Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

A study of the moderating effect of organizational training on the impact of employees' behavioral resistance to AI technology and the application of structural equation modeling

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ABSTRACT

The development of artificial intelligence has brought new development opportunities for modern enterprises, but employees present a certain degree of resistance to the introduction of AI technology. The author tries to dissipate employees' resistance and improve their acceptance of AI through organizational training. After researching organizational training and employees' perceived awareness of AI, organizational training and employees' acceptance of AI are taken as antecedent and consequent factors to construct a structural equation research model of the two. The research hypotheses are proposed based on the theoretical study of the two. Regression analysis of the effect of organizational training on employees' AI acceptance is conducted through structural equations. The regression results show that training investment, employee motivation and knowledge training in organizational training all have a significant positive effect on both employees' AI perceived ease of use and AI perceived usefulness. Employee AI perceived ease of use and AI perceived usefulness have a positive effect on employee behavioral intention to use AI for knowledge creation and automation. Employees' behavioral intention to use AI for knowledge creation will have a positive effect on AI for knowledge creation, and behavioral intention to use AI for automation will have a positive effect on AI for automation.

Keywords: structural equation modeling, organizational training, AI acceptance, regression analysis

1. Introduction

With the rapid development of science and technology, Artificial Intelligence (AI) as an emerging technology has attracted widespread attention and discussion. In the workplace, the application of AI

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Received 05 March 2024; Revised 10 May 2024; Accepted 05 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-346

is gradually penetrating into various industries and positions, which has a certain impact on people's work style and attitude, however, the attitude of the workplace towards AI can be said to be mixed [1-4]. On the one hand, the emergence of AI has brought a lot of convenience and opportunities to the workplace. For example, in terms of data analysis, artificial intelligence can help enterprises quickly analyze a large amount of data through rapid algorithms and modeling operations to provide an accurate basis for decision-making. The application of such technology can greatly improve work efficiency, save human resources, and make the enterprise run more efficiently [5-8]. On the other hand, there are certain concerns and worries about the attitude of the workplace towards artificial intelligence.

The first is the worry about the replacement of jobs, the development of artificial intelligence makes some simple and repetitive work can be replaced by automation, which may lead to some people engaged in this kind of work face the risk of unemployment [9-12]. For example, in the manufacturing industry, traditional assembly work can be replaced by robots, which makes some practitioners face the dilemma of re-employment. Secondly, it is the application of AI may also lead to some privacy and security issues. Through the analysis of big data, AI can obtain a large amount of personal information, which poses a challenge to the protection of personal privacy [13-16]. At the same time, the algorithms of AI may also have certain loopholes, which can be utilized by unscrupulous elements to carry out criminal activities. Therefore, in order to better adapt to the development of AI, AI training is essential [17-20]. Organizations adapt to the needs of the AI era by carrying out appropriate skills training and enhancement, and structural equation modeling can play an important role in this training process [21-22].

This paper analyzes the psychological attribution of organizational training and employees' resistance to AI technology from the perspective of organizational training and employees' perceived awareness of AI. And the research object is converted to the effect of organizational training on employees' AI acceptance, so as to better explore the relationship between organizational training and employees' AI resistance. Structural equation modeling is chosen as the research method, and antecedent and outcome variables are defined to construct the research model. Relevant research hypotheses are proposed on the basis of theoretical analysis. Before conducting empirical research, the validity of the model and variables is ensured through methods such as common method bias analysis and reliability test. The effects between organizational training and employee AI acceptance variables are explored in depth through structural equations.

2. Theoretical foundations

2.1. Organizational training

2.1.1. Concept of training. Training is a management activity that enhances the knowledge and skills of employees and changes their perceptions, attitudes, values and psychological qualities through the systematic optimization of the design of educational programs to promote the achievement of organizational goals.

The positive role of training for the enterprise lies only in its ability to increase the labor productivity of the enterprise's employees, thus bringing higher profits to the enterprise. At the same time, the importance of the environment can not be ignored, the enterprise to design a kind of employees can feel satisfied with the environment and will maintain it, so as to maximize the efficiency of the staff is the core of employee training, so that the staff in the organization with high efficiency to complete the goals set by the company. At the same time, the purpose of corporate training is to enable employees to have an understanding of the objectives of the work they are engaged in, and to enable the trained employees to quickly master the required knowledge and skills, so as to carry out the rational use of the situation in the daily work.

