

Article

The Impact of Artificial Intelligence Adoption on Organizational Decision-Making: An Empirical Study Based on the Technology Acceptance Model in Business Management

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Abstract

With the rapid development of artificial intelligence technology, its widespread application in the field of business management has become a significant issue faced by contemporary enterprises. Based on the Technology Acceptance Model, this study explores the impact of AI technology acceptance on organizational decision-making efficiency, performance, and the depth of technology application. It also reveals the driving mechanisms of top management support, perceived usefulness, and perceived ease of use on AI technology adoption through path analysis. To validate the research hypotheses, the study employed structural equation modeling (SEM) based on survey data collected from 420 respondents across various industries. The study found that top management support significantly enhances technology acceptance through perceived variables, while perceived usefulness is the core factor driving technology adoption. Although perceived ease of use has a weaker effect, it is equally important in lowering the psychological barriers during the initial stages of technology adoption. The adoption of AI technology has significantly improved organizational decision efficiency and overall performance, promoting the deep application of technology by optimizing resource allocation and enhancing scientific decision-making capabilities. This study further validates the applicability of the TAM theory in the context of AI technology, expanding its theoretical explanatory power in complex technology-adoption mechanisms. At the same time, the research provides practical guidance for enterprises in the introduction and application of technology, emphasizing that managers need to shape an open and innovative organizational culture at a strategic level and enhance employees' willingness to accept technology through technical training and value transmission. Future research can incorporate cross-cultural and multi-level analytical frameworks to explore the dynamic adaptation paths of AI technology adoption and its potential risks in sustainable development.

Keywords: artificial intelligence; technology acceptance model; top management support; organizational decision-making efficiency



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1. Introduction

The rapid development of artificial intelligence (AI) has transformed organizational decision-making by enhancing analytical capacity and reducing human bias in dynamic environments. While traditional TAM-based studies emphasize perceived usefulness and

ease of use [1,2], the recent literature expands this view, suggesting that AI adoption is shaped by leadership support, cultural openness, and ethical governance [3,4]. Scholars emphasize that perceived usefulness now entails not just task efficiency but also real-time insight and organizational learning, while trust in AI depends on transparency and ethical design [5,6]. AI improves not only schedule accuracy and forecasting but also reshapes internal information flows and collaborative intelligence [7]. However, adoption challenges persist, including the “black-box” effect, training deficits, and cultural resistance, particularly in conservative environments [8,9]. Organizational culture and top management support are therefore critical enablers of successful implementation [10,11], influencing employees’ willingness to integrate AI into daily workflows. Furthermore, AI adoption is not solely technical but embedded in cognitive and affective processes, ranging from rational judgment to emotional resonance and value interpretation [12,13]. This study builds a multi-level structural model extending TAM by integrating top management support, perceived variables, and organizational performance indicators, empirically validating their mediating roles in shaping AI adoption and its influence on decision-making efficiency and technological depth. By addressing both functional drivers and ethical concerns, this research offers a comprehensive framework that bridges cognition, leadership, and trust, ultimately guiding enterprises toward more effective, responsible, and human-centered AI integration strategies.

While the Technology Acceptance Model (TAM) has been widely applied to explain individual adoption of digital technologies, its application in the context of artificial intelligence (AI) integration within organizations still leaves room for further refinement. Existing research has primarily focused on users’ cognitive appraisals—particularly perceived usefulness and perceived ease of use—yet relatively few studies have extended these constructs to capture how AI adoption unfolds in complex organizational environments where leadership behavior, cultural readiness, and ethical considerations also play influential roles. As AI systems become increasingly embedded in strategic decision-making, issues such as algorithmic transparency, managerial endorsement, and the alignment between AI functionality and business goals warrant deeper investigation. Moreover, although extensions of TAM have incorporated organizational factors in other domains, empirical validation remains limited in the context of AI, especially when it comes to modeling the cascading effects of perception, leadership, and adoption on broader performance outcomes. Against this backdrop, there is an opportunity to enhance existing models by integrating organizational-level constructs and examining the mechanisms through which AI technologies are not only accepted but effectively institutionalized in enterprise decision-making processes.

This study, in exploring the impact of artificial intelligence (AI) technology on organizational decision-making, presents several important innovations by integrating the Technology Acceptance Model (TAM) with AI applications, thereby extending the applicability of TAM. The traditional TAM is primarily used to explain user adoption behavior of information technology. Secondly, this study innovatively refines the specific impact of AI technology on the organizational decision-making process to multiple levels. Although the existing literature extensively discusses the potential applications of AI in business management, few studies have deeply explored the actual role of AI in various aspects of organizational decision-making. By detailing AI’s performance in enhancing decision efficiency, addressing decision complexity, and providing personalized decision support, the study systematically reveals the mechanisms of AI technology in specific decision-making processes.

