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Factors influencing employee adoption of artificial intelligence technologies and the moderating role of organizational training: an analysis based on structural equation modeling

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Abstract In the context of enterprise digital transformation, the application of artificial intelligence (AI) technology has become a key strategy to enhance the competitiveness of enterprises. However, the effect of technology implementation largely depends on the degree of acceptance and adoption by employees. Based on the TOE framework, this study constructs a structural equation model to investigate the key factors affecting employees' adoption of AI technology and the moderating role of organizational training. By distributing questionnaires to employees of smart home decoration and other enterprises, 245 valid samples were collected, and the data were analyzed using SPSS and structural equation modeling. The results show that relative advantage (path coefficient 0.215), organizational top management support (path coefficient 0.335), organizational resource readiness (path coefficient 0.647), and government policy support (path coefficient 0.461) have a significant positive impact on employees' adoption of AI technology, while technological complexity (path coefficient -0.287) exerts a significant negative impact. The independent variables in the model collectively explained 75.1% of the variance in AI technology adoption, indicating strong explanatory power of the model. Organizational training showed a significant moderating effect in the relationship between environmental factors and adoption (β=-0.113, $p<0.01$), but did not show a significant moderating effect in the path of influence of organizational and technological factors. The findings of the study have practical guidance value for enterprises to promote the application of AI technology, and it is suggested that enterprises should focus on enhancing the relative advantages of technology, strengthening organizational resource allocation and high-level support, and at the same time, reducing the negative impacts of technological complexity through organizational training to promote the effective adoption of AI technology by employees.

Index Terms artificial intelligence technology, adoption, TOE framework, structural equation modeling, organizational training, moderating effect

I. Introduction

Currently, AI technologies are developing rapidly and beginning to affect all aspects of the enterprise value chain, not only performing a large number of tasks at lower costs, faster speeds, and better quality, but also affecting the relationship between the enterprise and its customers and other stakeholders [1], [2]. For this reason, more and more organizations are introducing AI technologies to improve efficiency and build competitive advantage. However, AI technologies applied to organizations can only be truly effective if they are adopted by employees [3]. Considering that willingness to adopt is the strongest predictor of adoption behavior [4]. And there are problems in organizations where employees have low willingness to adopt AI technologies or even do not use new technologies, it is of great theoretical value and practical significance to study how to drive employees to generate high willingness to adopt AI technologies.

In the existing research in the field of AI technology adoption, scholars have focused on exploring consumers' willingness to adopt intelligent products such as chatbots and AI assistants that serve their daily lives and their behavior [5], [6]. For example, literature [7] constructed a comprehensive model based on structural equation modeling and deep neural networks to explore consumer adoption of AI-based virtual assistants while identifying key factors such as effort expectations and perceived innovativeness. Literature [8] explored consumers' perceptions of AI adoption in the countries of the industry continent, analyzed the factors influencing the willingness to adopt AI technologies, and provided insights for companies to consider in terms of strategic decision-making in building consumer trust and improving service quality. Literature [9] used symmetric and asymmetric data analysis methods to explore how consumers develop a strong willingness to adopt AI products or services, with trust and perceived usefulness having a significant impact on willingness to adopt, while perceived risk negatively affects it.

A few scholars have explored organizational and individual willingness to adopt AI technologies in industries such as manufacturing, finance, medicine and health, and education [10], [11]. For example, literature [12] explored the prerequisites for the adoption of AI technologies in the manufacturing industry, including technological, organizational, and environmental factors, and found that organizational factors, such as digital skills and R&D intensity, are crucial in influencing the degree of adoption. Literature [13] examined the factors influencing the adoption of AI-powered clinical decision support systems by Chinese physicians, identifying different AI adoption paths, as well as core conditions such as performance expectations and personal innovativeness. Literature [14] quantitatively analyzed the adoption intention of using AI in higher education using structural equation modeling, and by analyzing the feedback results from 329 respondents, it pointed out the direction to promote the use of AI in higher education.