Training is a kind of learning activity that can promote the knowledge and skills of the company's employees, while the activity has a collective, planned and purposeful. Training means to cultivate plus training, cultivation is the enterprise through the molding of a good training environment, so that employees to learn and master new skills or knowledge in line with the development of the company. Training refers to the simulation and training of practical aspects, which are beneficial to the development of the company. In other words, the purpose of training is to strengthen the employees' overall strength, business level and work performance and other personal abilities. In short, the essence of training is to impart relevant knowledge, train personal skills and develop professional thinking.

2.1.2. Adult Learning. Adult learning theory refers to the combination of the guiding ideology of adult education and training and learning theory, based on the physiological and psychological characteristics of adults, the desire to learn and the system as a basis for summarizing the special guidance for the training of adults in the theory of education. This theory has its own uniqueness, but also to fill the previous training model is mainly for the training of children and beginners and the establishment of this blank field, is another major breakthrough in training theory research. The theory mainly combines adult training, adult psychology, with the special characteristics of adult education to build the system of adult learning mode.

Enterprise employee training belongs to the category of adult education. Corporate trainers should follow the following training principles in teaching in order to ensure the success of training.

1) Create a sense of security for employees. Since adult employees have independent personality and desire to be respected and understood by others in learning, trainers must focus on making adult employees have a sense of security in the learning environment and process. One of the principles of making employees feel safe is to respect them and treat them as the main body of learning. The second is that the learning tasks, learning groups and learning materials and classroom environment should be designed to make employees feel that this learning experience is suitable and useful for them, and is conducive to their personal career development.

2) Various methods to encourage employees to participate in learning. Due to the large differences in age, education and position of adult employees, and they all have independent personalities, like to arrange their own learning with their own different learning methods formed over a long period of time, and their learning is more purposeful and centered on solving their own problems in work and life. Therefore, trainers should treat different employees differently, using a variety of methods to mobilize employees to participate in learning activities.

2.2. AI Perception Awareness

2.2.1. Concepts and connotations. AI awareness refers to employees' awareness that AI machines, such as robots and algorithms, may replace their current jobs in the future, leading to a sense of uncertainty about the workplace in the digital age. The goal of AI is to give machines human capabilities, such as teaching them to think, reason, and even learn. Currently, AI is increasingly integrated into business operations and is also driving the development of Industry 4.0.The use of AI is increasing, especially in the service industry. For example, AI can be used as an intelligent chatbot to solve problems encountered by users during consumption, or as a guestroom robot to enhance the consumer experience. Hotel chains are installing intelligent assistants in guest rooms to fulfill consumer needs. Food and beverage companies can utilize robots and sensors to achieve precise and dynamic management of the food supply chain. Depending on the needs and preferences of different consumers, online retail platforms intelligently extract and combine raw materials from databases to create ever-changing content containing text, images or other creative elements.

As mentioned above, AI is playing an increasingly important role in the service industry, constantly replacing employees. Some recent predictions support this view. So, while AI is a great convenience for businesses, it is also taking up jobs that would otherwise belong to humans. AI adoption has had a significant impact on the work of employees, who are the most important segment of the population for AI acceptance. Considering that AI adoption is still in its infancy, it is important to pay more attention to how employees perceive the technology's impact on them and their acceptance of it.

2.2.2. Formation of AI perceptual awareness. The idea that the formation of AI-perceived awareness is influenced by multiple factors cannot be ignored. First, the rapid development of AI technology has not only changed the dynamics of the workplace, but has also profoundly affected the allocation and utilization of employee resources. With the spread of automation and intelligent technologies, some traditional jobs may be challenged, while other emerging occupations may come to the fore. Such changes will not only affect employees' employment prospects, but also present new challenges and opportunities for their career paths and skill needs.

Second, AI also has a profound impact on employee motivation and behavior. In a work environment driven by AI technology, employees may face higher productivity requirements and tighter work schedules. This pressure may affect employee motivation and satisfaction, and even trigger problems such as burnout or anxiety.

In addition, employees' cognitive and behavioral responses to AI are critical. With the development and application of AI technology, employees' attitudes and perceptions of AI are constantly changing. On the one hand, some employees may have fear or rejection of AI, worrying that it will replace human jobs and even affect their personal livelihood and social status. On the other hand, there are some employees who are optimistic about AI, believing that it can bring convenience and enhancement to their work. Moreover, the national policy of focusing more and more on the combination of AI and enterprises and the many AI models and practical achievements have formed a culture of reverence for AI applications, which is also profoundly affecting various industries and the people in them.

Job Demand-Resource (JD-R) believes that all the work qualities in the world can be divided into two states: job demand and job resource. Work demand is for the work of material, psychological, social or organizational needs, employees need to pay for these needs have been material and mental labor. In other words, job demands are material conditions that must be achieved through hard work. Specifically, difficult tasks, intense workloads and performance pressures imposed by the organization are job demands.

