store operations, and providing analytical insights with minimal hardware requirements (Shekhawat, 2023). AI is indeed revolutionizing the retail business by improving various aspects of customer engagement, decision-making, and operational efficiency. Studies highlight the impact of AI on fast-moving consumer goods (FMCG) marketing, emphasizing strategies such as personalized recommendations and advanced analytics (Maheswari, 2023). E-commerce in fashion, AI significantly shapes customer interactions and market trends, offering insights for further research and development (Goti et al., 2023). The role of AI in improving demand forecasting, pricing decisions, and product placement in retail is evident, leading to improved customer experience and optimized operations (R., M. Devi, 2022). Furthermore, research shows how consumers' moral behavior differs when interacting with AI agents and self-service machines, demonstrating the importance of understanding moral intentions in technology interactions in retail environments (Giroux et al., 2022). *E-commerce* businesses are increasingly leveraging AI to predict customer behavior and personalize the shopping experience, highlighting the potential for increased conversion rates through personalized recommendations while emphasizing the importance of ethical considerations and transparency in AI implementation (Sharma, 2023).

AI adoption behavior is related to several theories on technology acceptance such as the *Technology Acceptance Model* (TAM) theory, TAM developed by Davis (1989) focuses on two main factors: perceived*usefulness* and*perceived* ease of use. This model is used to predict how well a new technology, such as AI, will be adopted based on users' perceptions of its usefulness and ease of use. The Technology Acceptance Model (TAM) serves as a valuable framework for understanding consumer acceptance of Artificial Intelligence (AI) in retail businesses. Studies have shown that trust plays an important role in consumer attitudes towards AI in online shopping (Nagy & Hajdú, 2021), while factors such as effort expectancy, performance expectancy, facilitating conditions, and social influence positively influence customer adoption of AI-based autonomous decision-making processes (Shavneet Sharma, Nazrul Islam, Gurmeet Singh, 2018). In addition, the extended TAM has been used to predict consumer acceptance and purchase intention towards AI devices in the fashion industry, highlighting the importance of attitude, usability, ease of use, enjoyment, and performance risk in shaping consumer behavior (Shavneet Sharma, Nazrul Islam, Gurmeet Singh, 2018). Furthermore, research on AIOT-based unmanned convenience stores shows that perceived usefulness and ease of use positively impact consumer attitudes and behavioral intentions, with perceived risk playing a moderating role in consumer decision-making (Giroux et al., 2022). These findings collectively emphasize the relevance of TAM in explaining the adoption of AI technologies in retail settings (Yang et al., 2022).

The *Unified Theory of Acceptance and Use of Technology* (UTAUT) developed by Venkatesh et al. (2003), which combines eight existing theories on technology acceptance, emphasizes four core constructs: *performance expectancy*,*effort expectancy*,*social influence*, and*facilitating conditions*. UTAUT theory plays an important role in understanding AI adoption in retail businesses.

Research studies have applied the UTAUT model to investigate the factors that influence the adoption of AI-based solutions in retail settings. Factors such as effort expectancy, performance expectancy, facilitating conditions, social influence, attitude, habit, and perceived quality have been identified as significant determinants of behavioral intention to adopt AI technology in retail (Shavneet Sharma, Nazrul Islam, Gurmeet Singh, 2018), (Shavneet Sharma, Nazrul Islam, Gurmeet Singh, 2018), (García de Blanes Sebastián et al., 2022). Additionally, the UTAUT model has been used to explore customer adoption of AI-based autonomous decision-making processes, revealing positive relationships with effort expectancy, performance expectancy, facilitating conditions, and social influence (Shavneet Sharma, Nazrul Islam, Gurmeet Singh, 2018). Understanding these factors is critical for retail businesses looking to successfully integrate AI solutions and improve their operations in the evolving digital landscape.

The*Technology Organization Environment* (TOE) *Framework* developed by Tornatzky and Fleischer (1990) emphasizes on three main elements that influence technology adoption in organizations: technology, organization, and environment. The TOE framework plays an important role in understanding AI adoption in retail businesses. Research emphasizes that factors such as technological context (e.g., relative advantage, compatibility, observability), organizational context (e.g., top management support, entrepreneurial orientation), and environmental context (e.g., perceived trends, government support) significantly influence AI adoption in retail settings (Nguyen et al., 2022) (Tjondronegoro et al., 2022). In addition, the TOE framework highlights the importance of human-centered design and trust in the successful implementation of AI technologies in business (Shavneet Sharma, Nazrul Islam, Gurmeet Singh, 2018). Moreover, the unified theory of technology acceptance and use, along with cultural dimensions such as collectivism and uncertainty avoidance, also influence customer adoption of AI-based autonomous decision-making processes in retail, providing valuable insights for system developers and managers (Shavneet Sharma, Nazrul Islam, Gurmeet Singh, 2018).