2. Theoretical Foundation and Research Hypotheses

Since its introduction by Davis in 1989, the Technology Acceptance Model (TAM) has been one of the core theories in the field of information technology for explaining user technology adoption behavior [1]. Its main concept is based on two key factors: perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness refers to the degree to which a user believes that using a particular technology can effectively enhance their work or task performance, while perceived ease of use is the user's subjective judgment of whether the technology is easy to use. These two factors jointly influence the user's behavioral intention (BI), which in turn determines the actual use of the technology. The simple and clear framework structure of the TAM model makes it the foundational model for numerous technology adoption studies, applicable to a wide range of technology types and application environments, as shown in Figure 1:

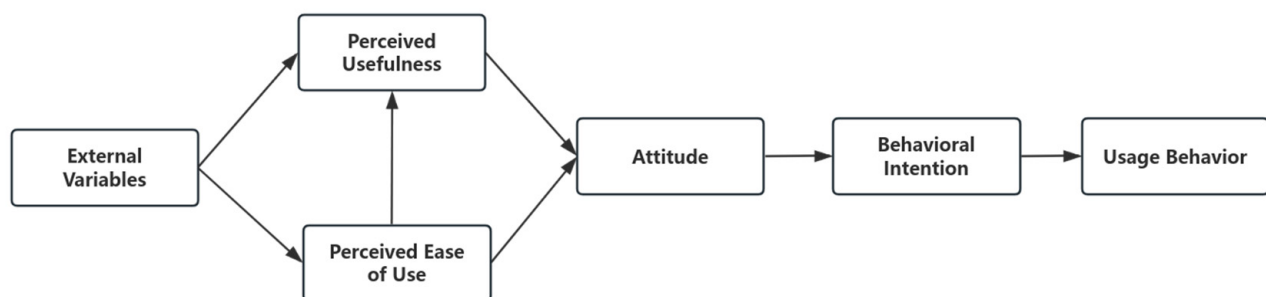


Figure 1. Technology Acceptance Model (TAM).

As digital technologies—particularly artificial intelligence—become deeply integrated into enterprise systems, technology adoption can no longer be conceptualized solely as an individual behavioral intention. Instead, it must be understood as a process embedded within the broader structures of organizational decision-making. In this study, organizational decision-making is defined as the structured, collective process through which organizations gather information, evaluate alternatives, and implement actions to achieve strategic objectives. Unlike traditional user-centric models, this perspective foregrounds how AI systems reshape the logic, flow, and authority of decisions within organizations.

To account for such complexity, classic models like the Technology Acceptance Model (TAM) have been extended and recontextualized. Venkatesh and Davis (2000) incorporated constructs such as social influence and cognitive instrumental processes, while Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), integrating performance expectancy and organizational context as key determinants. In AI-related contexts, adoption is increasingly viewed as intertwined with institutional mechanisms of decision-making [14,15]. As Gursoy et al. (2023) and Kim and Park (2023) observe, AI tools influence not only operational efficiency but also strategic reasoning, making interpretability and trust central to their organizational use [16,17]. Rahman and Chowdhury (2024) further emphasize that leadership support, employee training, and technological complexity significantly shape organizational perceptions of AI [18]. Similarly, Nguyen et al. (2021) show that innovation-oriented cultures enable more effective integration of AI technologies [19]. At the same time, the opaque, “black-box” nature of many AI systems [6] raises critical concerns about transparency, accountability, and legitimacy—underscoring the need to move beyond individual-level explanations toward institutionally grounded analyses of technology adoption.

Perceived usefulness is one of the core factors in the TAM, referring to the degree to which a user believes that using a particular technology can enhance their work or task performance. In the context of AI technology application, perceived usefulness mainly

reflects the subjective judgment of managers or employees on whether AI technology can bring benefits in actual work. According to Davis's (1989) TAM, perceived usefulness is one of the main driving factors for users to adopt technology [1]. The efficient data processing and analysis capabilities of AI technology enable managers to obtain the information needed for decision-making more quickly and accurately, thereby improving the quality and efficiency of decisions. After perceiving this usefulness, users' intention to adopt AI technology will significantly increase. Especially in organizational management and decision-making processes, the application of AI technology can not only optimize resource allocation but also reduce human bias in decision-making, thereby improving the accuracy of decisions. Perceived usefulness is one of the core factors in the TAM, referring to the extent to which users believe that using a particular technology can enhance their work or task performance. In the context of AI technology application, perceived usefulness mainly reflects the subjective judgment of managers or employees on whether AI technology can bring benefits in actual work. According to Davis's (1989) TAM, perceived usefulness is one of the main driving factors for users to adopt technology. The efficient data processing and analysis capabilities of AI technology enable managers to obtain the information needed for decision-making more quickly and accurately, thereby improving the quality and efficiency of decisions [1]. After perceiving this usefulness, users' intention to adopt AI technology will significantly increase. Especially in organizational management and decision-making processes, the application of AI technology can not only optimize resource allocation but also reduce human bias in decision-making, thereby improving the accuracy of decisions. Therefore, the following idea is proposed:

H1. *Perceived usefulness positively influences the technology acceptance of AI.*