According to the JD-R model, difficult tasks, intense workloads and performance pressures presented by the organization are job demands. Therefore, we consider AI awareness as an employee's job demand. Recent studies have shown that AI-perceived awareness inhibits employees' organizational commitment, occupational competence, job engagement, and career satisfaction and promotes work overload, burnout, turnover intention, and depressive attitudes. However, AI perceptual awareness does not always have a negative impact on employees. AI adoption has an inverted U-shaped curve relationship with employee job performance. These findings are doubly impeded with job demands. The challenge properties are consistent. The AI perceptual awareness under the JD-R model is shown in Figure 1.

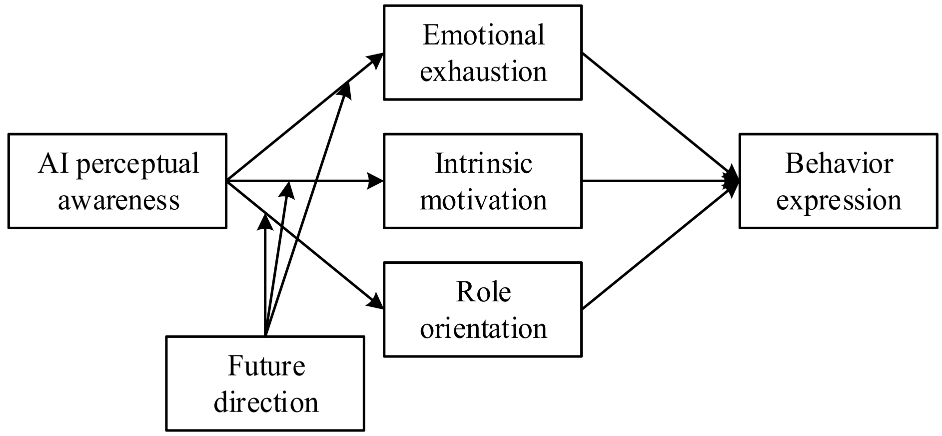

Fig. 1. AI sensory awareness model in the case of JD-R

3. Research design

3.1. Data collection

This research survey was conducted over a period of one month from the end of June 2024 to August 2024 on two enterprises and a number of their subsidiaries in Hangzhou, Zhejiang Province. The research was conducted mainly by utilizing the form of on-site questionnaire distribution on-site collection. In the process of research, in order to ensure the respondents' understanding of the relevant management and organizational training of the enterprise, we eliminated the questionnaire that entered the company for less than one year, regarded it as an invalid questionnaire, and processed the recovery questionnaire to eliminate the questionnaire with incomplete data and obvious problems, and the questionnaire recovery situation was as follows: the total number of questionnaires issued was 500, 487 were recovered, the number of valid questionnaires was 415, and the effective recovery rate was 83%.

3.2. Research Model and Assumptions

3.2.1. Structural equation modeling:

1) Fundamentals. Structural equation modeling (SEM), also known as latent variable modeling (LVM), was earlier known as linear structural relationship modeling, covariance structural analysis, latent variable analysis, validated factor analysis, and simple LISREL analysis [23-24]. It has been widely used in economics, sociology, behavioral sciences, psychology and other research fields, often used to deal with complex multivariate data with multiple causes and multiple outcomes, or containing latent variables, usually categorized in the field of advanced statistics, and has been respected by many scholars as the “second generation of multivariate statistical methods”.

Structural Equation Modeling (SEM) combines the statistical methods of factor analysis and path analysis, respectively, to simultaneously verify the causal relationships between latent, manifest, confounding, or error variables included in the model, and to obtain the direct, indirect, and total effects due to the influence of the independent variables on the dependent variable. SEM consists of both measured and latent variables as the basic variables. The basic units that are actually analyzed and calculated by the SEM are the information that the researcher observes in relation to the measured variables, while the latent variables are derived from the measured variables by extrapolation and are not directly observable. In a typical structural equation modeling analysis, i.e., reactive structural equation modeling, the variance of the measured variable may be affected by one or more latent variables at the same time, hence the name latent variable measured variable or apparent variable.

