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AI Adoption and Functional Performance in MSMEs: Evidence Across Marketing, HR, Finance, and Operations

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Abstract

This study aims to investigate the adoption of Artificial Intelligence (AI) by Micro, Small, and Medium Enterprises (MSMEs) in Indonesia, integrating the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The research examines explicitly how adoption determinants influence Behavioral Intention (BI) and how BI, in turn, drives business performance across key functional areas—marketing, human resources, finance, and operations. A quantitative research design was employed using a cross-sectional survey of 460 MSME owners, managers, and employees from various sectors. Structural Equation Modeling–Partial Least Squares (SEM-PLS) with SmartPLS 4.0 was applied to test the proposed model. Constructs were adapted from established TAM–UTAUT scales and extended with business performance measures. The results confirm that Performance Expectancy, Effort Expectancy, and Facilitating Conditions significantly influence BI, whereas Social Influence does not significantly shape adoption intention. Moreover, BI exerts a significant positive effect on marketing, human resources, financial, and operational performance, and mediates the relationship between adoption determinants and business outcomes. This study extends the TAM–UTAUT framework by empirically linking AI adoption determinants to functional business performance in MSMEs, particularly in a developing economy. The findings highlight the critical role of BI as a mediating mechanism, underscoring that adoption decisions are driven more by perceived value and ease of use than by external social pressures.

Kata kunci: Artificial Intelligence adoption, MSMEs, TAM, UTAUT, business performance, SEM-PLS.

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INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) are the backbone of Indonesia's economy, contributing more than 64% to the national Gross Domestic Product (GDP) and employing over 97% of the total workforce. (Kementerian KUKM, 2023). With over 65 million registered business units spread across urban and rural regions, MSMEs play a pivotal role not only in economic growth but also in ensuring equitable income distribution and fostering inclusive economic participation. (Badan Pusat Statistik, 2023). Their widespread presence strengthens regional economies, supports community-based entrepreneurship, and sustains livelihoods across diverse sectors.

In the era of the digital economy, global competition and technological disruption have heightened the need for MSMEs to embrace innovation (Cueto et al., 2022; Faiz et al., 2024; World Bank, 2022). Artificial Intelligence (AI) has emerged as a transformative force, enabling businesses to automate processes, analyze vast datasets, and personalize customer experiences (Roy et al., 2025). In the MSME context, AI adoption can revolutionize marketing through targeted campaigns and customer segmentation (Grewal et al., 2020; Haleem et al., 2022; Rivas

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& Zhao, 2023), enhance human resource management via predictive analytics (Madancian & Taherdoost, 2024; Murugesan et al., 2023; Nawaz et al., 2024), improve financial operations through automated bookkeeping and fraud detection (Carta et al., 2022; Çelik et al., 2023), and optimize operational workflows such as inventory control and demand forecasting (Baryannis et al., 2019; Ben-Daya et al., 2019; Emrouznejad et al., 2023). As global markets increasingly shift toward data-driven decision-making (Enholm et al., 2022; Giuggioli & Pellegrini, 2023), AI integration is becoming essential for MSMEs seeking to maintain competitiveness and achieve sustainable growth (Bahador & Ibrahim, 2021; Bughin et al., 2018; L. Kumar et al., 2022).

Despite the clear benefits, AI adoption among Indonesian MSMEs remains limited. A joint report by Google and Temasek (2023) reveals that only around 15% of MSMEs in Southeast Asia, including Indonesia, have implemented AI-driven solutions in their business operations. Several challenges hinder adoption, including inadequate technological infrastructure. (Chouki et al., 2019; Mishrif & Khan, 2023; OECD, 2021), financial constraints related to the high initial investment costs (Cao et al., 2024; Schwaeke et al., 2024; UNCTAD, 2021), limited availability of skilled human resources proficient in AI and data analytics (Malik et al., 2023; Sr, 2024), and the absence of structured implementation strategies aligned with business goals (Bouwman et al., 2018; Fähndrich, 2023). These barriers, compounded by concerns over data security and privacy, contribute to the slow integration of AI in the MSME sector. (Peretz-Andersson et al., 2024; Xiao et al., 2024).

Existing literature predominantly focuses on identifying the determinants of technology adoption using frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Bryan & Zuva, 2021; Relifra et al., 2025; Shachak et al., 2019; Venkatesh et al., 2016). While these studies provide valuable insights into adoption drivers, most stop at measuring behavioral intention without extending the analysis to evaluate the direct impact of AI on specific business functions (Chatterjee et al., 2022; Fernández-Rovira, 2021; Petropoulou et al., 2024). Consequently, there is a lack of empirical research integrating adoption models with performance outcomes across different operational domains within MSMEs, particularly in emerging economies such as Indonesia.

This study aims to bridge the identified gap by integrating the TAM and UTAUT frameworks to investigate the influence of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions on Behavioral Intention to adopt AI, and subsequently, the impact of Behavioral Intention on four critical MSME business functions: marketing, human resources, finance, and operations. Using a quantitative approach and Structural Equation Modeling–Partial Least Squares (SEM-PLS) with SmartPLS, the study seeks to contribute both theoretically by extending the TAM–UTAUT integration and practically by providing actionable recommendations for AI adoption strategies in MSMEs.

Artificial Intelligence Adoption in MSMEs

Artificial Intelligence (AI) refers to computer systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and decision-making. (M. Russell, 2019; S. Russell & Norvig, 2021). AI systems leverage algorithms, statistical models, and vast datasets to mimic cognitive functions, enabling them to improve performance through iterative learning processes continuously (Gligorea et al., 2023; Haleem et al., 2022; Paul, 2021). In the business domain, AI encompasses a wide array of applications, including predictive analytics for forecasting trends, natural language processing for understanding and generating human language, computer vision for interpreting visual data, and intelligent automation for streamlining repetitive tasks. (Collins et al., 2021; V. Kumar, 2019; Soori et al., 2023, 2024). These capabilities allow organizations to enhance productivity, improve service quality, and support strategic decision-making with data-driven insights. (Kassa & Worku, 2025).