AI adoption in the retail business sector is an important aspect of modern business strategy (Santos et al., 2020). Research on information technology governance in retail companies highlights the importance of AI implementation, particularly to improve operational efficiency and goal achievement (Pranoto, 2022). Furthermore, the development of software applications for asset procurement emphasizes the utilization of technology, such as AI, to streamline processes and improve business management (Pranoto, 2022). Understanding the impact of the modern retail marketing mix on customer satisfaction and loyalty underscores the importance of AI integration in creating positive shopping experiences and fostering customer loyalty in the retail industry (Nadhir & Karismariyanti, 2015). Overall, the adoption of AI in retail businesses is essential to optimize operations, improve customer satisfaction, and drive business growth. This study aims to analyze the key factors that can influence AI adoption intention in retail businesses from various theoretical perspectives.

METHOD

This study used a quantitative research design with a survey method. Data was collected through questionnaires distributed to retail businesses in Surakarta City that have or are considering adopting AI in their business operations. The sample in this study was 135 randomly selected retailers. The variables measured in this study are *perceived usefulness*, *perceived ease of use*, *performance expectancy, effort expectancy*, *environment*, and *intention to adopt AI*. Data was collected using a questionnaire based on a 5-point Likert scale. This questionnaire was tested for validity and reliability before being distributed to ensure the reliability of the data obtained. Data analysis was conducted using the *Partial Least Squares Structural Equation Modeling* (PLS-SEM) method (Hair, Joe F., Sarstedt, M., Hopkins, L., and Kuppelwieser, 2014). The conceptual framework in this study is as shown in the figure below.

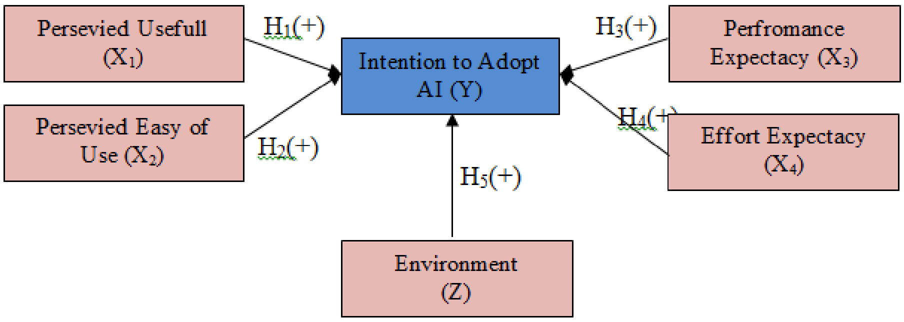

Figure 1. Research Conceptual Framework

RESULTS AND DISCUSSION

Characteristics of Respondents

The characteristics of respondents according to gender in this study are as in table 1.

Table 1. Characteristics of Respondents Based on Gender

Gender	Frequency	Percentage (%)
Male	74	54.8
Female	61	45.2
Total	**135**	**100**

Source: Processed Primary Data, May 2024.

The majority of respondents in this study had male gender, namely 74 respondents or 54.8% of the total respondents, while the remaining 61 respondents or 45.2% had female gender.

Characteristics of respondents according to age in this study as in table 2.

Table 2. Characteristics of Respondents Based on Age

Age	Frequency	Percentage (%)
<30	34	25.2
30-40	47	34.8
41-50	34	25.2

Age	Frequency	Percentage (%)
>50	20	14.8
Total	**135**	**100**

Source: Processed Primary Data, May 2024.

The majority of respondents in this study were aged 30-40 years, namely 47 respondents or 34.8% of the total respondents, while respondents aged less than 30 years were 34 respondents or 25.2%, respondents aged 41-50 years were 34 respondents or 25.2%, and respondents aged more than 50 years were 20 respondents or 14.8% of the total respondents in the study.

The characteristics of respondents according to the length of business in this study are as in table 3.