The term structural equation means that, ordinarily, typical structural equation modeling can be described using general equations (1) that represent specific research hypotheses:

$$
\begin{aligned}
y &= \Lambda_y \eta + \varepsilon \\
x &= \Lambda_x \xi + \delta \\
\eta &= \beta\eta + \Gamma\xi + \varsigma
\end{aligned}
\tag{1}
$$

In Equation (1), the first two equations represent the measurement model and the last equation represents the structural model. Structural equation modeling pays great attention to the use of conceptual path diagrams, and when using SEM to do research, the first step is to construct the path diagram of SEM step by step based on the theoretical analysis and the proposed hypotheses, and then calculate the numerical results by using the statistical software, such as R, EQS, LISTRL, Mplus, SPSS, AMOS, etc., and then finally, the obtained results are interpreted as well as evaluated.

Regarding the estimation methods in the SEM analysis process, there are generally seven methods, namely: instrumental variables method, two-stage least squares method, weighted least square method, generalized least square method, general weighted least square method, great likelihood method, and diagonal weighted square method. If the theoretical model provided by the researcher is correct (no serial errors or identification errors in the model) and the sample size is large enough, the estimates produced by the above seven methods will be close to the true parameter values.

2) Measurement model. Measurement modeling is what is generally known as a validated factor analysis (CFA) [25] of models in SEM, which is mainly used to test the extent to which multiple measured variables can constitute latent variables, i.e., to test whether the causal model established between the observed variables in the measurement model and their corresponding latent variables is consistent with the observed data.

As indicator variables of latent variables, observed variables can be categorized into reflective and formative indicators according to the nature of the indicator variables. Since only the reflective indicator measurement model is used in the model constructed in this paper, only that model is presented. The reflective indicator measurement model is shown in Figure 2.

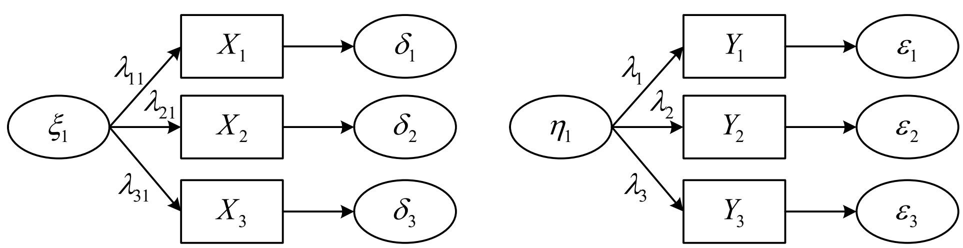

Fig. 2. Reflection index measurement model

The regression equation for the measurement model shown above is as follows:

$$
\begin{aligned}
X_1 &= \lambda_{11}\xi_1 + \delta_1 \\
X_2 &= \lambda_{21}\xi_2 + \delta_2 \\
X_3 &= \lambda_{31}\xi_3 + \delta_3 \\
Y_1 &= \lambda_1\eta_1 + \varepsilon_1 \\
Y_2 &= \lambda_2\eta_1 + \varepsilon_2 \\
Y_3 &= \lambda_3\eta_1 + \varepsilon_3
\end{aligned}
\tag{2}
$$

The matrix is of the form:

$$
\begin{aligned}
X &= \Lambda_X \xi + \delta \\
Y &= \Lambda_Y \eta + \varepsilon
\end{aligned}
\tag{3}
$$

Among them, ε is uncorrelated with η, ξ and δ, and δ is also uncorrelated with η, ξ and ε. Λ_X and Λ_Y are the factor loadings of indicator variables X and Y respectively, δ and ε are the measurement errors of the explicit variables, ξ and η represent the externally derived latent variables and endogenously derived latent variables respectively, and it is hypothesized in the SEM measurement model that there can be no causal path relationship or covariate relationship between the measurement errors and the latent variables (co-factors).

3) Structural model. The structural model is the description of the causal relationship between latent variables, if a latent variable is "cause", it is called an extrinsic latent variable (or an extrinsic latent variable, a latent independent variable), which is represented by symbol ξ; If a latent variable exists as an "effect" in the structural model, it is called an intrinsic latent variable (or an intrinsic latent variable, a latent dependent variable), which is denoted by symbol η. The explanatory variance of an exogenous latent variable on an endogenous latent variable is more or less influenced by other variables, and we usually call this influencing variable the interfering latent variable, denoted by the symbol ζ. The structural model of the influence of an exogenous latent variable on an endogenous latent variable is shown in Figure 3.

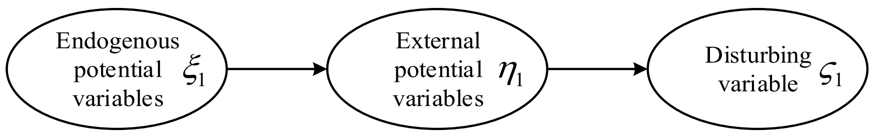

Fig. 3. Simple structure model

The regression equation between the above potential variables is:

$$\eta_1 = \gamma_{11}\xi_1 + \zeta_1 \tag{4}$$

The basic structural model of two exogenous latent variables and one endogenous latent variable is shown in Figure 4.