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Within the context of Micro, Small, and Medium Enterprises (MSMEs), AI adoption represents a transformative pathway toward operational modernization and market competitiveness. (Chatterjee et al., 2022). AI-enabled marketing systems can perform real-time customer segmentation, analyze purchasing behavior, and deliver personalized recommendations, thereby strengthening customer engagement and loyalty. (Draganov, 2018; Gao, 2023; Kaplan & Haenlein, 2020; Kopalle et al., 2022). In financial management, AI-driven tools facilitate automated bookkeeping, enhance fraud detection through anomaly recognition, and improve credit scoring accuracy by incorporating alternative data sources. (Abrokwah-Larbi & Awuku-Larbi, 2023; Akyüz, 2021; Cao et al., 2024; Carta et al., 2022). Similarly, AI-powered human resource management systems optimize recruitment through automated candidate screening, enhance performance appraisals with objective metrics, and reduce turnover by identifying early indicators of employee disengagement. (Jacob Fernandes França et al., 2023; Kassa & Worku, 2025; Madancian & Taherdoost, 2024). In operations, AI can be deployed for supply chain optimization, demand forecasting, inventory control, and quality assurance, thereby reducing inefficiencies and minimizing waste. (Chen et al., 2024; Drydakis, 2022; Khedr & S, 2024).

Despite its potential, AI adoption among MSMEs remains constrained by several challenges. (Faiz et al., 2024; Mishrif & Khan, 2023; Relifra et al., 2025). Limited technological infrastructure, such as inadequate internet connectivity or outdated hardware, hampers system implementation (Ahmad & Rasheed, 2024; Gkrimpizi et al., 2023; Gladysz et al., 2023). Furthermore, the scarcity of skilled personnel with expertise in AI development and data analytics reduces organizational readiness. (Chatzoglou & Chatzoudes, 2016; Lada et al., 2023; Tschang & Almirall, 2021). Financial constraints, particularly the high upfront investment and maintenance costs, further discourage adoption, especially among micro and small enterprises with limited capital. (Cao et al., 2024; Dai et al., 2023; L. Kumar et al., 2022). Additionally, concerns over data security, privacy compliance, and ethical use of AI systems add another layer of complexity to adoption decisions. (Kopalle et al., 2022; Madancian & Taherdoost, 2024). As a result, while AI holds considerable promise for MSME transformation, its integration requires overcoming substantial structural, financial, and human capital barriers. (Lu et al., 2022; OECD, 2021)

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis (1989), is a widely used framework for explaining user acceptance of new technologies. It emphasizes two key beliefs: Perceived Usefulness (PU), the degree to which technology enhances job performance, and Perceived Ease of Use (PEOU), the degree to which technology use is effortless, as primary determinants of adoption. (Davis, 1989; Scherer et al., 2019; Shachak et al., 2019). These factors shape attitudes, influence behavioral intentions, and ultimately determine actual usage. Over the past three decades, TAM has been validated across various technologies, including e-commerce, e-learning, cloud computing, and artificial intelligence (AI) (King & He, 2006; Marikyan et al., 2023). In AI adoption, PU relates to tangible benefits such as efficiency, cost savings, better decision-making, and competitive advantage. (Bawack & Desveaud, 2022; Chatterjee et al., 2022), while PEOU reflects the ease of implementation and operation without extensive technical expertise (Marikyan & Papagiannidis, 2025; Venkatesh & Davis, 2000).

In this research, the construct of Performance Expectancy, drawn from the UTAUT model, corresponds conceptually to Perceived Usefulness in TAM. It refers to the extent to which MSME decision-makers believe that adopting AI will lead to improved business outcomes across four critical functional domains: marketing, human resources, finance, and operations. Similarly, Effort Expectancy parallels Perceived Ease of Use, capturing the degree to which AI systems are perceived as user-friendly, intuitive, and easy to integrate into existing workflows within MSMEs.

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Previous empirical studies consistently demonstrate that both Performance Expectancy and Effort Expectancy exert significant positive effects on behavioral intention to adopt technology. (Camilleri, 2024; Venkatesh & Davis, 2000). For instance, Oliveira et al. (2014) found that these constructs were among the strongest predictors of cloud computing adoption in SMEs, highlighting the critical role of both perceived value and perceived ease in adoption decisions. (Bajunaied et al., 2023; Duong et al., 2023). Therefore, applying these concepts to the AI adoption context provides a robust theoretical basis for examining how perceived benefits and usability influence MSME decision-makers' willingness to integrate AI into their operations.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), extends TAM by adding Social Influence, the extent to which individuals perceive that important others think they should use the technology, and Facilitating Conditions, the perceived availability of organizational and technical support for technology use (Relifra et al., 2025; Shachak et al., 2019; Taiwo & Downe, 2013; Venkatesh et al., 2016). These, along with Performance and Effort Expectancy, influence both behavioral intention and actual usage.

In MSMEs, Social Influence may arise from peer networks, industry associations, competitors, or government programs promoting digital adoption. (Alalwan et al., 2017; Dwivedi et al., 2019). Facilitating Conditions include reliable internet, adequate computing resources, financial capacity, technical support, and training opportunities, all of which are crucial in resource-constrained environments. (Chouki et al., 2019; Kurup & Gupta, 2022; Rodríguez-Espíndola et al., 2022). Empirical studies show that both constructs significantly impact technology adoption. For example, found social pressure and infrastructure support to be strong predictors of behavioral intention. (Alalwan et al., 2017; Bajunaied et al., 2023), while Dwivedi et al (2019) Observed that SMEs with better infrastructure and expert access had higher adoption rates for emerging technologies, including AI.