Perceived ease of use refers to the user's subjective judgment of whether a particular technology is easy to operate. In the TAM, perceived ease of use is another important factor influencing users' intention to adopt technology. For AI technology, its complexity and high technical requirements may cause users to feel that it is difficult to operate when first encountered, so it is crucial to enhance users' perceived ease of use of AI technology. The study by Kim and Park (2023) indicates that when AI systems are designed to be easy to understand and operate, users are more inclined to use the technology [17]. Perceived ease of use not only reduces the cognitive burden on users during the learning and operation process but also enhances users' confidence in the technology. For many technologically complex AI systems, simplifying the user interface and providing clear guidance and training have become key aspects of technology promotion to enhance users' perception of ease of use. The positive relationship between perceived ease of use and technology acceptance has also been validated in studies of other technologies. Venkatesh and Bala (2008) [2] found in their study of complex technical systems that when the ease of use of a technology is widely recognized by users, the acceptance of the technology significantly increases. As a highly complex technical system, AI technology has a high operational difficulty and learning cost, making the enhancement of perceived ease of use crucial for the successful application of AI technology. By reducing the cognitive load and operational difficulty for users, perceived ease of use can positively influence the acceptance of AI technology, thereby promoting its application within the organization. The following idea is thus proposed:

H2. *Perceived ease of use positively influences the acceptance of AI technology.*

The management level plays a crucial role in organizational technological innovation; they are not only responsible for formulating strategies but also determining the priorities

for technology introduction and resource allocation. Huang et al. (2018) [11] pointed out that the support of top managers can significantly enhance the effectiveness of technology application within the organization. Managers can effectively strengthen employees' perceptions of both usefulness and ease of use by providing resources, establishing supportive policies, and encouraging active participation in digital transformation. In particular, top management can help employees understand the strategic relevance and operational utility of AI by setting clear application pathways and offering consistent guidance. Rahman and Chowdhury (2024) emphasize that leadership support involves not only material investment but also soft support through training, feedback, and cultural alignment. Such engagement helps mitigate psychological resistance, reduces uncertainty, and builds trust toward new technologies.

Building on this perspective, recent theoretical developments suggest that the influence of top management is not only direct but also operates through critical psychological mediators. Specifically, their involvement can enhance perceived usefulness by framing AI as a tool that improves efficiency and decision quality [1] and increases perceived ease of use by ensuring intuitive system design and sufficient training [2]. These mediating pathways are essential in understanding how leadership commitment translates into concrete adoption outcomes. Thus, the following idea is proposed:

H3. *Top management support positively influences the technology acceptance of AI.*

H3a. *Top management support has a positive effect on the technological acceptance of AI through perceived usefulness.*

H3b. *Top management support has a positive effect on the technological acceptance of AI through perceived ease of use.*

The efficient data processing and decision support functions of AI technology can significantly optimize the decision-making process of organizations [16]. By reducing human bias in decision-making and enhancing the scientific and accurate aspects of decisions, AI technology has a profound impact on the strategic planning and resource allocation of organizations. The study by Rahman and Chowdhury (2024) further reveals that when organizations exhibit a high level of acceptance of AI technology, managers can quickly obtain key information through this technology and use it in more efficient decision-making scenarios, thereby significantly improving decision efficiency [18]. Based on this, the following hypothesis can be proposed:

H4. *The acceptance of AI technology positively affects organizational decision-making efficiency.*

In addition to its significant impact on organizational decision-making efficiency, the acceptance of AI technology also positively influences overall organizational performance by enhancing operational efficiency. In the context of artificial intelligence application, the adoption of AI technology not only enhances employee productivity but also brings direct performance improvements to organizations in areas such as production management, customer service, and supply chain optimization [17]. Specifically, artificial intelligence provides unprecedented possibilities for organizations to reduce costs and improve production efficiency through automated data analysis, accurate prediction, and real-time monitoring. Rahman and Chowdhury (2024) pointed out through studies in multiple industries that the widespread application of AI technology can significantly enhance an organization's competitiveness in the market [18]. This is especially true in technology-oriented enterprises, where there is a significant correlation between high acceptance of AI technology

and organizational performance. This positive effect is reflected not only in short-term financial indicators but also in long-term market share growth and customer satisfaction improvement. Therefore, the following hypothesis can be proposed:

H5. *AI technology acceptance positively affects organizational performance.*

The study by Nguyen et al. (2021) shows that when organizational members have a high acceptance of AI technology, they are more inclined to apply this technology to a broader range of business scenarios, including decision-making support, production optimization, and customer service. Meanwhile, high acceptance means that users' sense of trust in the technology is enhanced, thereby promoting the scalable application of technology within the organization [2]. Rahman and Gündoğdu (2024) further point out that the depth and breadth of AI technology application largely depend on users' positive evaluation of the technology and its perceived value [18]. Organizations with high technology acceptance are more likely to achieve efficient resource allocation and precise strategic planning through the multi-level intervention of AI technology. Therefore, the following hypothesis can be proposed:

H6. *AI technology acceptance positively affects the degree of AI technology intervention.*

In summary, by exploring the relationship between AI technology acceptance, organizational decision-making efficiency, organizational performance, and the degree of AI technology intervention, as shown in Figure 2, this study attempts to further enrich the theoretical explanatory power of the Technology Acceptance Model in the context of artificial intelligence technology. These hypotheses not only provide a more systematic theoretical framework for the mechanism of AI technology adoption but also offer practical guidance for organizations in the introduction and application of technology. Specifically, by emphasizing the direct impact of technology acceptance on decision-making efficiency, performance, and the degree of intervention, this study provides a new perspective for understanding the comprehensive role of technology adoption at the organizational level. The proposal and validation of these hypotheses will provide richer theoretical support and empirical evidence for future research and practice in technology adoption.