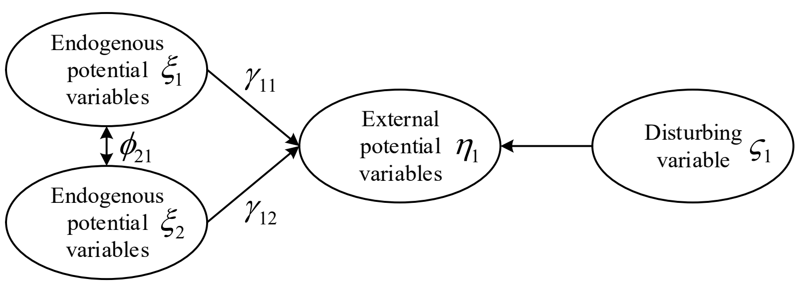

Fig. 4. Two-external-and-one-internal basic structural model

The regression equation between the above latent variables is as follows:

$$\eta_1 = \gamma_{11}\xi_1 + \gamma_{12}\xi_2 + \zeta_1 \tag{5}$$

Other more complex structural models are extensions of the models presented in Figures 3 and 4, and the principles and equation patterns can be derived from them.

In structural modeling, exogenous latent variables can be uncorrelated or correlated with each other, but the relationship between exogenous and endogenous latent variables must be unidirectional, with the former being the "cause" and the latter being the "effect" ($\xi \rightarrow \eta$), and the unidirectional arrows cannot be inverted. The one-way arrow cannot be inverted. The relationship between two endogenous latent variables is allowed to be both unidirectional and bi-directional, i.e., a mutual prediction relationship, as follows: $\eta_1 \rightarrow \eta_2$, or $\eta_2 \rightarrow \eta_1$, or η_2 □ η_1, and the portion of the endogenous latent variable that cannot be explained by the exogenous latent variable, or the predicted error value (ζ), is known as the residual term or the disturbance variable.

3.2.2. Research hypotheses. Training in business organizations is the most important way of investing in human capital, through which the knowledge and skills of employees can be optimized, thus influencing their attitudes and behaviors towards the organization. The process of organization training and development of employees in exchange for improved efficiency is a typical social exchange. First of all, the content of the exchange needs to meet the needs of both parties: in the employment relationship, the employee needs to obtain vocational training and self-development opportunities at all stages of his or her career. The employer expects the employee to demonstrate identification, commitment and loyalty to the organization. Secondly, the two parties to the exchange are equals: it is the equals that will facilitate the continuation of the exchange behavior.

In this paper, organizational training is taken as an antecedent factor, and training input (TI), organizational support (OS), employee motivation (EM), and knowledge training (KT) in organizational training are selected as antecedent research variables. Employee AI acceptance as an outcome factor, in which AI perceived ease of use (PE), AI perceived usefulness (PU), behavioral intention of AI for automation (ABI), behavioral intention of AI for knowledge creation (KBI), behavioral intention of AI for automation (AUB), and behavioral intention of AI for knowledge creation (KUB) were selected as outcome research variables. The construction of the conceptual model mainly verifies the mechanism of the influence of organizational training on employees' AI acceptance.

Based on the theoretical analysis, hypotheses were made about the relationship between the variables.

H1a: There is a positive effect of training input (TI) for organizational training on employees' perceived ease of use (PE) of AI.

H1b: There is a positive effect of training input (TI) of organizational training on employees' perceived usefulness (PU) of AI.

H2a: There is a positive effect of organizational support (OS) of organizational training on employees' perceived ease of use (PE) of AI.

H2b: There is a positive effect of organizational support (OS) of organizational training on employees' perceived usefulness (PU) of AI.

H3a: There is a positive effect of employee motivation (EM) of organizational training on employees' perceived ease of use (PE) of AI.

H3b: There is a positive effect of employee motivation (EM) of organizational training on employees' perceived usefulness (PU) of AI.

H4a: There is a positive effect of knowledge training (KT) of organizational training on employees' perceived ease of use (PE) of AI.

H4b: There is a positive effect of knowledge training (KT) of organizational training on employees' perceived usefulness (PU) of AI.

H5a: There is a positive effect of employees' perceived ease of use (PE) of AI systems on their behavioral intention to use AI systems for knowledge creation (KBI).