Table 3. Characteristics of Respondents Based on Length of Business

Length of Business	Frequency	Percentage (%)
<5 tahun	41	30.4
5-10 tahun	54	40.0
11-20 tahun	27	20.0
>20 tahun	13	9.6
Total	**135**	**100**

Source: Processed Primary Data, May 2024.

The majority of respondents in this study had a length of business between 5-10 years, namely 54 respondents or 40.0% of the total respondents, 41 respondents or 30.4% of the total respondents had a length of work between 11-20 years, 13 respondents or 9.6% of the total respondents had a length of business of more than 20 years.

The characteristics of respondents according to the level of education in this study are as in table 4.

Table 4. Characteristics of Respondents Based on Education Level

Tingkat Pendidikan	Frekuensi	Persentase (%)
SMA/Sederajat	30	22.2
Diploma	40	29.6
Sarjana (S1)	50	37.0
Pascasarjana (S2/S3)	15	11.2
Total	**135**	**100**

Source: Processed Primary Data, May 2024.

The majority of respondents in this study had a Bachelor's degree (S1), namely as many as 50 respondents or 37.0% of the total respondents, there were 30 respondents or 22.2% of the total respondents had a high school / equivalent education level, there were 15 respondents or 11.2% of the total respondents had a postgraduate education level. The results of this study indicate that education level has relevance to AI understanding and AI adoption intention.

Descriptive Statistical Results of Variable Assessment

The reults od descriptive analysis of each variable in this tsudy can be seen in table 5.

Table 5. Descriptive Statistics

Variabel	Mean	Std. Dev	Min	Max	Kurang Baik (%)	Kurang Baik (n)	Sedang (%)	Sedang (n)	Sangat Baik (%)	Sangat Baik (n)
Perceived Usefulness	3.8	0.5	3	4	0	0	20	27	80	108
Perceived Easy of Use	4.0	0.6	3	5	0	0	30	41	70	94
Performance Expectancy	4.1	0.5	3	5	0	0	10	14	90	121
Effort Expectancy	4.0	0.6	3	5	0	0	20	27	80	108
Environment	3.9	0.5	3	4	0	0	20	27	80	108
Intention to Adopt AI	4.0	0.5	3	4	0	0	10	14	90	121

Source: Processed Primary Data, May 2024.

Hasil statistic deskriptif dalam penelitian ini menerangkan bahwa *perceived usefulness* mayoritas responden menilai kegunaan yang dirasakan AI sangat baik, dengan 80% responden memberikan skor 4 atau 5 dengan nilai rata-rata skor untuk variabel ini adalah 3.8. Hasil statistic deskriptif untuk variabel *perceived easy of use* diketahui terdapat sebanyak 70% responden menilai kemudahan penggunaan AI sangat mudah, dengan rata-rata skor 4.0. Hasil statistic deskriptif untuk variabel *performance expectancy* sebagian besar responden (90%) mempunyai penilaian terkait dengan harapan kinerja AI sangat baik, dengan rata-rata skor 4.1. Hasil statistic deskriptif untuk variabel *effort expectancy* menunjukkan bahwa 80% responden merasa mempunyai ekspektasi usaha terhadap AI sangat baik, dengan rata-rata skor 4.0. Statistik deskriptif untuk variabel *environment* menunjukkan bahwa responden merasa bahwa dukungan lingkungan dinilai sangat baik oleh 80% responden, dengan rata-rata skor 3.9. Hasil statistic deskriptif untuk variabel *intention to adopt AI* dalam penelitian ini dinilai sangat baik oleh 90% responden, dengan rata-rata skor 4.0. Data deskriptif menunjukkan bahwa mayoritas responden memiliki persepsi positif terhadap variabel-variabel yang dianalisis, yang menunjukkan kesiapan yang tinggi untuk mengadopsi teknologi AI dalam bisnis ritel.

Validity and Reliability Test Results

Convergence Validity Value

The validity value for each indicator in this model is as shown in Figure 2.