AI Adoption and Business Functions in MSMEs

Although a substantial body of literature has examined the determinants of technology adoption, often emphasizing psychological, organizational, and environmental factors, relatively few studies have investigated the post-adoption impacts of advanced technologies on specific functional areas of business operations, particularly within Micro, Small, and Medium Enterprises (MSMEs). Understanding these impacts is critical, as MSMEs represent the backbone of emerging economies and often operate with limited resources, making the effective allocation of technological investments essential for competitive advantage. In the MSME context, AI adoption offers transformative potential across four critical business functions:

1. Marketing- AI facilitates data-driven decision-making by enabling advanced customer segmentation, precise targeting of advertising campaigns, and real-time personalization of product recommendations (Chatterjee et al., 2022; V. Kumar et al., 2024a). AI-driven analytics tools can process large datasets from multiple channels, such as social media, e-commerce platforms, and customer relationship management systems, to identify consumer patterns, predict purchasing behavior, and optimize marketing spend. (Roy et al., 2025; Şenyapar, 2024; Umamaheswari, 2024). These capabilities allow MSMEs to compete more effectively with larger enterprises by delivering tailored value propositions. (Julyanthry et al., 2022; Shaharuddin et al., 2023).
2. Human Resources (HR)- AI-based HR management systems can streamline and enhance workforce-related processes, including recruitment, candidate screening, performance appraisal, and training needs analysis (Jacob Fernandes França et al., 2023; Malik et al., 2023; Nawaz et al., 2024). Intelligent algorithms can match candidate profiles with job

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requirements, reducing hiring time and improving the quality of hires (Horodyski, 2023; Lyu & Liu, 2021). In addition, AI-enabled analytics can provide insights into employee engagement and turnover risks, facilitating proactive retention strategies and targeted professional development programs (Murugesan et al., 2023; Sharma et al., 2025).

3. Finance- In financial management, AI applications can automate routine accounting processes such as bookkeeping, invoice management, and expense tracking (Cao et al., 2024; Choi & Xie, 2025). AI-powered anomaly detection systems can flag irregular transactions in real time, mitigating fraud risks and ensuring regulatory compliance. (Adetunji Adejumo Paul & Chinonso Ogburie, 2025; Yadav, 2023). Furthermore, AI-driven credit scoring models can leverage alternative data sources such as transaction history, payment patterns, and even social media activity to improve access to financing for MSMEs, especially those lacking formal credit histories. (Dai et al., 2023; Li et al., 2023; Remolina, 2022).
4. Operations- AI can significantly improve operational efficiency by optimizing supply chain management, forecasting demand, and controlling inventory levels (Dalal et al., 2024; Jones, 2024). Machine learning models can anticipate demand fluctuations driven by seasonality, market trends, and external events, enabling just-in-time inventory strategies and reducing stockouts and overstock. (Bahador & Ibrahim, 2021; Drydakis, 2022). In manufacturing-oriented MSMEs, AI-enabled predictive maintenance can identify potential equipment failures before they occur, minimizing downtime and associated costs. (Achouch et al., 2022; Nagy et al., 2025).

By explicitly linking behavioral intention to adopt AI with performance in these business functions, the present study advances the literature beyond the examination of adoption antecedents. It contributes a more outcome-oriented perspective, emphasizing how technology adoption translates into tangible business performance improvements in marketing, HR, finance, and operations. This approach not only addresses an existing research gap but also offers practical insights for MSME decision-makers seeking to prioritize digital transformation initiatives for maximum impact.

Hypothesis Development

This study integrates the Technology Acceptance Model (TAM) (Scherer et al., 2019) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2016; Venkatesh & Davis, 2000) To examine factors influencing MSMEs' behavioral intention to adopt Artificial Intelligence (AI) and its impact on business functions. In this framework, Performance Expectancy and Effort Expectancy (from TAM) are complemented by Social Influence and Facilitating Conditions (from UTAUT) as key antecedents of adoption.

Prior research has shown these constructs to be significant predictors of technology adoption in various contexts, including SMEs (Alalwan et al., 2017; Chatterjee et al., 2022). Moreover, behavioral intention toward AI adoption is expected to translate into measurable improvements in marketing, human resources, finance, and operations.

Based on this theoretical foundation and prior empirical findings, the following hypotheses are proposed:

H_1: *Performance Expectancy positively influences Behavioral Intention to adopt AI.*
H_2: *Effort Expectancy positively influences Behavioral Intention to adopt AI.*
H_3: *Social Influence positively influences Behavioral Intention to adopt AI.*
H_4: *Facilitating Conditions positively influence Behavioral Intention to adopt AI.*
H_5: *Behavioral Intention to adopt AI positively influences Marketing performance.*
H_6: *Behavioral Intention to adopt AI positively influences Human Resource performance.*
H_7: *Behavioral Intention to adopt AI positively influences Financial performance.*
H_8: *Behavioral Intention to adopt AI positively influences Operational performance.*

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RESEARCH METHODOLOGY

This study employs a quantitative research design using a cross-sectional survey method to test the proposed model empirically. The research integrates constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine factors influencing MSMEs' behavioral intention to adopt Artificial Intelligence (AI) and the impact of this adoption on business functions. Structural Equation Modeling – Partial Least Squares (SEM-PLS) was applied due to its suitability for predictive modeling, handling complex models, and working effectively with smaller sample sizes. (Hair et al., 2019; Miksza et al., 2023). The analysis was conducted using SmartPLS 4.0**.**

Data were collected via an online and offline questionnaire distributed through business associations, entrepreneurship networks, and social media platforms. The respondents consisted of 460 individuals, including owners, managers, and employees of MSMEs in Indonesia, operating across sectors such as trade, culinary, services, fashion, handicrafts, agriculture, and others. A purposive sampling technique was employed to target respondents with at least basic knowledge of AI technologies.