Very few scholars have explored the factors influencing employees' willingness to adopt the use of AI technology [15]. Overall, existing studies have paid insufficient attention to the adoption of AI technology by employees in organizations, and are limited by linear regression research methodology, which prevents them from studying in depth the synergistic effect of the interdependence and combination of various influencing factors on employees' willingness to adopt AI technology [16]-[18]. In particular, there is a lack of inter-industry comparative research, which seriously limits the understanding of the mechanism of the influence of employees' willingness to adopt AI technology in different industries, and is not conducive to the in-depth exploration of employee AI technology adoption behavior in academia [19]-[21].

Currently, the development of digital economy has given rise to the wide application of artificial intelligence technology in various industries, and the digital transformation of enterprises has become a necessary way to improve market competitiveness. Artificial intelligence technology helps enterprises optimize operational processes, improve efficiency and create new business value through automation, intelligent decision-making and data analysis capabilities. However, the advanced nature of the technology itself does not automatically translate into improved enterprise performance; the key lies in the acceptance and effective application of these technologies by employees within the enterprise. As a core issue in the field of information systems research, a large number of studies have explored technology adoption behavior from the perspectives of technology acceptance model and diffusion of innovation theory, but there are relatively few studies specifically focusing on emerging technologies such as AI, especially in the consideration of multi-dimensional influences on employees' adoption of technology in the organizational context, where there is a research gap. Compared with traditional information technology, AI technology has higher complexity and uncertainty, and its adoption process is influenced by more factors. As the end-users of the technology, employees' attitudes and adoption behaviors directly determine the success or failure of technology implementation. Enterprises have invested a lot of resources in the introduction of AI technology, but often face employee resistance, low acceptance and other problems, resulting in a significant reduction in the benefits of technology investment. The mechanism behind this phenomenon needs to be explored in depth. Understanding the influencing factors of employees' adoption of AI technology is important for enterprises to formulate effective technology promotion strategies and realize the synergistic development of technology and organization. Meanwhile, organizational training, as an important means to enhance employees' skills and cognition, may play a moderating role in the process of technology adoption, a mechanism that also needs to be empirically verified. Based on the TOE framework, this study constructs a comprehensive analytical model containing technological, organizational, and environmental factors to explore the key factors affecting employees' AI technology adoption. The technology dimension examines relative advantage, compatibility, and complexity; the organizational dimension includes top management support, organizational resource preparation, and organizational environment management; and the environmental dimension focuses on stakeholder pressure, government policy support, and government regulation. Data were collected through questionnaires, and structural equation modeling was used to verify the influence paths of each factor on adoption, and organizational training was introduced as a moderating variable to analyze its moderating effect in different influence paths. The results of the study will help to understand the intrinsic mechanism of employee AI technology adoption, provide theoretical basis and practical guidance for enterprises to promote the application of AI technology, and also expand the research space for the application of technology adoption theory in the field of AI.

II. Research models and hypotheses

II. A.TOE framework

In 1990, Tornatzky and Flescher proposed the TOE (T-Technology, O-Organization, E-Environment) framework theory in their book The Process of Technological Innovation.

The book depicts the impact of various contexts on the process of technology adoption and use, of which TOE is a firm-level theory on the adoption and application of new technologies, which explains that there are three factors that influence the decision-making of firms in terms of adoption. These three factors are technological, organizational and environmental factors. All three are believed to influence firms to adopt innovations in technology. Technology, organization and environment have a significant impact on firms' technological innovation. In addition TOE theory is used as a framework in which different factors can be placed and the factors can be freely adapted according to different adoption technologies and research contexts, which makes the TOE framework highly adaptable and can be widely used in the adoption of innovative technologies in many firms.

II. B.Analysis of Factors Influencing Adoption

II. B. 1) Adoption behavior

In this paper, adoption behavior refers to the strong or weak degree of enterprise users' own willingness to use AI technology services, enterprise adoption behavior is a result of comprehensive consideration, the behavior is driven by cognition, through the study of the influencing factors before the emergence of the behavior, we can have a better grasp of the antecedent factors affecting the behavior, and through the study of these factors, we can better understand the process of adoption behavior.