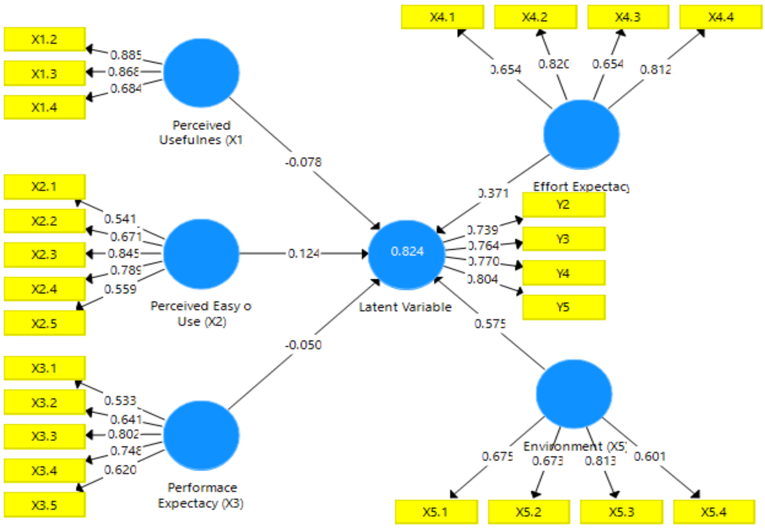

Figure 2. Convergent Validity Test Results

Based on the picture above, it can be seen that the outer loading value of each indicator in this research model has a value above 0.50, meaning that all indicators of the variables in this model are valid.

Discriminant Validity Value

In addition to convergent validity by looking at the outer loading value, the validity value of the indicator variables in this model can also be seen from the AVE value and the AVE root value. The AVE value and AVE root in this model can be seen in table 6.

Table 6. Discriminant Validity Test Results

	Effort Expectacy	Environment	Intention to Adopt AI	Perceived Easy of Use	Perceived Usefulnes	Performace Expectacy
Effort Expectacy)	0.740					
Environment	0.854	0.695				
Intention to Adopt AI	0.849	0.886	0.770			
Perceived Easy of Use	0.562	0.513	0.538	0.692		
Perceived Usefulnes	0.675	0.501	0.504	0.660	0.817	

Performace Expectacy	0.599	0.621	0.564	0.761	0.776	0.676

Source: Processed Primary Data, May 2024.

The AVE value of each variable is greater than the root AVE of its correlation with other variables so that discriminant validity has been fulfilled, so this instrument is suitable for use in this study.

Construct Reliability and Validity Value

In this research model, the reliability value can be seen in table 7.

Table 7. Construct Reliability dan Validity Value

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Effort Expectacy (X4)	0.722	0.751	0.827	0.547
Environment (X5)	0.736	0.753	0.787	0.583
Intention to Adopt AI (Y)	0.771	0.774	0.853	0.592
Perceived Easy of Use (X2)	0.719	0.768	0.816	0.678
Perceived Usefulnes (X1)	0.742	0.747	0.856	0.668
Performace Expectacy (X3)	0.794	0.712	0.804	0.656

Source: Processed Primary Data, May 2024.

Based on the table above, it can be seen that the Cronbach's Alpha value of each variable construct has a value above 0.7, the rho A value of each variable construct has a value above 0.7 and the composite reliability of each construct has a value above 0.6 so that it can be seen that this model is reliable.

Model Structure Test

The inner model test in this study was carried out using the R^2 (*R Square*) value test. R^2 is a measure of the proportion of variation in the value of the influenced variable (*endogenous*) that can be explained by the influencing variable (*exogenous*). The results of the model structure test in this study are as in table 7.

Table 8. Uni Model Structure with R^2

	R Square	R Square Adjusted
Intention to Adopt AI (Y)	0.824	0.818

Source: Processed Primary Data, May 2024.

Based on the table above, it can be seen that the^{R2} value of 0.818 is included in the substantial proportion (strong proposition), which means that the proportion of variation in the value of endogenous variables that can be explained by ecosen variables in this study is 81.8%, the remaining 18.2% is explained by other variables outside the model in this study.

Research Hypothesis Test Results

The results of hypothesis testing conducted using the Smarth PLS application in this study can be seen in table 8.

Table 9. Path Coefficient

	Original Sample	Sample Mean	Standard Deviation	T Statistics	P Values
Effort Expectancy (X4) -> Intention to Adopt AI (Y)	0.371	0.375	0.105	**3.544**	**0.000**
Environment (X5) -> Intention to Adopt AI (Y)	0.575	0.570	0.097	**5.921**	**0.000**
Perceived Easy of Use (X2) -> Intention to Adopt AI (Y)	0.124	0.128	0.057	**2.166**	**0.031**
Perceived Usefulnes (X1) -> Intention to Adopt AI (Y)	0.078	0.082	0.078	**0.999**	**0.318**
Performace Expectacy (X3) -> Intention to Adopt AI (Y)	0.050	0.046	0.075	**0.663**	**0.508**

Source: Processed Primary Data, May 2024.