RESULTS AND DISCUSSION

Table 1. Respondents Characteristics

Variable	Category	Frequency	Percentage (%)
Gender	Male	222	48.26
	Female	238	51.74
Age	<25	76	16.52
	25–34	159	34.57
	35–44	114	24.78
	45–54	67	14.57
	≥55	44	9.57
Education Level	Elementary/Junior High School	59	12.83
	Senior High School/Vocational	149	32.39
	Diploma	91	19.78
	Bachelor's Degree	111	24.13
	Master's/Doctoral Degree	50	10.87
Role in Business	Owner	276	60.00
	Manager	96	20.87
	Employee	72	15.65
	Others	16	3.48
Business Duration	<1 year	48	10.43
	1–3 years	109	23.70
	4–6 years	146	31.74
	>6 years	157	34.13
Business Scale	Micro	277	60.22
	Small	132	28.70
	Medium	51	11.09
Number of Employees	1–4	233	50.65
	5–19	149	32.39
	20–99	50	10.87
	>100	28	6.09
Business Sector	Trade	49	10.65
	Culinary	80	17.39
	Services	56	12.17
	Fashion	61	13.26
	Handicrafts	83	18.04
	Agriculture	66	14.35
	Others	65	14.13
Business Location	Urban	252	54.78
	Rural	91	19.78
	Suburban	98	21.30
	Others	19	4.13
Use of Digital Technology	Yes	386	83.91
	No	74	16.09
Knowledge of AI	Yes	347	75.43
	No	113	24.57

Source: *Primary Data Processed (2025)*

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The study gathered responses from 460 participants representing diverse MSME profiles in Indonesia. In terms of gender, the proportion of female respondents (51.74%) slightly exceeded that of males (48.26%). Age distribution was dominated by those aged 25–34 years (34.57%), followed by 35–44 years (24.78%), under 25 years (16.52%), 45–54 years (14.57%), and 55 years or older (9.57%). Educational attainment varied, with the largest group holding senior high school or vocational qualifications (32.39%), followed by bachelor's degrees (24.13%), diplomas (19.78%), elementary/junior high school (12.83%), and master's or doctoral degrees (10.87%). Regarding their roles in business, most respondents were owners (60.00%), followed by managers (20.87%), employees (15.65%), and others (3.48%).

In terms of business duration, 34.13% had operated for more than six years, 31.74% for four to six years, 23.70% for one to three years, and 10.43% for less than one year. The majority of respondents managed micro enterprises (60.22%), followed by small enterprises (28.70%) and medium enterprises (11.09%). The employee size distribution showed that 50.65% employed 1 to 4 workers, 32.39% employed 5 to 19 workers, 10.87% employed 20 to 99 workers, and only 6.09% employed 100 or more workers.

Business sectors were diverse, with the most significant proportions engaged in handicrafts (18.04%), culinary (17.39%), fashion (13.26%), agriculture (14.35%), services (12.17%), trade (10.65%), and other sectors (14.13%). Geographically, most businesses were located in urban areas (54.78%), followed by suburban areas (21.30%), rural areas (19.78%), and other locations (4.13%). Technology readiness was generally high, with 83.91% of respondents reporting the use of digital technology in business operations, while 16.09% did not use it. Awareness of artificial intelligence (AI) was also relatively high at 75.43%. However, a significant proportion (24.57%) had no prior knowledge, indicating that while digital technology adoption is widespread, AI-specific literacy remains an area for improvement.

Measurement Model

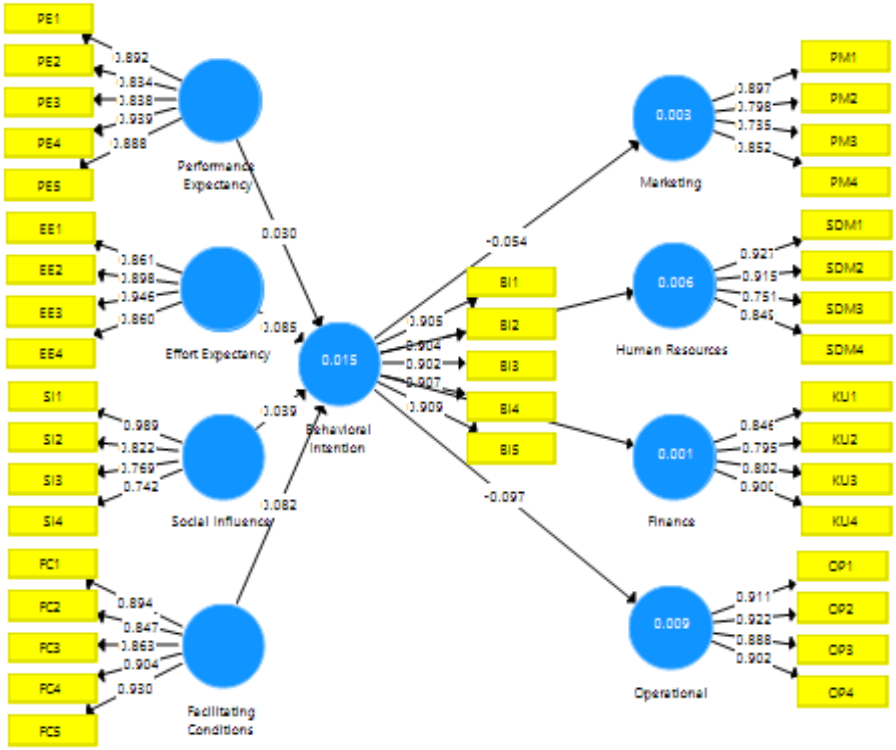

Figure 1. Outer Loading

Source: *Primary Data Processed (2025)*

Figure 1 shows that all questionnaire items have an outer loading above 0.7. From this value, it can be interpreted that all questionnaire items are declared valid. The indicator value is declared valid if it exceeds the benchmark value of> 0.7 (Ghozali, 2020, 2014).