II. B. 2) Technical factors

Technical factors are one of the core factors affecting employee adoption of AI technology, and 10 key indicator elements that have a large impact on technology adoption: including relative advantage, compatibility, technical complexity, cost factor, communicability, divisibility, ability to deliver benefits, social acceptance, experimentability, and observability. Among them, generally speaking, relative advantage, technical complexity and compatibility are the three most important factors.

(1) Relative Advantage

Relative advantage is a relative concept that refers to the degree of advancement of a new technology or a new product relative to an old technology or product. As far as AI technology services are concerned, theoretical studies have shown that AI technology advantages are significant and revolutionary.

(2) Technical complexity

Technical complexity in general terms is the degree of difficulty for business users to learn this set of technologies. Later, scholars, through unremitting efforts, extended the concept of complexity to the new technology to create the adoption of this field of research, and systematically elaborated the concept of technological complexity.

(3) Compatibility of technology organization

Technology organization compatibility refers to the degree of compatibility between the original structure of the enterprise and the new technology to be adopted, and whether major changes are required. Any enterprise users in the consideration of the adoption of new technologies, will take into account the new technology and the current enterprise organizational structure is compatible or not, IT technology is ultimately for the service of business, enterprise organizational structure is also for the service of business, so the degree of compatibility between new technologies and the enterprise organization is particularly important.

II. B. 3) Organizational factors

Since enterprise users are the main body of adoption, when studying the adoption behavior of enterprises, we must pay extra attention to and study the influence of enterprise organization factors. Organizations in the harsh market competition, the market environment is changing rapidly, with great uncertainty, so the organization needs to maintain a high degree of vigilance and competitive awareness of the value of the relevant adoption behavior is particularly cautious, especially artificial intelligence technology services as the most emerging form of innovative technology, in the face of this form of time, the enterprise can not be learned from the same industry or to consult the relevant personnel in the industry In the face of this form, enterprises cannot learn from the same industry or consult relevant people in the industry to gain experience, but can only rely on high-level management to collect information and make comprehensive judgment to meet their own business needs, so the adoption of new technology at this time mainly depends on the attitude of the company's top management.

II. B. 4) Environmental factors

Enterprise user adoption behavior will be subject to the constraints of the objective environmental factors, must be from the practical point of view, in order to carry out the technology selection, through the results of previous research shows that the enterprise technology adoption behavior by imitation pressure, forced pressure, normative pressure and other related pressure.

(1) Imitation pressure

Imitation pressure is the habit or behavior of people who freely or interestingly follow the example of successful or high-status people. When business users see the results or effects of the success of the same industry, will produce imitation behavior, this behavior can reduce the risk of failure, or minimize the cost of behavior.

(2) Coercive pressure

The source of coercive pressure on enterprises often have government departments, trade associations and related interest institutions, these organizations have a direct dependence on the production and operation of the enterprise, their attitudes and behaviors for the enterprise to bring coercive pressure.

(3) Normative pressure

Normative pressure is from the normative binding force within an industry itself. Normative pressure through the relevant power institutions in society related to policies and regulations to regulate industry behavior, so that the competition in the same industry in an orderly industry competition and so on. When a certain technology and services become an industry agreed upon “norms”, the relevant services and technologies can influence and “dominate” the direction of development of the industry.

II. C.Research hypotheses and modeling

Based on the above, the research hypotheses of this paper are summarized as shown in Table 1.

Table 1: Continued Summary of Research Hypotheses

Hypothesis number	Hypothetical content
H1	The relative advantages of technology have a significant positive effect on the willingness of employees to adopt the artificial intelligence technology.
H2	The compatibility of technology has a significant positive effect on the willingness of employees to adopt the artificial intelligence technology
H3	The complexity of the technology has a significant negative effect on the willingness of employees to adopt the artificial intelligence technology.
H4	Organizational high-level management support has a significant positive effect on the willingness of employees to adopt a degree of adoption of artificial intelligence technology.
H5	The preparation of resources is a significant positive effect on the willingness of employees to adopt a degree of adoption.
H6	Organizational environment management has a significant positive effect on the willingness of employees to adopt the ai technology.
H7	The pressure of stakeholders has a significant negative impact on the adoption will of employees for artificial intelligence.
H8	Government policy support has a significant positive effect on the willingness of employees to adopt the ai technology.
H9	Government regulation has a significant positive effect on the willingness of employees to adopt the ai technology.