H5b: There is a positive effect of employees' perceived ease of use (PE) of the AI system on their behavioral intention to use the AI system for automation (ABI).

H6a: There is a positive effect of employees' perceived usefulness (PU) of AI systems on their behavioral intention to use AI systems for knowledge creation (KBI).

H6a: There is a positive effect of employees' perceived usefulness (PU) of AI systems on their behavioral intention to use AI systems for automation (ABI).

H7a: There is a positive effect of employees' behavioral intention to use AI systems for knowledge creation (KBI) on their behavior to use AI systems for knowledge creation (KUB).

H7b: There is a positive effect of employees' behavioral intention to use AI system for automation (ABI) on their behavior of using AI system for automation (AUB).

4. Analysis of empirical results

4.1. Common methodology bias analysis

This study examined common method bias by controlling for non-measurable latent factors. Constructs including training investment (TI), organizational support (OS), employee motivation (EM), knowledge training (KT), AI perceived ease of use (PE), AI perceived usefulness (PU), AI behavioral intention to use for knowledge creation (KBI), AI behavioral intention to use for automation (ABI), AI behavioral use for knowledge creation (KUB), and AI behavior for automation (AUB), etc., and compared them to the 10-factor model including the 11-factor model with the addition of a common method bias latent factor model and the 1-factor model. If the various fit indices of the model were not better after control than before control, it indicated that there was no serious common method bias.

The results of the analysis are shown in Table 1. According to the analysis results, the χ^2/df of the original hypothetical model is 2.525, which is between the range of 1-3, the RMSEA is 0.065, which is between the range of 0.55-0.08, and the values of IFI, CFI, and TLI are also greater than the criterion of 0.9, which indicates that the original model is relatively good.

In addition, comparing the original model 10-factor model and the 1-factor model, the fitting results of the 1-factor model were poorer and the fitted values of the fitness indicators did not fall within the range of the recommended values, so it can be considered that the fitting results of the 1-factor model were unacceptable. Comparing the 11-factor model with the addition of the method latent factor, the changes in the fit indices of the model were all less than 0.03, indicating that the original hypothesized model was not significantly improved by the addition of the common method factor, and there was no obvious common method bias in the measurements.

In summary, it can be concluded that in this inquiry, the original hypothesized model fits well, the fit index and information index reach the ideal value, there is no obvious common method bias, and the subsequent data analysis can be carried out.

Table 1. Validation factor analysis results

Model	χ^2	Df	χ^2/df	RMSEA	IFI	CFI	TLI
10-Factor	762.554	400	2.525	0.065	0.956	0.958	0.926
11-Factor	596.578	360	1.936	0.056	0.974	0.972	0.964
1-Factor	2215.384	425	5.894	0.118	0.789	0.785	0.758
Saturation model	0	0	/	0.268	1	1	/

4.2. Reliability test

The internal consistency coefficient (Cronbach's Alpha) was chosen in this study to analyze the internal consistency of the variables. A scale or questionnaire can be considered reliable when its Cronbach's Alpha and combined reliability (CR) are both greater than 0.7. The results of the reliability test using SPSS 26.0 in this study are shown in Table 2. The Alpha coefficients of the variables were all greater than 0.7. It indicates that the reliability of the questionnaire is good and meets the needs of the study. All factor loadings were greater than 0.7, indicating high convergent validity of the latent variables. Finally, the AVE values of each variable in this study were calculated based on the factor loadings, and it was found that the AVE values of the variables were all greater than 0.5, which overall indicates good convergent validity of the measured variables in this study.

Table 2. Reliability and validity test results

Variable	Item	Factor load	AVE	CR	Cronbach’s Alpha
TI	TI1	0.733	0.652	0.836	0.863

	TI2	0.881			
	TI3	0.707			
OS	OS1	0.766	0.593	0.827	0.824
	OS2	0.803			
	OS3	0.781			
EM	EM1	0.794	0.654	0.864	0.869
	EM2	0.767			
	EM3	0.776			
KT	KT1	0.761	0.639	0.863	0.874
	KT2	0.876			
	KT3	0.848			
PE	PE1	0.868	0.647	0.882	0.859
	PE2	0.888			
	PE3	0.829			
	PE4	0.822			
PU	PU1	0.754	0.674	0.875	0.847
	PU2	0.763			
	PU3	0.758			
	PU4	0.873			
KBI	KBI1	0.833	0.689	0.869	0.854
	KBI2	0.773			
	KBI3	0.736			
ABI	ABI1	0.784	0.683	0.859	0.863
	ABI2	0.714			
	ABI3	0.782			
KUB	KUB1	0.743	0.634	0.779	0.762
	KUB2	0.877			
AUB	AUB1	0.715	0.621	0.785	0.779
	AUB2	0.858			