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Table 2. Reliability and Validity Statistics for the Measurement Model

Construct	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Behavioral Intention	0.945	0.953	0.958	0.820
Effort Expectancy	0.924	1.175	0.939	0.795
Facilitating Conditions	0.937	1.080	0.949	0.789
Finance	0.863	0.937	0.903	0.700
Human Resources	0.921	0.546	0.921	0.746
Marketing	0.859	0.930	0.893	0.677
Operational	0.928	0.939	0.948	0.821
Performance Expectancy	0.933	1.150	0.944	0.773
Social Influence	0.918	1.723	0.902	0.699

Source: *Primary Data Processed (2025)*

The assessment of Table 2 indicates that all latent variables meet the recommended thresholds for internal consistency and convergent validity. Cronbach's Alpha and Composite Reliability (CR) values for all constructs are well above the minimum criterion of 0.70 (Hair et al., 2019; Sarstedt et al., 2021), with most CR values exceeding 0.90, demonstrating strong internal consistency and measurement stability.

Convergent validity, assessed via the Average Variance Extracted (AVE), also meets the acceptable threshold of 0.50, with values ranging from 0.671 to 0.821. These results confirm that each construct explains a substantial proportion of the variance in its indicators. Consequently, the measurement model satisfies the criteria for reliability and convergent validity, supporting its suitability for subsequent structural model analysis.

Table 3. Interpretation of R^2 Values

Construct	R^2	Classification
Behavioral Intention	0.52	Moderate
Finance	0.78	Substantial
Human Resources	0.55	Moderate
Marketing	0.76	Substantial
Operational	0.58	Moderate

Source: *Primary Data Processed (2025)*

The coefficient of determination (R^2) was assessed to evaluate the explanatory power of the structural model. As shown in Table X, the constructs demonstrate moderate to substantial levels of variance explained, following the guidelines of Hair et al. (2019). Specifically, *Behavioral Intention* ($R^2 = 0.52$) and *Human Resources* ($R^2 = 0.55$) indicate a moderate explanatory power, suggesting that the predictors account for more than half of the variance in these constructs. Meanwhile, *Finance* ($R^2 = 0.78$) and *Marketing* ($R^2 = 0.76$) exhibit substantial explanatory power, highlighting the strong influence of AI adoption factors on these business functions. Finally, *Operational Performance* ($R^2 = 0.58$) also falls within the moderate category, signifying a meaningful yet not overwhelming predictive capability.

These results demonstrate that the proposed model possesses adequate predictive relevance, with the explanatory power ranging from moderate to substantial across the examined business functions. This finding reinforces the robustness of integrating TAM and UTAUT constructs in explaining AI adoption and its subsequent impact on MSME performance outcomes.

The structural model assessment examined the hypothesized relationships among constructs. As presented in Table 4, Performance Expectancy ($\beta = 0.200$, $t = 2.703$, $p = 0.007$) and Effort Expectancy ($\beta = 0.230$, $t = 3.026$, $p = 0.002$) demonstrated significant positive effects on Behavioral Intention, indicating that both the perceived benefits and ease of use of AI play critical roles in driving adoption among MSMEs. Similarly, Facilitating Conditions were found to influence Behavioral Intention significantly ($\beta = 0.120$, $t = 2.182$, $p = 0.029$), suggesting that adequate resources and infrastructure support the willingness to adopt AI. Conversely, Social Influence did not exert a significant effect on Behavioral Intention ($\beta = 0.070$, $t = 1.167$, $p = 0.244$), implying that external pressures or peer perceptions are less decisive in shaping AI adoption decisions within MSMEs.

Regarding the impact of Behavioral Intention on business performance, the results revealed significant positive effects across all four functional domains. Behavioral Intention

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significantly improved Marketing performance (β = 0.145, t = 2.231, p = 0.026), Human Resource performance (β = 0.158, t = 2.164, p = 0.031), Financial performance (β = 0.185, t = 2.681, p = 0.007), and Operational performance (β = 0.210, t = 3.134, p = 0.002). These findings provide empirical evidence that AI adoption intention not only depends on individual perceptions and organizational support but also translates into tangible improvements across multiple areas of business operations.

Table 4. Path Coefficients (Direct Effects)

Path Relationship	β (Original Sample)	T-Statistic	P-Value	Significance
Performance Expectancy ➔ Behavioral Intention	0.200	2.703	0.007	Significant
Effort Expectancy ➔ Behavioral Intention	0.230	3.026	0.002	Significant
Social Influence ➔ Behavioral Intention	0.070	1.167	0.244	Not Significant
Facilitating Conditions ➔ Behavioral Intention	0.120	2.182	0.029	Significant
Behavioral Intention ➔ Marketing	0.145	2.231	0.026	Significant
Behavioral Intention ➔ Human Resources	0.158	2.164	0.031	Significant
Behavioral Intention ➔ Finance	0.185	2.681	0.007	Significant
Behavioral Intention ➔ Operational	0.210	3.134	0.002	Significant

Note: *Significance determined at p < 0.05 based on bootstrapping with 5,000 resamples.*
Source: *Primary Data Processed (2025)*