Combined with the TOE framework and then based on the variables and research hypotheses in the previous section, the structural equation theoretical model constructed in this paper is shown in Figure 1.

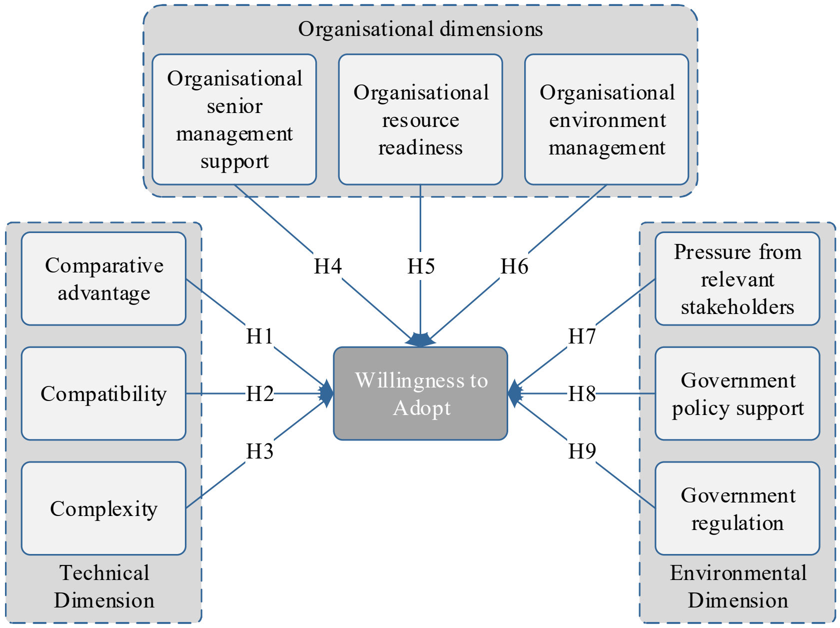

Figure 1: The willingness model of employees' willingness to adopt artificial intelligence technology

III. Employee Adoption of Artificial Intelligence Technology Analysis

III. A. Questionnaire design

The measurement portion of the questionnaire uses a Likert 5-point scale to quantify the relationship between different factors and adoption intention. The scale is set on a score range of 1, 2, 3, 4 and 5, corresponding to "strongly disagree", "disagree", "neutral", "agree" and "strongly agree", respectively. A higher score indicates that the respondent agrees with the question description more likely, or indicates that the respondent's actual behavior is more consistent with the questionnaire description.

III. B. Questionnaire development

III. B. 1) Measurement of technical factor variables

Based on the research in the previous section, three main factors of relative advantage, compatibility, and complexity were identified as influencing factors for the adoption of Artificial Intelligence technology (AI) by the employees of the organization at the technical level. The measurement topics are shown in Table 2.

Table 2: Technical Dimension Measurement Scale

Measuring variable	Topic number	Subject content
Relative advantage	A1	New technologies can improve resources/energy efficiency
	A2	New technologies can improve corporate environmental performance
	A3	New technologies can reduce the environmental costs of companies
	A4	New technologies can improve product quality
Compatibility	B1	New technology is compatible with existing equipment and technology
	B2	New technology matches existing production practices
	B3	The change of new technology and the faith/value of our company
Complexity	C1	consensus
	C2	The new technology is complex with the existing production process
	C3	New technologies can improve resources/energy efficiency

III. B. 2) Measurement of organizational factor variables

Based on the research in the previous section, three main factors were identified as influencing factors on the adoption of AI technology by corporate employees at the organizational level, namely, organizational top management support, organizational resource readiness and organizational environment management. The measurement topics are shown in Table 3.