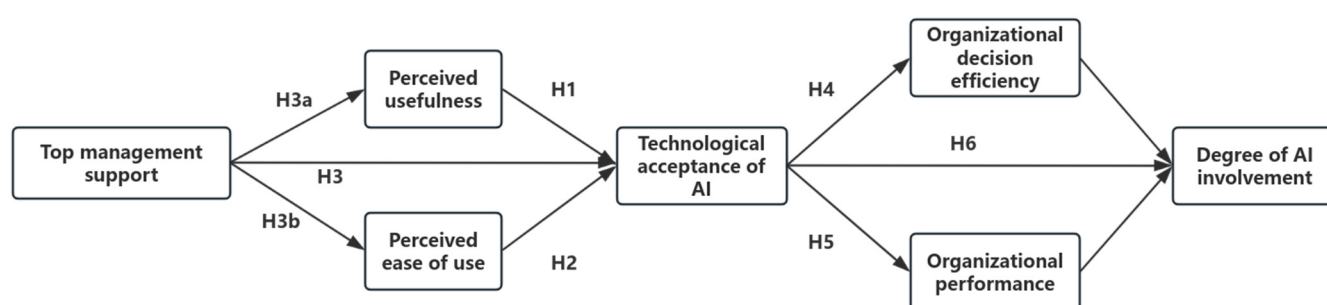


Figure 2. Research Framework.

3. Research Design

3.1. Independent Variable

Top Management Support: This refers to the strategic, financial, and cultural support provided by senior leadership in the adoption of AI technologies. It serves as an external enabling condition that influences employees' perception of AI's usefulness and usability. Top management support plays a crucial role in overcoming organizational resistance and in legitimizing AI implementation at all levels [20,21].

3.2. Mediating Variable

Perceived Usefulness: As a core construct from the Technology Acceptance Model (TAM), perceived usefulness is defined as the degree to which an individual believes that using AI will enhance job performance or organizational outcomes. It directly influences the intention to adopt AI technologies [1].

Perceived Ease of Use: This refers to users' perception of the effort required to learn and operate AI systems. It has both a direct effect on AI acceptance and an indirect effect through its influence on perceived usefulness. It reflects the system's intuitiveness and compatibility with existing workflows [2].

Technological Acceptance of AI: This variable captures employees' behavioral intention and attitudinal readiness to use AI tools within organizational processes. It mediates the effects of perceived usefulness and ease of use on downstream outcomes such as decision-making efficiency and performance. It reflects the psychological readiness for technology adoption.

Organizational Decision Efficiency: This denotes the extent to which AI improves the speed, quality, and rationality of decision-making processes within the organization. As a process-level outcome, it acts as a key mediating factor linking AI acceptance to organizational performance and engagement.

3.3. Dependent Variables

Organizational Performance: This variable reflects the overall impact of AI adoption on operational and strategic performance outcomes, including productivity, profitability, customer satisfaction, and competitive advantage. It is a core evaluative metric for assessing the organizational returns of AI implementation [22,23].

Degree of AI Involvement: This refers to the breadth and depth of AI integration across organizational functions and strategic domains. It captures the maturity of AI usage, from initial experimentation to full institutionalization, and indicates the extent of digital transformation within the enterprise [7].

Control variables include **enterprise scale, industry type, organizational culture, and employee technical ability**. Enterprise scale and industry type are important factors affecting the level of AI application. Enterprises of different scales and types have differences in technology needs and resource configuration, so they need to be used as control variables to eliminate the interference effects of these differences. The supportive or obstructive nature of organizational culture also significantly impacts the degree of AI application. An innovative culture helps enhance technology acceptance [24]. Employees' technical skills reflect their ability to adapt to and master new technologies. Employees with high technical skills are more likely to accept and use new technologies, which also affects the implementation effectiveness of AI technology.

In the empirical survey of this study, the questionnaire was distributed using a random sampling method, sent via email and internal enterprise systems to the management and employees of various large and medium-sized enterprises. The survey covered enterprises from different industries, with 500 questionnaires distributed and 420 valid questionnaires returned, resulting in a response rate of 84%. All questionnaires are filled out anonymously to ensure that respondents can truthfully reflect their views on AI technology. After data collection, the structural equation model (SEM) is used to test each hypothesis, analyzing the relationships between independent variables, mediating variables, and dependent variables, ultimately determining the application effects of AI technology in organizations and its impact on decision-making and performance.