4.3. Descriptive statistics

The demographic variables in the recovered questionnaires were analyzed by descriptive statistics and the statistical results are shown in Table 3. From the gender point of view, the enterprises in the recovered questionnaires are mainly dominated by men, with a total of 219 persons, accounting for 52.77% of the effective sample size, and a total of 196 women, accounting for 47.23% of the effective sample size. In terms of age, the number of personnel under 25 years old is relatively small, accounting for 2.65% of the effective sample size, a total of 116 personnel aged 26-30 years old, accounting for 27.95% of the effective sample size, a relatively large number of personnel aged 31-35 years old, a total of 134, accounting for 32.29% of the effective sample size, and the largest number of personnel aged 35 years old and above, a total of 154, accounting for 37.11% of the effective sample size. In terms of educational background, the number of people with bachelor's degree and above is relatively high, among which the number of people with bachelor's degree is the largest, with a total of 243 people, accounting for 58.56% of the effective sample size, there are 85 people with college degree, accounting for 20.48% of the effective sample size, and there are a total of 87 people of postgraduate degree and above, accounting for 20.96% of the effective sample size. In terms of years of experience, there are more people who have been working in the industry for 3-6 years and 6-10 years, among which the number of people with 6-10 years of experience is the largest, with a total of 189 people, accounting for 45.54% of the effective sample size, the number of people with 3-6 years of experience totals 122 people, accounting for 29.40% of the effective sample size, the number of people with more than 10 years of experience totals 81 people, accounting for 19.52% of the effective sample size, the number of people with 1-3 years of experience totals 19.52%, the number of people with 1-3 years of experience totals 20.48%. The number of practitioners with 1-3 years of experience is the lowest, with a total of 23 practitioners, accounting for 5.54% of the valid sample size.

Table 3. Descriptive statistical table of demographic characteristics

Basic information	Type	Sample number	Percentage
Gender	Female	196	47.23%
	Male	219	52.77%
Age	<25 years old	11	2.65%
	25-30 years old	116	27.95%
	31-35 years old	134	32.29%
	>35 years old	154	37.11%
Education background	Junior college	85	20.48%
	Bachelor	243	58.56%
	Master and above	87	20.96%
Working life	1-3 years	23	5.54%
	3-6 years	122	29.40%
	6-10 years	189	45.54%
	>10 years	81	19.52%

In order to confirm that the data can be used in the analysis of structural equation modeling, a normal distribution test was performed. In this paper, the data were tested by skewness- kurtosis test, which usually considers the skewness and kurtosis values between (-3, 3) as conforming to normal distribution. With the help of SPSS 22.0, the collected data were tested for normal distribution and the test results are shown in Table 4. From Table 4, it can be seen that among the skewness values of all dimensions, the maximum value is 1.266 and the minimum value is -0.271, and the maximum value of kurtosis is 2.526 and the minimum value is -1.202, which are between (-3, 3) and pass the test of normal distribution, therefore, it is considered that the collected data can be used for the subsequent analysis of structural equation modeling.

Table 4. Descriptive statistics of variables

Variable	N	Min	Max	Mean	SD	Skewness		Kurtosis	
						Statistics	SE	Statistics	SE
TI	415	1	5	3.249	1.044	1.066	0.145	1.036	0.257
OS	415	1	5	3.131	1.127	0.861	0.145	-1.202	0.257
EM	415	1	5	3.035	1.055	1.042	0.145	0.943	0.257
KT	415	1	5	3.223	1.054	-0.255	0.145	0.874	0.257
PE	415	1	5	3.219	0.949	-0.158	0.145	-1.116	0.257
PU	415	1	5	3.047	0.981	-0.271	0.145	1.012	0.257
ABI	415	1	5	3.096	1.137	0.299	0.145	1.092	0.257
KBI	415	1	5	3.089	1.049	0.499	0.145	-1.074	0.257
AUB	415	1	5	3.163	1.181	0.663	0.145	-0.942	0.257
KUB	415	1	5	3.248	1.078	1.266	0.145	2.526	0.257

4.4. *Correlation analysis*

In order to further explore the degree of closeness between the variables, this part will use the Pearson correlation coefficient method to calculate the degree of correlation between each variable. The Pearson correlation coefficient method determines the degree of closeness between the variables by the size of the absolute value of the correlation coefficient r. The judgment criteria are shown in Table 5. When the value of r is in (0, 1), it means that there is a positive correlation between the two variables. When the value of r is at (-1, 0), it indicates a negative influence between the variables. In addition, the level of significance is also taken into account, when the level of significance reaches more than 95% in order to indicate the existence of correlation between the variables. Therefore, the data from the formal questionnaire were tested for correlation, and the results of the correlation analysis of the variables are shown in Table 6.