Table 3: Organizational Dimension Measurement Scale

Measuring variable	Topic number	Subject content
High-level management support	D1	Senior management team is interested in artificial intelligence technology.
	D2	The senior management team believes that the adoption of artificial intelligence technology is strategically important.
	D3	Senior management teams are willing to accept the risks of artificial intelligence.
	D4	The senior management team of the enterprise has arranged reasonable funds for the new technology and its resources
Organization resources preparation	E1	The enterprise has the demand for new technologies and infrastructure
	E2	Enterprises have professional talents and employees
	E3	Businesses have knowledge related to new technologies
Organizational environment management	F1	Business has knowledge related to artificial intelligence
	F2	Enterprise culture

III. B. 3) Measurement of environmental factor variables

Based on the research in the previous section, three main factors were identified as stakeholder pressure, government policy support and government regulation for the environmental level influences on the adoption of AI technology by corporate employees. The measurement topics are shown in Table 4.

Table 4: Environmental Dimension Measurement Scale

Measuring variable	Topic number	Subject content
Stakeholder pressure	G1	The choice of new technologies and the pressure of partners
	G2	The choice of new technologies and the pressure of consumers
	G3	The choice of new technologies and the pressure of consumers.
Government policy support	H1	The government provides financial support for new technologies
	H2	The government provides technical support for the adoption of new technologies
	H3	The government provides talent training for new technologies.
Government regulation	I1	Enterprise production process needs to meet national and local environmental laws and standards
	I2	Enterprise products need to meet national and local environmental laws and standards
	I3	Companies need to strictly apply performance-based standards
	I4	Companies need to strictly apply technical standards

III. B. 4) Measurement of Adoption Variables

The question items of the scale were mainly referred to the scale, and then appropriately modified by combining the artificial intelligence technology in this paper. The specific measurement questions are shown in Table 5.

Table 5: Scale for measuring willingness to adopt

Measuring variable	Topic number	Subject content
Willingness to adopt	J1	The enterprise adopts the will of artificial intelligence technology in this article
	J2	The enterprise adopts the will of resource/energy alternative technology
	J3	The enterprise adopts the will to improve the artificial intelligence technology
	J4	The willingness of enterprises to adopt artificial intelligence technology

III. C. Structural equation modeling

Structural equation modeling is a statistical analysis technique based on the existing causal theory, with the corresponding system of linear equations to represent that causal theory, which aims to explore the causal relationship between things and express this relationship in the form of causal patterns, path diagrams, etc [22].

Structural equation modeling consists of two sets of equations, a set of equations for the relationship between structural variables, called the structural equation set, and a set of equations for the relationship between structural variables and observed variables, called the observation equation set.

In a typical Chinese customer satisfaction index model, the set of structural equations contains 6 structural variables (hidden variables) ξ_1, $\eta_1 \sim \eta_5$ with 11 relationships (the relationship between the role of the independent variables is $\gamma_1 \sim \gamma_4$, and the relationship between the role of the dependent variables is β_{ij}), as (1) Shown.

$$\begin{pmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ \beta_{21} & 0 & 0 & 0 & 0 \\ \beta_{31} & \beta_{32} & 0 & 0 & 0 \\ \beta_{41} & \beta_{42} & \beta_{43} & 0 & 0 \\ 0 & 0 & 0 & \beta_{54} & 0 \end{pmatrix} \begin{pmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \end{pmatrix} + \begin{pmatrix} \gamma_{11} \\ \gamma_{12} \\ \gamma_{13} \\ \gamma_{14} \\ 0 \end{pmatrix} \xi_1 + \begin{pmatrix} \varepsilon_{\eta 1} \\ \varepsilon_{\eta 2} \\ \varepsilon_{\eta 3} \\ \varepsilon_{\eta 4} \\ \varepsilon_{\eta 5} \end{pmatrix} \tag{1}$$