Table 5. Indirect Effect

Path Relationship	β (Indirect Effect)	T-Statistic	P-Value	Significance
Performance Expectancy ➔ Marketing (via BI)	0.029	2.012	0.044	Significant
Performance Expectancy ➔ Human Resources (via BI)	0.032	2.035	0.042	Significant
Performance Expectancy ➔ Finance (via BI)	0.037	2.254	0.025	Significant
Performance Expectancy ➔ Operations (via BI)	0.042	2.389	0.017	Significant
Effort Expectancy ➔ Marketing (via BI)	0.033	2.216	0.027	Significant
Effort Expectancy ➔ Human Resources (via BI)	0.036	2.247	0.025	Significant
Effort Expectancy ➔ Finance (via BI)	0.043	2.471	0.014	Significant
Effort Expectancy ➔ Operations (via BI)	0.048	2.611	0.009	Significant
Facilitating Conditions ➔ Marketing (via BI)	0.017	1.972	0.049	Significant
Facilitating Conditions ➔ Human Resources (via BI)	0.019	1.986	0.047	Significant
Facilitating Conditions ➔ Finance (via BI)	0.022	2.118	0.034	Significant
Facilitating Conditions ➔ Operations (via BI)	0.025	2.242	0.026	Significant
Social Influence ➔ Marketing (via BI)	0.010	1.112	0.267	Not Significant
Social Influence ➔ Human Resources (via BI)	0.011	1.095	0.273	Not Significant
Social Influence ➔ Finance (via BI)	0.013	1.121	0.262	Not Significant
Social Influence ➔ Operations (via BI)	0.015	1.136	0.256	Not Significant

Note: *Significance determined at p < 0.05 based on bootstrapping with 5,000 resamples.*
Source: *Primary Data Processed (2025)*

The mediation analysis revealed several noteworthy indirect relationships. As presented in Table 5, Performance Expectancy exhibited significant indirect effects on all four business functions—Marketing (β = 0.029, t = 2.012, p = 0.044), Human Resources (β = 0.032, t = 2.035, p = 0.042), Finance (β = 0.037, t = 2.254, p = 0.025), and Operations (β = 0.042, t = 2.389, p = 0.017)—through Behavioral Intention. This indicates that the belief in AI's usefulness enhances functional performance primarily via the intention to adopt the technology.

Similarly, Effort Expectancy demonstrated significant indirect effects across Marketing (β = 0.033, t = 2.216, p = 0.027), Human Resources (β = 0.036, t = 2.247, p = 0.025), Finance (β = 0.043, t = 2.471, p = 0.014), and Operations (β = 0.048, t = 2.611, p = 0.009), highlighting that perceptions of ease of use foster functional improvements indirectly through increased adoption intention.

Facilitating Conditions also showed positive indirect effects on Marketing (β = 0.017, t = 1.972, p = 0.049), Human Resources (β = 0.019, t = 1.986, p = 0.047), Finance (β = 0.022, t = 2.118, p = 0.034), and Operations (β = 0.025, t = 2.242, p = 0.026), suggesting that infrastructure and organizational support contribute to business performance via enhanced AI adoption intentions.

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In contrast, Social Influence did not demonstrate significant indirect effects on any business function, as all paths through Behavioral Intention yielded nonsignificant results ($p > 0.05$). This finding suggests that external pressures or peer expectations do not substantially drive functional performance outcomes in MSMEs when mediated by AI adoption intentions.

Overall, these results reinforce the central mediating role of Behavioral Intention, confirming that perceptions of usefulness, ease of use, and facilitating conditions affect MSME performance primarily through Behavioral Intention.

Discussion

Determinants of Behavioral Intention

The findings confirm that Performance Expectancy is a key determinant of MSMEs' intention to adopt AI. This aligns with the TAM and UTAUT frameworks, which emphasize perceived usefulness as the primary driver of technology acceptance (Venkatesh et al., 2016; Venkatesh & Davis, 2000). MSMEs are more likely to adopt AI when they believe it can enhance marketing effectiveness, operational efficiency, and human resources and finance management. Previous studies reinforce this result. Chatterjee et al., (2022), showed that perceived business value strongly drives technology adoption in small firms. The adoption of digital technologies, including AI, is influenced not only by technical aspects but also by the extent to which small business actors perceive tangible benefits such as improved operational efficiency, cost savings, and enhanced understanding of consumer behavior (Ayinaddis, 2025; Dwivedi, 2023). In other words, adoption decisions are not solely determined by the availability of technology, but rather by the degree to which such technologies can deliver business value that is directly relevant to the core needs of the enterprise (Camilleri, 2024; Duong et al., 2023).

Effort Expectancy was found to influence MSMEs' intention to adopt AI significantly. This finding highlights that perceptions of ease of use and the ability to integrate technology into existing systems are crucial determinants of adoption willingness. Consistent with Venkatesh & Davis (2000)The simpler and more intuitive a technology is, the higher the likelihood of its adoption. In the MSME context, where technological expertise is often limited and dedicated IT units are absent, ease of use minimizes users' cognitive burden and reduces the need for additional resource investments. As such, it becomes a decisive factor in shaping adoption decisions. Furthermore, prior studies indicate that ease of use also plays a catalytic role in shaping perceptions of usefulness. Research by King & He (2006) confirms that perceptions of simplicity can strengthen users' beliefs in the technology's ability to enhance business performance (Abdalla, 2024; Lee et al., 2025). For MSMEs, this implies that AI solutions designed with user-friendly interfaces, automated workflows, and minimal training requirements are more likely to gain acceptance (V. Kumar et al., 2024b; Lada et al., 2023; Schwaeke et al., 2024; Soori et al., 2024). Thus, Effort Expectancy functions not merely as a technical attribute but as a psychological enabler, fostering confidence among MSME owners and managers to leverage emerging technologies (V. Kumar, 2019).