In terms of data processing, the study first conducted missing value detection and outlier treatment to ensure data quality. Descriptive statistical analysis was then employed

to present the distribution characteristics of the variables, followed by correlation analysis to preliminarily explore the structural relationships among them. During the measurement model testing phase, Confirmatory Factor Analysis (CFA) was used to assess the convergent and discriminant validities of the latent constructs, while Cronbach's alpha coefficients were calculated to evaluate internal consistency reliability, ensuring the consistency and stability of variable measurement. In the final modeling stage, structural equation modeling (SEM) was employed, using the AMOS software (version 29.0.1) as the analytical tool to construct the overall path relationships among variables. SEM allows for the simultaneous examination of multiple causal paths, measurement errors of latent variables, and mediation effects, making it the core analytical approach for investigating the interrelated mechanisms of AI adoption in this study. To control for potential multicollinearity, Variance Inflation Factor (VIF) tests were additionally conducted to examine the correlation structure among independent variables, thereby ensuring the robustness and explanatory power of the model estimations.

4. Empirical Study

4.1. Descriptive Analysis

The data for this study is based on a questionnaire survey and statistical analysis of 420 samples, covering multiple industries and types of organizations, aiming to explore the relationship between AI technology acceptance, organizational factors, decision efficiency, and organizational performance. Table 1 presents the basic statistical description of the study variables, including the degree of AI involvement, enterprise scale, industry type, organizational culture, employee technical ability, and perceived factors related to technology adoption (perceived usefulness, perceived ease of use, top management support), as well as decision efficiency and organizational performance.

Table 1. Basic Indicators.

Name	Sample Size	Minimum Value	Maximum Value	Average Value	Standard Deviation	Median
Degree of AI Involvement	420	45.000	115.000	77.049	16.760	73.000
Enterprise Scale	420	1.000	2.000	1.826	0.380	2.000
Industry Type	420	1.000	2.000	1.564	0.497	2.000
Organizational Culture	420	1.000	4.000	2.423	0.779	3.000
Employee Technical Ability	420	2.000	5.000	3.607	0.844	4.000
Perceived Usefulness	420	1.436	5.000	3.321	0.947	3.226
Perceived Ease of Use	420	1.329	5.000	3.334	0.956	3.176
Top Management Support	420	1.249	5.000	3.419	0.818	3.493
Positive Emotion	420	1.488	5.000	3.367	0.993	3.489
Decision Efficiency	420	1.000	5.000	3.361	1.159	4.000
Organizational Performance	420	1.000	5.000	3.331	1.164	3.000

In terms of the degree of AI involvement, the sample scores range from 45 to 115, with an average of 77.049 and a standard deviation of 16.760, indicating that there is some variation in the depth and breadth of AI application among the sample enterprises, but the overall level of involvement is relatively high. Enterprise scale is represented as a binary variable, with an average of 1.826, indicating that most are larger-scale enterprises. The distribution of industry types is relatively balanced, with an average of 1.564, indicating that the sample covers multiple industries, but is primarily focused on a specific industry. The organizational culture score ranges from 1 to 4, with an average of 2.423, indicating that enterprises tend to favor an open or neutral culture, but there is significant variation in culture types. The range of employee technical ability scores is from 2 to 5, with an

average of 3.607, indicating that most employees possess above-average technical ability, supporting the adoption of AI technology. The score ranges for perceived usefulness and perceived ease of use are from 1.436 to 5 and 1.329 to 5, respectively, with averages of 3.321 and 3.334, indicating that most respondents find AI technology helpful for work and easy to operate, although the perceived levels are not entirely consistent. The average score for top management support is 3.419, showing that management generally supports technology adoption. The range of positive emotion scores is from 1.488 to 5, with an average of 3.367, indicating that employees have a relatively positive attitude towards AI application, but there is significant individual variation. The score range for decision efficiency and organizational performance is from 1 to 5, with averages of 3.361 and 3.331, respectively, indicating that AI adoption has a certain impact on improving efficiency and performance.

4.2. Correlation Analysis

The Pearson correlation analysis and VIF test results in Table 2 provide in-depth insights into the relationships and multicollinearity among the research variables.

Table 2. Pearson Correlation and VIF Test.

	1	2	3	4	5	6	7	8	9	10	11	VIF Value
Degree of AI Involvement (1)	1											3.974
Enterprise Scale (2)	0.055	1										1.023
Industry Type (3)	0.033	0.002	1									1.015
Organizational Culture (4)	0.049	0.084	0.045	1								1.081
Employee Technical Ability (5)	0.012	0.009	0.044	0.046	1							1.023
Perceived Usefulness (6)	0.826 **	0.078	0.024	0.038	0.010	1						1.353
Perceived Ease of Use (7)	0.750 **	0.025	0.001	0.154 **	0.054	0.405 **	1					6.432
Top Management Support (8)	0.617 **	0.019	0.080	0.037	0.045	0.365 **	0.347 **	1				6.005
Positive Emotion (9)	0.684 **	0.041	0.032	0.037	0.039	0.370 **	0.446 **	0.403 **	1			2.627
Decision Efficiency (10)	0.580 **	0.046	0.051	0.006	0.031	0.311 **	0.364 **	0.379 **	0.855 **	1		4.594
Organizational Performance (11)	0.600 **	0.049	0.012	0.059	0.009	0.352 **	0.365 **	0.336 **	0.862 **	0.643 **	1	5.230