In the general case, the number of structural variables need not be five, the form of the coefficients of the structural equations can be different from (1) except for the requirement that the diagonal is zero and it is a lower triangular matrix, and the number of independent variables can be more than one. We use vector and matrix notation for the general description. Let there be m dependent variables, arranging $\eta_1, \cdots, \eta_m$ into a column vector, denoted as η; and k independent variables, arranging $\xi_1, \cdots, \xi_k$ into a column vector, denoted as ξ;The coefficient matrix of η is a m-order square matrix denoted B;The coefficient matrix of ξ is the $m \times k$ matrix denoted as Γ; By arranging the residual vectors $\varepsilon_1, \cdots, \varepsilon_m$ into column vectors denoted as ε_η, the system of structural equations (1) can be expanded as:

$$\eta = B\eta + \Gamma\xi + \varepsilon_\eta \tag{2}$$

The structural variables of SEM are implicit and cannot be observed directly, but correspond to a number of observed variables. Let there be a total of M observational variables, for each observational variable there are N observations, in the customer satisfaction index analysis is that there are N customer assessments, so that the data we have in hand is a $N \times M$ matrix.

The relationship between the role of structural variables and observed variables can also be expressed in equations, according to the causal path of the role of two representations. Let the $S(t)$ observation variable corresponding to the independent variable ξ_t be x_{tj}, $j = 1, \cdots, S(t)$, and the $L(i)$ observation variable corresponding to the dependent variable η_i be y_{ij}, $j = 1, \cdots, L(i)$, and so the system of observation equations from the observation variables to the structural variables can be expressed as:

$$\xi_t = \sum_{j=1}^{S(t)} \psi_{tj} x_{tj} + \varepsilon_{\xi t}, t = 1, \cdots, k \tag{3}$$

$$\eta_i = \sum_{j=1}^{L(i)} \omega_{ij} y_{ij} + \varepsilon_{\eta i}, i = 1, \cdots, m \tag{4}$$

where υ_{tj}, λ_{ij} are the load terms.

Remember the observation vectors $x_t = (x_{t1}, x_{t2}, \cdots)'$, $t = 1, \cdots, k$ and $y_i = (y_{i1}, y_{i2}, \cdots)'$, $i = 1, \cdots, m$; and remember that $\upsilon_t = (\upsilon_{t1}, \cdots, \upsilon_{tj})'$, and $\lambda_i = (\lambda_{i1}, \cdots, \lambda_{ij})'$, the system of observational equations (4) can be expanded as:

$$x_t = \upsilon_t \xi_t + \varepsilon_{xt}, t = 1, \cdots, k \tag{5}$$

(5) can be expanded to:

$$y_i = \omega_i \eta_i + \varepsilon_{yi}, i = 1, \cdots, m \tag{6}$$

Similarly, remember that $\psi = I_k \otimes \psi_t$, $\Omega = I_m \otimes \omega_j$, where $\psi_t = (\psi_{t1}, \psi_{t2}, \cdots)'$, $\omega_j = (\omega_{j1}, \omega_{j2}, \cdots)$, I is the unit square matrix, and remembering that $x = (x_1, \cdots, x_k)'$ and $y = (y_1, \cdots, y_m)'$, the system of observation equations (3) and (4) can be written as

$$\xi = \psi x + \varepsilon_\xi \tag{7}$$

$$\eta = \Omega y + \varepsilon_\eta \tag{8}$$

We refer to (2), (5), and (6) together (or (3), (7), and (8) together) as structural equation modeling (SEM), or sometimes as path analysis modeling.

IV. Data collection and analysis

IV. A. Data collection and sample descriptive statistics

In terms of data source, with intelligent home decoration and other enterprises as the survey object, the questionnaire was mainly distributed through the expo site, WeChat group, e-mail, enterprise on-site interviews, etc. A total of 355 copies were recovered, and through checking all the recovered samples one by one and removing invalid samples such as missing key data and obvious contradictions between the front and back, the final valid samples were 245, with an effective recovery rate of 69%.

In terms of age structure, nearly 91.55% of the respondents are between 24 and 40 years old, which indicates that the current leaders of the middle and senior levels of traditional enterprises, especially the departmental leaders, are a relatively younger group, and they are more receptive to new things, which helps traditional enterprises to adopt AI technology. Descriptive statistics found that the vast majority of respondents have more than 1 year of work experience, and more than 55% of them have been or are engaged in intelligent work, which makes the questionnaire fillers have a clearer understanding and awareness of the enterprise's operational situation, and helps this study to draw more scientific, reasonable and real conclusions.