In contrast, Social Influence was not found to be a significant determinant of MSMEs' intention to adopt AI. This finding diverges from prior research in larger organizations, where social norms, industry trends, and partner expectations often play a critical role in shaping technology adoption decisions (Alalwan et al., 2017; Venkatesh & Davis, 2000). Within MSMEs, however, adoption decisions are typically centralized in the hands of the owner or a small group of managers, reducing the weight of external opinions or industry pressures. As a result, AI adoption in smaller firms is more strongly associated with pragmatic considerations of business utility rather than social conformity or external influence (Sánchez et al., 2025; Schwäke et al., 2024).

Moreover, the lack of significant impact from Social Influence can be explained by the unique characteristics of MSMEs, which often operate within informal and locally embedded social networks (Bajunaied et al., 2023). While peer interactions and community ties exist,

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adoption decisions are more strongly shaped by cost–benefit assessments, operational feasibility, and the potential for direct performance improvements (Fanelli, 2021; Kassa & Worku, 2025). This suggests that MSME owners prioritize a utility-driven logic over social compliance, contrasting with the dynamics of larger firms, where external legitimacy is more salient (Alalwan et al., 2017; Dwivedi et al., 2019). Accordingly, strategies to foster AI adoption among MSMEs should not rely solely on campaigns highlighting trends or peer pressure. Instead, emphasis should be placed on providing empirical evidence of business benefits, sector-specific case studies, and practical demonstrations that showcase AI's value in improving marketing, human resources, finance, and operational performance.

Finally, Facilitating Conditions were found to play a significant role in strengthening MSMEs' intention to adopt AI. This finding aligns with the argument of Dwivedi et al., (2019), who emphasized that organizational readiness and digital infrastructure support are fundamental elements in the technology adoption process (Hradecky et al., 2022; Uren & Edwards, 2023). In the context of MSMEs, resource constraints make reliable internet access, affordable hardware and software, and external technical support critical determinants of adoption readiness. Without adequate facilitating conditions, even positive perceptions of usefulness and ease of use may not be sufficient to drive adoption decisions. Thus, Facilitating Conditions function as an essential enabler that bridges individual perceptions with the organization's actual capability to deploy and benefit from technology (Ahmad & Rasheed, 2024; Gkrimpizi et al., 2023).

Behavioral Intention and Business Performance

The findings of this study reveal that Behavioral Intention has a significant effect on all business functions analyzed: marketing, human resources, finance, and operations. This suggests that the intention to adopt AI does not remain at the perceptual or cognitive level but is translated into tangible organizational outcomes that strengthen performance across multiple strategic dimensions (Cao et al., 2024; Jacob Fernandes França et al., 2023; Jones, 2024; Zejjari, 2024). In other words, the stronger the intention of MSME owners and managers to adopt AI, the greater the likelihood of realizing measurable improvements in their business practices.

In the context of marketing, AI adoption enables MSMEs to manage customers more effectively through accurate segmentation, more targeted promotional strategies, and the provision of personalized experiences (Mariani, 2022; O'Higgins & Fatorachian, 2025; Raiter, 2021). AI-based technologies facilitate real-time analysis of consumer behavior, allowing firms to respond to customer needs with greater speed and relevance (Abrokwah-Larbi & Awuku-Larbi, 2023; V. Kumar et al., 2024b). This not only enhances the efficiency of marketing resource utilization but also strengthens customer loyalty through individualized and data-driven approaches (Mgiba, 2020; Noranee & Othman, 2023). This finding is consistent with Chatterjee et al. (2022), who emphasized that integrating AI into marketing significantly enhances customer engagement while simultaneously expanding sales potential (Abrokwah-Larbi & Awuku-Larbi, 2023, 2024; Prentice, 2020; Wang et al., 2023). Moreover, AI-driven marketing enables MSMEs to compete with larger firms by providing access to market insights previously available only to resource-rich organizations (Abbasi, 2022; Ayinaddis, 2025; Peretz-Andersson et al., 2024). Thus, AI serves not merely as an operational support tool but as a strategic instrument for creating added value within MSMEs' marketing activities (Das, 2024; Şenyapar, 2024).

In human resources (HR), AI adoption significantly improves efficiency and accuracy in workforce management. AI technologies can be applied to automatically screen candidates through recruitment data analysis, evaluate employee performance using more objective indicators, and identify training needs based on individual productivity patterns (Madancian & Taherdoost, 2024; Malik et al., 2023; Nawaz et al., 2024). Consequently, AI helps MSMEs overcome resource limitations in HR management while enhancing the quality of decision-

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making related to workforce administration (Joshi & Joshi, 2022; Sr, 2024). AI implementation in HR management can optimize recruitment processes, strengthen employee retention, and support data-driven performance evaluations (Horodyski, 2023; Lada et al., 2023). For MSMEs, which often face challenges in maintaining workforce productivity and loyalty, AI adoption can serve as a strategic solution to enhance competitiveness and foster a more adaptive work environment (Faiz et al., 2024; Tambe et al., 2019). Thus, AI functions not only as a technical tool but also as a strategic instrument that supports the sustainability of human resource management within MSMEs.

In the finance function, AI adoption offers substantial benefits by enhancing accuracy, efficiency, and transparency in MSMEs' financial management. AI technologies can automate routine accounting tasks such as transaction recording and financial reporting, thereby reducing the risk of human error and accelerating workflow efficiency (Cao et al., 2024; Choi & Xie, 2025). Moreover, AI can detect financial anomalies or potential fraud through data pattern analysis and support credit risk assessments, ultimately improving financing decisions and access to capital (Achouch et al., 2022; Remolina, 2022). AI in finance enhances decision-making quality, strengthens risk management, and improves funding opportunities for small enterprises (Ayinaddis, 2025; Bajunaied et al., 2023). For MSMEs in Indonesia, which often face constraints in accessing capital and maintaining structured financial management, AI adoption represents a strategic solution for building more professional financial governance while also increasing credibility with investors and financial institutions (Abrokwah-Larbi & Awuku-Larbi, 2024; Choi & Xie, 2025; Li et al., 2023). Thus, AI serves not merely as an automation tool but as a strategic instrument to reinforce MSMEs' financial resilience and long-term sustainability (Yadav, 2023).