** $p < 0.01$.

The degree of AI involvement shows a significant positive correlation with variables such as perceived usefulness, perceived ease of use, top management support, positive emotion, decision efficiency, and organizational performance, with correlation coefficients of 0.826 and 0.750 for perceived usefulness and perceived ease of use, respectively. This indicates that the actual application depth of AI technology is highly driven by users' perception of its functional value and operational convenience, which is fully consistent with the theoretical framework of the Technology Acceptance Model (TAM). In particular, the strong correlation between perceived usefulness and the degree of AI involvement suggests that enterprise users' cognition of whether AI technology can effectively enhance performance directly affects the actual application of the technology. The correlation coefficient between positive emotion and decision efficiency is as high as 0.855, further indicating that employees' attitudes towards AI technology directly affect the effectiveness of its application in their work. This attitude is not only an emotional recognition of the technology but may also stem from the efficiency improvements and increased job satisfaction brought by the technology. At the same time, the significant correlation between organizational performance and positive emotion (0.862) as well as decision efficiency (0.643) reveals the indirect role of AI technology adoption in enhancing overall enterprise operations.

Employees' positive emotional attitudes towards AI technology can ultimately translate into significant performance improvements through higher decision efficiency. This causal pathway provides significant theoretical support for the positive impact of technology adoption on organizational benefits. In the impact at the management level, the correlations of top management support with perceived usefulness and perceived ease of use are 0.365 and 0.347, respectively, indicating that the role of managers in promoting technology adoption is not limited to resource allocation or policy support but also influences the use and promotion of technology by enhancing user perception. Management support not only directly enhances the acceptance of AI technology but also indirectly promotes the deep application of AI by influencing perceived variables. Although organizational culture has a low correlation with the degree of AI involvement, its potential supportive role may indirectly affect the effectiveness of technology adoption by enhancing employees' ability to adapt to new technology. The VIF test indicates that there is no severe multicollinearity issue in the model. Although the VIF values for perceived ease of use (6.432) and top management support (6.005) are relatively high, they are within an acceptable range. This may reflect that these two variables play important mediating roles in multiple relationships. The significant correlation of variables in the model further indicates that AI technology adoption is the result of multiple factors working together, with the interaction of perceived factors, management support, and positive emotion being particularly important. Positive emotion, as a bridging variable, enhances the practical utility of AI technology in enterprise management through its significant positive impact on decision efficiency and organizational performance.

4.3. Path Analysis

From the results of the path analysis in Table 3, it can be seen that top management support has a significant impact on AI technology acceptance and related outcome variables through multiple paths. Top management support indirectly promotes the enhancement of AI acceptance by influencing perceived usefulness (with a non-standardized path coefficient of 0.423 and a standardized path coefficient of 0.365) and perceived ease of use (with a non-standardized path coefficient of 0.406 and a standardized path coefficient of 0.347). This result confirms the indispensable role of management support in the technology adoption process, as it shapes employees' willingness to accept AI by influencing their perception of technological value and convenience. The impact of perceived usefulness on AI acceptance is particularly significant, with a standardized path coefficient as high as 0.779, indicating that the functionality of the technology and task relevance are the core driving forces influencing user adoption behavior. In contrast, the standardized path coefficient of perceived ease of use on AI acceptance is 0.212, which, although significant, has a weaker influence. This is consistent with the theory of the Technology Acceptance Model (TAM), indicating that in complex technological contexts, users are more concerned with the actual benefits of the technology rather than mere ease of use.

AI acceptance shows a significant positive impact on both organizational performance and decision efficiency, with standardized path coefficients of 0.301 and 0.222, respectively. This indicates that the adoption of AI technology can enhance overall enterprise performance and decision quality by optimizing resource allocation and data analysis capabilities. Further analysis reveals that organizational performance, AI acceptance, and decision efficiency all have a significant impact on the degree of AI involvement, with standardized path coefficients of 0.253, 0.558, and 0.320, respectively. This suggests that the deep integration of AI technology not only depends on employees' willingness to accept it but is also closely related to the overall performance of the enterprise and an efficient decision-making mechanism. The direct impact of top management support on

AI acceptance (standardized path coefficient of 0.239) and its indirect impact (through the mediation of perceived variables) together constitute an important driving force for AI adoption. Although the impact of perceived ease of use on AI acceptance is relatively low, it significantly enhances users' technological experience and confidence as an important transmission mechanism of top management support. Moreover, the path coefficient of AI acceptance on the degree of AI involvement (standardized path coefficient of 0.558) is much higher than other variables, further indicating that acceptance is a core element driving the scope and depth of technology application.

Table 3. Summary of Path Analysis.