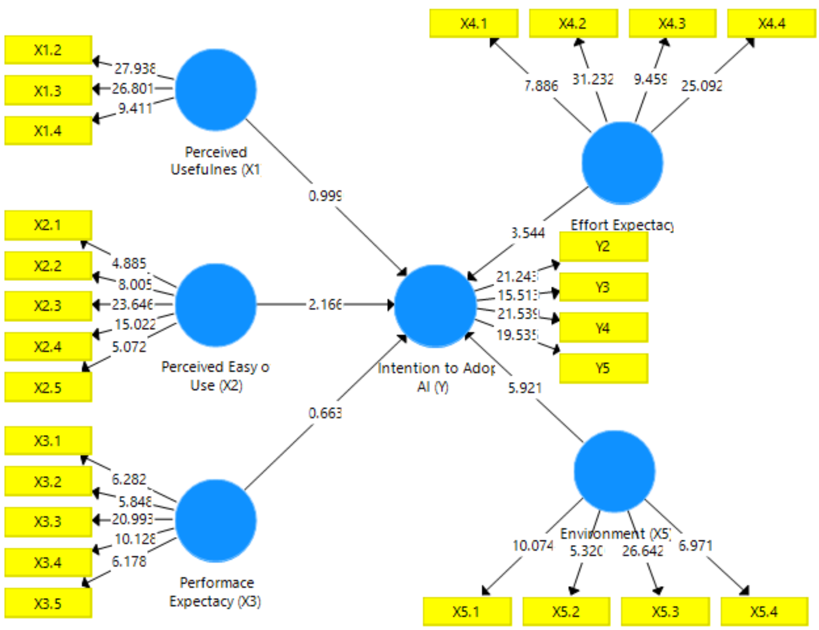

Figure 3. Path Coefficient

Based on table 8 and figure 3, it can be seen that the effect of *perceived usefulness* on *intention to adopt AI* on retail business actors, it is known that the path coefficient value of 0.078 is positive, with a t value = 0.999 and a significance value (*p-value*) of 0.318 greater than 0.05, meaning that *perceived ease of use* has a positive but insignificant effect on the intention to adopt AI on retail business actors. The results of this study indicate that greater perceived usefulness of AI will increase an individual's intention to adopt AI technology but not significantly. Perceived usefulness plays an important role in influencing AI adoption intention in various fields. Studies in mental healthcare (Wijaya, 2023), education (Li, 2023), accounting (Sudaryanto et al., 2023), sports industry (Chin et al., 2022), and tourism and hospitality sector (Ho et al., 2022) consistently highlight the positive impact of perceived usefulness on intention to adopt AI technologies. The perceived usefulness of an AI system or tool is shown to positively influence user attitudes, behavioral intentions, and actual use of AI-based systems. These perceptions are key drivers in shaping individuals' decisions to utilize AI technologies, suggesting that when individuals perceive AI as useful and valuable in improving their tasks or experiences, then they are more likely to adopt and utilize AI-powered solutions across multiple domains.

The effect of *perceived ease of use* on *intention to adopt AI* on retail business actors, it is known that the path coefficient value of 0.124 is positive, with a t value = 5.921 and a significance value (*p-value*) of 0.000 smaller than 0.05, meaning that *perceived ease of use* has a positive and significant influence on AI adoption intentions on retail business actors. The results of this study indicate that higher perceived ease of use of AI increases AI adoption intention. Perceived ease of use plays an important role in the adoption of AI-based technologies in various industries. Research has shown that perceived ease of use positively affects the acceptance of AI technology (Na et al., 2023); (Sudaryanto et al., 2023); (Alboqami, 2023). It has been found to significantly influence the adoption of artificial intelligence technology among accounting students, suggesting that when technology is perceived as easy to use, individuals are more likely to adopt it (Li, 2023). Moreover, in the context of the tourism and hospitality sector, perceived ease of use has been identified as a key factor influencing behavioral intention towards AI-powered online services, highlighting its importance in driving adoption in this industry as well (Ho et al., 2022). Overall, perceived ease of use is consistently recognized as an important factor influencing individuals' attitudes and intentions to adopt AI technologies in various professional and educational settings.