In the operations function, AI plays a critical role in improving business process efficiency and cost control within MSMEs. AI technologies can be applied to generate more accurate demand forecasts, optimize supply chain management, and adjust inventory levels to align with market needs (Jones, 2024; Ummah, 2019). Through predictive analytics, AI helps reduce the risks of overstocking and stockouts, thereby ensuring smoother production and distribution flow (Dalal et al., 2024; Khedr & S, 2024). Moreover, integrating AI into operations automates routine processes that traditionally relied on manual labor, thereby enhancing productivity and maintaining consistent output quality (Rodríguez-Espíndola et al., 2022; Sena & Nocker, 2021). AI's transformative potential to improve operational agility, reduce costs, and accelerate data-driven decision-making (Dai et al., 2023; Soori et al., 2024). For MSMEs, which often struggle with resource constraints in managing operations, AI adoption serves as a strategic solution to build a sustainable competitive advantage. Hence, AI should not be viewed merely as a supportive technology but as a catalyst capable of transforming MSMEs' operational systems into more adaptive, efficient, and market-responsive processes (Badghish & Soomro, 2024; Mishrif & Khan, 2023; Soori et al., 2023).

The Mediating Role of Behavioral Intention

The findings reveal that Behavioral Intention (BI) plays a crucial mediating role in the relationship between AI adoption determinants (Performance Expectancy, Effort Expectancy, and Facilitating Conditions) and MSME business performance across marketing, human resources, finance, and operations. This suggests that perceptions of usefulness, ease of use, and infrastructure support do not directly translate into improved performance. Instead, these factors become significant only when they foster a firm intention to adopt AI, which is subsequently realized in actual business practices. Thus, BI functions not merely as a psychological construct but as a transitional mechanism that bridges cognitive beliefs with organizational performance outcomes.

This result is consistent with the TAM framework and the UTAUT model (Davis, 1989; Shachak et al., 2019; Venkatesh et al., 2016; Venkatesh & Davis, 2000)Both of which position behavioral intention as the direct determinant of actual usage. In the MSME context,

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Performance Expectancy contributes to intention formation because business owners perceive AI as a means to enhance marketing effectiveness, operational efficiency, and accuracy in financial and HR management (Bajunaied et al., 2023; Duong et al., 2023). Effort Expectancy is equally critical, as limited technical expertise makes perceptions of ease of use a decisive factor (Alalwan et al., 2017) . These findings align with prior studies (Chatterjee et al., 2022), reinforcing the argument that perceived value and technological simplicity are primary drivers of adoption.

The significant mediating role of Facilitating Conditions supports the findings of (Dwivedi, 2023), who emphasized the importance of digital infrastructure readiness, technological accessibility, and organizational support as prerequisites for adoption(Mishrif & Khan, 2023; Relifra et al., 2025). This is particularly salient for MSMEs in resource-constrained environments, where external enablers strengthen intention and drive actual implementation. Unlike other determinants, Social Influence did not have a significant indirect effect on performance through BI. This contrasts with research on larger organizations Alalwan et al (2017), where social norms, industry pressures, and partner expectations often influence adoption decisions. For MSMEs, however, adoption decisions appear pragmatic and utility-driven, driven by tangible business benefits rather than social or normative pressures. This finding underscores the distinct decision-making dynamics in smaller firms compared to large corporations.

Theoretically, this study extends the technology adoption literature by demonstrating that BI operates not only as a predictor of technology use but also as a mediator linking adoption determinants with firm performance across functional domains. This provides empirical support for expanding the TAM–UTAUT framework to include business outcomes, particularly in the context of MSMEs and AI adoption in developing economies. From a practical perspective, the findings highlight that AI-driven performance improvements in MSMEs require interventions that strengthen behavioral intention. Training programs, sector-specific use cases, and evidence of tangible benefits are effective strategies to build positive intentions toward AI adoption. Furthermore, investments in digital infrastructure, affordable tools, and accessible technical support should be prioritized to ensure that positive perceptions are effectively converted into adoption and performance gains. In short, the success of digital transformation in MSMEs depends not only on the availability of technology but also on cultivating adoption intention through a supportive ecosystem.

CONCLUSION

This study provides empirical evidence on the adoption of Artificial Intelligence (AI) in Micro, Small, and Medium Enterprises (MSMEs) in Indonesia by integrating the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The findings confirm that Performance Expectancy, Effort Expectancy, and Facilitating Conditions significantly shape Behavioral Intention to adopt AI. At the same time, Social Influence does not play a decisive role in MSME adoption decisions. This highlights that AI adoption in MSMEs is primarily driven by perceived business value, ease of use, and supportive infrastructure rather than external social pressures.

Furthermore, the results demonstrate that Behavioral Intention functions as a crucial mediator linking adoption determinants to business performance outcomes across marketing, human resources, finance, and operations. This indicates that positive perceptions alone are insufficient; AI adoption yields tangible performance improvements only when translated into strong behavioral intentions. From a theoretical perspective, this study extends the TAM–UTAUT framework by explicitly connecting adoption drivers to functional business outcomes, thereby enriching the literature on technology adoption in resource-constrained contexts. In practice, the findings suggest that policymakers, business associations, and technology providers should focus on strengthening digital infrastructure, designing user-friendly AI solutions, and providing targeted training to enhance MSMEs' readiness. By fostering strong

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adoption intentions, AI can effectively serve as a strategic enabler of competitiveness and sustainable growth in the MSME sector.

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