IV. B. Analysis of the reliability of the questionnaire

IV. B. 1) Reliability test

Reliability, i.e., the reliability of the measurement information, refers to the degree of reliability of the measurement data and conclusions, or the degree to which the measurement instrument is able to stably characterize the matter it is intended to measure. In this study, SPSS 21.0 was used to test the reliability of the questionnaire as shown in Table 6, and the results of the study in the table show that the Cronboch'sa values of the measured variables are higher than 0.7, and the reliability of the measurement system is acceptable.

Table 6: Reliability test results

Measurement project	Topic number	Cronbach'sa coefficient
Compatibility	3	0.759
Relative advantage	4	0.811
Complexity	3	0.843
Government policy support	3	0.761
Government regulation	4	0.893
The pressure of the stakeholders	3	0.872
Organization resources preparation	3	0.895
Organizational environment management	2	0.843
High-level management support	4	0.944
Willingness to adopt	4	0.896

IV. B. 2) Tests of aggregation validity

The convergent validity was measured by constructing the corresponding factor model through the method of validated factor analysis. Aggregate validity can be measured from three indicators: factor loading, average variance extracted AVE and combination reliability CR. The discriminating criteria are: the value of factor loading should be higher than 0.5, and the ideal state is more than 0.7; the value of combined reliability of each latent variable is greater than 0.7, which indicates that each variable has good internal consistency; the value of AVE of the latent variables is greater than the acceptable value of 0.5, which indicates that the percentage of variation explained by a latent variable for the index it belongs to is more than 50%, which indicates a better reliability and convergent validity of the measurement model.

The AVE values of each variable are calculated as shown in Table 7, and the average variance extracted of all variables in the scale is greater than 0.5, and its combined reliability index is above 0.7, which indicates that the scale has good convergent validity.

Table 7: The polymerization validity test table

Variable	Item	Load factor	AVE	Composite reliability
Relative advantage (RA)	A1	0.758	0.517	0.747
	A2	0.710		
	A3	0.648		
	A4	0.736		
Compatibility (CP)	B1	0.691	0.583	0.801
	B2	0.775		
	B3	0.842		
Complexity (CI)	C1	0.683	0.631	0.827
	C2	0.853		
	C3	0.819		
High-level management support(TMS)	D1	0.741	0.511	0.749
	D2	0.802		
	D3	0.758		
	D4	0.833		
Organization resources preparation(OR)	E1	0.761	0.685	0.863
	E2	0.625		
	E3	0.841		
Organizational environment management(OC)	F1	0.911	0.717	0.882
	F2	0.797		
The pressure of the stakeholders(GP)	G1	0.835	0.737	0.889
	G2	0.782		
	G3	0.974		
Government policy support(GZ)	H1	0.814	0.665	0.857
	H2	0.833		
	H3	0.651		
Government regulation(CMP)	I1	0.602	0.837	0.931
	I2	0.941		
	I3	0.821		
	I4	0.754		
Willingness to adopt(FP)	J1	0.639	0.822	0.904
	J2	0.729		
	J3	0.618		
	J4	0.791		

IV. C. Structural equation modeling analysis

In this study, the coefficient of determination (R^2) is used to estimate the explanatory power of the model, and the value of R^2 ranges from 0 to 1, with larger values indicating stronger model explanatory power. Generally R^2 below 0.25 indicates a weak model explanatory ability, R^2 near 0.5 indicates a moderate model explanatory ability, and R^2 above 0.75 indicates a strong model explanatory ability. The R^2 value of AI technology adoption is 0.751, which means that the four dimensions of the independent variables together explain 75.1% of the variance in AI technology adoption, which has a high explanatory power. Also. The R^2 value of enterprise performance is 0.382, i.e., AI technology adoption explains 38.2% of the variance in enterprise performance, which has an average explanatory power, and the reason for this is that this study only considers the effect of a single factor of AI technology adoption on enterprise performance, and thus the model's explanatory power is acceptable.