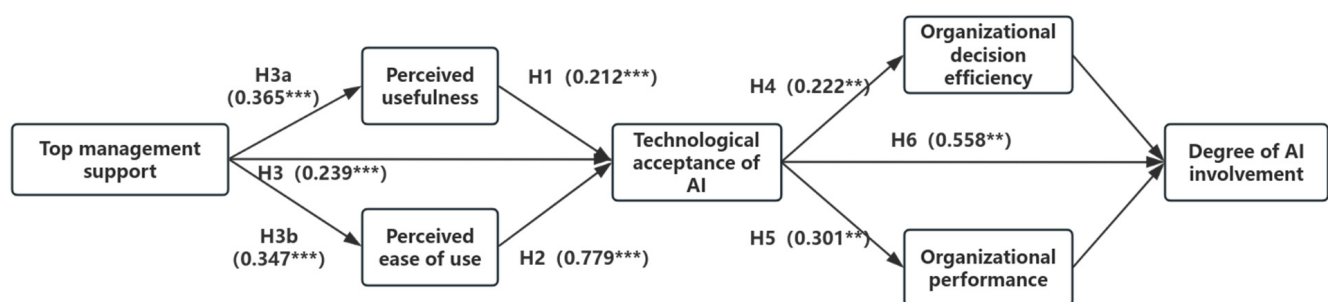
X	→	Y	Unstandardized Path Coefficient	SE	z (CR Value)	p	Standardized Path Coefficient
Top Management Support	→	Perceived Ease of Use	0.406	0.063	6.472	0.000	0.347
AI Acceptance	→	Organizational Performance	0.303	0.055	5.505	0.000	0.301
Top Management Support	→	AI Acceptance	0.055	0.056	0.981	0.000	0.239
Perceived Ease of Use	→	AI Acceptance	0.014	0.045	0.317	0.000	0.212
Perceived Usefulness	→	AI Acceptance	0.949	0.045	20.908	0.000	0.779
Top Management Support	→	Perceived Usefulness	0.423	0.062	6.850	0.000	0.365
AI Acceptance	→	Decision Efficiency	0.223	0.056	3.976	0.000	0.222
Organizational Performance	→	Degree of AI Involvement	3.484	0.486	7.162	0.000	0.253
AI Acceptance	→	Degree of AI Involvement	7.752	0.502	15.435	0.000	0.558
Decision Efficiency	→	Degree of AI Involvement	4.425	0.478	9.264	0.000	0.320

Note: → indicates the path influence relationship.

5. Results

This study, based on the Technology Acceptance Model (TAM), explores in depth the adoption process of artificial intelligence (AI) technology in business management and its impact on organizational decision-making and performance. Through path analysis and structural equation modeling, the study verifies the core mediating role of AI technology acceptance in this process, revealing the driving mechanisms of key variables such as top management support, perceived usefulness, and perceived ease of use on AI technology adoption and its subsequent effects.

From an overall analysis, the path model clearly reveals the hierarchical chain of effects in the technology adoption process. Top management support enhances AI acceptance through perceived variables, and AI acceptance further promotes the comprehensive involvement of AI technology by improving decision efficiency and organizational performance, as shown in Figure 3.



** p < 0.01 *** p < 0.001

Figure 3. Path Model Result Analysis Diagram.

This study verifies the validity of each hypothesis through path analysis, clearly revealing the significant impact of top management support, perceived usefulness, and perceived ease of use on AI technology acceptance, as well as their transmission mechanisms on decision efficiency, organizational performance, and the degree of AI technology involvement. In summary, this study validated all hypotheses, and the results indicate that top management support significantly enhances technology acceptance through perceived variables. Technology acceptance, as a core mediating variable, not only directly improves decision efficiency and organizational performance but also promotes the deep application of AI technology. These findings not only support the theoretical expectations of the Technology Acceptance Model but also further extend its applicability in the context of AI technology application. They provide a theoretical basis and practical guidance for enterprise technology adoption, while also laying the foundation for future research on complex technology adoption.

The results reveal that top management support significantly promotes AI technology acceptance (H3), both directly and indirectly through perceived usefulness (H3a) and perceived ease of use (H3b). Among the mediating factors, perceived usefulness plays a dominant role (H1), indicating that the perceived effectiveness of AI in improving decision-making and efficiency is key to adoption. Perceived ease of use also positively affects acceptance (H2), though its influence is comparatively weaker, suggesting that usability matters most during early implementation stages. Furthermore, the acceptance of AI significantly enhances decision-making efficiency (H4) and organizational performance (H5), demonstrating its practical value beyond individual perception. Finally, AI acceptance, together with performance and efficiency, strongly drives the degree of AI involvement across the organization (H6).

Top management support has been proven to be one of the important driving forces for AI technology adoption. Top management support has a significant positive impact on technology acceptance through both direct effects and the mediating effects of perceived usefulness and perceived ease of use. This indicates that the role of leadership in technology adoption is not limited to resource configuration and strategic planning but also involves shaping employees' perceptions of technological value and convenience. The influence mechanism of top management support aligns with the transformational leadership theory in management science, which suggests that leaders can significantly enhance organizational members' adaptability to technological change and willingness to accept it through motivation, support, and resource integration. The strategic promotion by managers is directly related to the deep application of AI technology in organizational decision-making, further indicating that technology adoption at the organizational level is a systematic project requiring multifaceted support. Secondly, perceived usefulness plays a core role in promoting AI technology acceptance, indicating that technological functionality and task relevance are key factors driving adoption behavior. This result is consistent with the core hypothesis of the TAM theory and further highlights the priority of perceived usefulness in complex technological contexts. For enterprise management practice, this means that when promoting AI technology, managers need to emphasize the actual benefits of the technology in enhancing decision efficiency, optimizing resource allocation, and reducing erroneous decisions. This not only enhances employees' sense of trust in technology but also lays the foundation for further promotion of technology within the organization. Although the role of perceived ease of use is relatively weak, its importance cannot be ignored. Especially in contexts with high technological complexity, enhancing users' perception of the ease of use of technology helps lower the psychological barriers during the initial adoption phase, facilitating the smooth introduction of the technology. Therefore, during the technology

implementation phase, enterprises should strengthen training, simplify the user interface, and provide clear usage guidance.