The effect of *performance expectacy* on *intention to adopt AI* on retail business actors, it is known that the path coefficient value of 0.050 is positive, with a t value = 0.663 and a significance value (*p-value*) of 0.508 greater than 0.05, meaning that *performance expectacy* has a positive but insignificant effect on AI adoption intentions on retail business actors. The results of this study indicate that higher AI performance expectancy will increase the intention to adopt AI but not significantly. Performance expectations play an important role in influencing the intention to adopt AI in retail businesses. Shavneet Sharma, Nazrul Islam, Gurmeet Singh, (2018) highlighted that performance expectancy is a significant factor in the technology acceptance model, which impacts the general acceptance of service robots and the acceptance of specific robots. In addition, the study by Upadhyay et al. (2022) emphasized the importance of technology orientation as an exogenous variable influencing AI adoption intentions in family businesses. These findings suggest that in the context of retail businesses, the perceived performance benefits of AI technologies, such as improved efficiency and customer service, may positively influence the intention to adopt AI solutions. Therefore, understanding and promoting the positive performance expectations of AI systems is essential to encourage their adoption in the retail sector.

The effect of *effort expectancy* on *intention to adopt AI* on retail business actors, it is known that the path coefficient value of 0.371 is positive, with a t value = 3.544 and a significance value (*p-value*) of 0.000 smaller than 0.05, meaning that *effort expectancy* has a positive and significant effect on AI adoption intentions on retail business actors. This indicates that an increase in *effort expectancy* will increase an individual's intention to adopt AI in retail business people. *Effort expectancy* plays an important role in influencing the intention to adopt artificial intelligence (AI) in business, including retail companies. Research has shown that neural representations of anticipated actions are sensitive to expected demands, such as effort, while being unaffected by the expected value of outcomes (Upadhyay, Nitin, Upadhyay et al., 2022). AI characteristics such as intelligence are also perceived to increase user satisfaction and perceived usefulness, leading to increased continuance intentions in engaging with AI-enabled applications (Lee et al., 2023). Therefore, understanding and managing *effort expectancy* is critical in driving a successful AI adoption strategy in retail businesses.

The effect of environmental support on *intention to adopt AI* on retail business actors, it is known that the path coefficient value of 0.575 is positive, with a t value = 5.921 and a significance value (*p-value*) of 0.000 smaller than 0.05, meaning that environmental support has a positive and significant effect on the intention to adopt AI on retail business actors. The results of this study indicate that better environmental support significantly increases the intention to adopt AI in retail businesses. Environmental impact plays an important role in influencing the intention to adopt AI in retail business. Environmental awareness and awareness of green practices can have a positive impact on consumer purchase intentions for green products, one of the strategies for creating *green products* can be done by utilizing AI (Gu et al., 2023). Attitudes towards sustainable fashion, which include the use of AI in promoting sustainability, can influence consumer purchasing decisions and corporate strategies in the fashion industry (Bolesnikov et al., 2022). Furthermore, the adoption of online retail (ORE) is influenced by factors such as environmental context, such as perceived trends and government support, demonstrating the importance of environmental considerations in digital transformation in retail businesses (Nguyen et al., 2022). Overall, incorporating environmental impact considerations can drive AI adoption in retail businesses towards more sustainable practices and strategies.

CONCLUSION

The results of the analysis in this study draw the conclusion that the variables of *effort expectancy, environment*, and *perceived ease of use* have a positive and significant influence on the intention of retail business actors to adopt AI in retail business actors. In contrast, *perceived usefulness* and *performance expectancy* did not show a significant influence. Therefore, to increase the adoption of AI among retailers, the main focus should be on aspects related to effort expectancy, environmental support, and ease of use of AI technology.

Retailers still need to increase awareness and understanding of AI so that they can optimize the benefits of AI technology. In developing the use of AI, it is still necessary to increase investment in infrastructure and technological support, provide experience for users in the use of AI, and build an environment that supports the use of AI in retail businesses.

This research is limited to the object of AI adoption intention so that future researchers can analyze other aspects of behavior such as attitude or consistency in the use of AI. This study used retail business subjects, in order to generalize the key factors in AI adoption, future researchers can use subjects from various business fields. This study uses the theoretical perspectives of TAM, UTAUT, TTF and TEO frame work, it is recommended that future researchers can use other theoretical approaches such as TPB theory, DIF and so on in analyzing key factors in AI adoption.

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