Partial least squares analysis estimated the path coefficients of the model. The path coefficients between the constructs, their respective t-values, standard errors and variance explained by the dependent variable are shown in Table 8. Of the proposed hypotheses, H1, H3, H4, H5, and H8 were supported. These results demonstrate the statistical significance of the defined relationships.The results of R^2 indicate that our model explains 75.1% of the variance in AI technology adoption and 38.2% of the variance in firm performance. As expected, Relative Advantage (RA), and Organizational Top Management Support (TMS) are significant predictors of AI technology adoption. In addition, Complexity (CI), Stakeholder Pressure (GP), Organizational Resource Readiness (OR), and Government

Policy Support (GA) have significant positive effects on AI technology adoption. Finally, the other factors are not significant and therefore do not support the relationship.

Table 8: Hypothesis test results

Hypothesize	path	Path coefficient	T statistic	P value	Test result□□
H1	RA→AI	0.215	2.261*	0.021	Set up
H2	CP→AI	0.019	0.119	0.895	Out of reach
H3	CI→AI	-0.287	2.674**	0.003	Set up
H4	TMC→AI	-0.335	2.103*	0.029	Set up
H5	OR→AI	0.647	6.014**	0.001	Set up
H6	OC→AI	0.128	1.274	0.158	Out of reach
H7	GP→AI	-0.084	0.815	0.395	Out of reach
H8	GZ→AI	0.461	3.515**	0.001	Set up
H9	FP AI	-0.181	1.374	0.165	Out of reach

Adjusted R^2 was 0.751 for AI and 0.382 for FP; *p<0.05**p<0.01.

IV. D. Analysis of the moderating role of organizational training

The results of the moderating effects test are shown in Table 9. Environment, organization, technology, and organizational training all positively affect the perceived usefulness of AI technology adoption. The cross term of environment and organizational training negatively affects the perception of AI technology adoption (β=-0.113, p<0.01), and the cross term of organization and organizational training and the quality of technology and organizational training do not have a significant effect on the perception of usefulness of AI technology adoption, i.e., affective quality diminishes the degree of influence of the environment in the pathway of the influence of product information on the perceived usefulness of AI technology adoption and does not organization and technology in the path of influence on perceived usefulness of AI technology adoption.

Table 9: The effect of the influence path of the relative advantage is tested

Study variable	M1	M2	M3
Environment	0.271**	0.215**	0.187**
Organization	0.281**	0.234**	0.241**
Technology	0.309**	0.238**	0.181**
Environment×Organizational training			-0.113**
Organization t×Organizational training			0.004
Technology×Organizational training			0.031
R^2	0.61	0.621	0.625
$\triangle R^2$	0.61	0.027	0.004
F value	391.013***	338.082***	197.147***

Note: ***, **, * denote □P<0.001, P<0.01, P<0.05 respectively

V. Conclusion

The analysis of structural equation modeling of employees' AI technology adoption shows that relative advantage, organizational top management support, organizational resource readiness and government policy support all have a significant positive impact on employees' adoption of AI technology, while technological complexity has a significant negative impact. The organizational resource readiness factor has the most prominent impact, with a path coefficient of 0.647, indicating that adequate resource allocation is the core element that drives employees' acceptance of new technologies. The four dimensional independent variables together explain 75.1% of the variance in AI technology adoption, confirming the strong explanatory power of the model. Organizational training exhibits a significant moderating effect (β = -0.113) in the relationship between environmental factors and adoption, a finding that implies that firms can mitigate the negative impact of external environmental pressures on technology adoption through targeted training programs. The data show that 91.55% of the survey respondents are between 24-40 years old, and this relatively younger group of employees is more receptive to new technologies, providing favorable conditions for the promotion of AI technology in enterprises. It is suggested that when promoting the application of AI technology, enterprises should focus on strengthening the publicity of the relative advantages of the technology, simplifying the technical operation process, ensuring sufficient resource support, while actively seeking government policy support, and improving the technical literacy of employees through organizational training, so as to promote the effective adoption of AI technology.

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