6. Discussion

This study also cites AI as an advanced knowledge tool that, through deep data mining and real-time analysis, provides organizations with more scientific and forward-looking decision support. In terms of performance improvement, AI technology reduces operational costs and enhances production efficiency through automated process optimization, accurate forecasting, and intelligent resource allocation. This performance enhancement not only manifests as short-term economic benefits but may also have a profound impact on the long-term strategic competitiveness of the enterprise. For managers, this emphasizes that AI technology is not just a tool but a strategic resource, whose effective integration needs to align with the overall goals and operational model of the enterprise. At the same time, AI acceptance not only directly promotes the practical application of technology but also indirectly expands the scope of its impact by enhancing decision efficiency and organizational performance. The results indicate that the success of technology adoption depends on the user's high recognition of the technological value, further emphasizing the importance of focusing on the willingness to accept technology in management practices. For enterprise managers, this means that when introducing AI technology, it is essential not only to focus on the deployment of hardware and software systems but also to enhance employees' technology acceptance through cultural shaping and value transmission. Specific measures include establishing an open organizational culture, encouraging technological innovation, and helping employees understand the contribution of technology to personal work and the overall benefits of the organization through proactive communication strategies.

In the recent literature, researchers have increasingly emphasized that the effectiveness of artificial intelligence depends not only on its algorithmic performance but also on the socio-organizational conditions under which it is implemented [25,26]. This study further substantiates that view through empirical evidence, showing that perceived usefulness and perceived ease of use—functioning as psychological enablers—can significantly enhance decision-making efficiency and performance outcomes when supported by top management. This finding is consistent with [27], who demonstrated that improvements in decision speed and knowledge coordination brought about by AI are largely contingent upon managerial intent and internal communication structures. Moreover, the roles of trust and explainability in AI application, as highlighted by Akbar et al. (2024) and Shin (2021), are indirectly reflected in this study through the mediating effect of user perception [4,28]. Our findings complement these earlier studies by validating TAM pathways in a broader organizational context, thereby triangulating theoretical expectations from both the technology management and organizational behavior literature.

Despite the theoretical contributions and empirical robustness of this study, several limitations merit critical reflection. First, while this research demonstrates that AI adoption significantly enhances organizational decision efficiency and performance via the mediating role of technology acceptance, it does not sufficiently address the ethical challenges intrinsic to AI deployment. Contemporary scholarship (e.g., [4,6]) has emphasized the risks associated with algorithmic opacity, data bias, and the “black-box” nature of AI systems. These concerns are particularly salient in high-stakes decision-making contexts where lack of interpretability may undermine trust, accountability, and fairness. Although this study references these risks, it does not systematically integrate them into the model, thereby limiting its ability to address ethical governance mechanisms as part of the AI acceptance framework. Second, the socioeconomic and labor-related implications of AI—such as workforce displacement, job restructuring, and psychological insecurity—are beyond the

scope of this study. As AI systems increasingly automate complex tasks, their potential to alter employment structures and generate new inequalities remains a pressing issue for organizational leaders and policymakers alike [29]. The absence of these considerations restricts the study's practical guidance on responsible AI deployment in human-centered organizational systems.

Third, this research is largely grounded in a single-country empirical setting, and while the sample spans multiple industries, it does not account for cross-cultural variations in technology acceptance and decision-making logic. Prior research [30,31] has shown that cultural dimensions such as power distance, uncertainty avoidance, and collectivism may significantly moderate perceptions of AI usefulness and ease of use, particularly in hierarchical or risk-averse organizational cultures. Future research should adopt a comparative framework to explore the cultural adaptability of AI adoption models and the differential impact of organizational norms on acceptance dynamics. Finally, while the study adopts a rational-structural approach to decision-making, it underrepresents the emotional and value-laden dimensions of organizational judgment. Cognitive and affective biases, ethical intuitions, and identity-based reasoning are known to shape managerial decisions, often in ways that transcend logic-based AI predictions [12,32]. Although the model incorporates constructs such as perceived usefulness and ease of use, it does not capture how emotional salience, moral framing, or symbolic meaning affect the integration of AI systems into human-led decision structures. Given that AI, as a system, operates on rational data logic, its interaction with non-rational, human decision-making processes demands further theoretical and empirical elaboration.

In sum, while this study offers a valuable organizational-level account of AI technology acceptance grounded in the Technology Acceptance Model (TAM), it calls for future research that incorporates ethical governance, labor impacts, cross-cultural sensitivity, and emotion-value dynamics to better account for the complex, multidimensional nature of AI-driven decision-making in organizations.

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