As shown in Table 6, training investment (TI), organizational support (OS), employee motivation (EM) and knowledge training (KT) are weakly or very weakly correlated ($r<0.4$), and the significance level reaches 95% or more, all of them are positively correlated. a weak or very weak correlation ($r<0.4$) is found between AI perceived ease of use (PE) and AI perceived usefulness (PU) and the significance level reaches 95% or more. level of 95% or more, all of them are positively correlated.Behavioral Intention of AI for Automation (ABI), Behavioral Intention of AI for Knowledge Creation (KBI), Behavioral Intention of AI for Automation (AUB), and Behavioral Intention of AI for Knowledge Creation (KUB) are weakly correlated or very weakly correlated ($r<0.4$), and the level of significance reaches 95% or more, all of them are positively correlated. From the analysis of the above results, it is concluded that the dimensions in the scale are independent of each other and satisfy the relationships of the variables in the model, and the variables can be further analyzed by structural equation modeling.

Table 5. Correlation standard table

Correlation coefficient	Correlation
$0.8<\|r\|\leqslant 1$	Extremely strong correlation
$0.6<\|r\|\leqslant 0.8$	Strong correlation
$0.4<\|r\|\leqslant 0.6$	Moderate correlation
$0.2<\|r\|\leqslant 0.4$	Weak correlation
$0<\|r\|\leqslant 0.2$	Extremely weak correlation or no correlation

Table 6. Correlation analysis of various variables

	TI	OS	EM	KT	PE	PU	ABI	KBI	AUB	KUB
TI	1									
OS	0.126**	1								
EM	0.315**	0.324**	1							
KT	0.285**	0.187**	0.334**	1						
PE	0.225**	0.326**	0.163**	0.317**	1					
PU	0.209**	0.352**	0.171**	0.356**	0.341**	1				
ABI	0.306**	0.278**	0.364**	0.245**	0.162**	0.241**	1			
KBI	0.263**	0.213**	0.322**	0.118**	0.274**	0.159**	0.146**	1		
AUB	0.134**	0.156**	0.225**	0.245**	0.267**	0.234**	0.206**	0.169**	1	
KUB	0.316**	0.228**	0.252**	0.337**	0.232**	0.216**	0.144**	0.175**	0.176**	1

4.5. Analysis of structural equations

Path analysis is a statistical method that can be used to study the multilayered causal relationships between multiple variables and the strength of their correlations. According to the relevant hypotheses proposed in this study, the path correlation coefficients between each variable in the structural equation model and their significance are shown in Table 7.

According to Table 7, it can be seen that the model contains a total of 14 paths, and the following hypothesis verification results can be obtained:

1) Organizational training and employees' AI perceived ease of use and AI perceived usefulness. The standardized path coefficients of training input (TI) to AI perceived ease of use (PE) and AI perceived usefulness (PU) are 0.426 ($P=0.002<0.01$) and 0.485 ($P=0.001<0.01$) respectively, which indicates that the training input of organizational training positively affects employees' AI perceived ease of use and AI perceived usefulness, and the hypotheses H1a and H1b hold.

The standardized path coefficients of Organizational Support (OS) to AI Perceived Ease of Use (PE), AI Perceived Usefulness (PU) are not significant ($P=0.405>0.05$), ($P=0.468>0.05$), which suggests that Organizational Support does not positively influence Employees' AI Perceived Ease of Use, AI Perceived Usefulness and Hypotheses H2a, H2b do not hold.

The standardized path coefficients of Employee Motivation (EM) to AI Perceived Ease of Use (PE) and AI Perceived Usefulness (PU) are 0.208 ($P=0.042 < 0.05$) and 0.248 ($P=0.018 < 0.05$), which suggests that Employee Motivation of Organizational Training positively affects Employees' AI Perceived Ease of Use, AI Perceived Usefulness, and Hypotheses H3a, H3b hold.

The standardized path coefficients of Knowledge Training (KT) to AI Perceived Ease of Use (PE) and AI Perceived Usefulness (PU) are 0.428 ($P=0.001<0.01$) and 0.306 ($P=0.007<0.01$), which suggests that Knowledge Training of Organizational Training positively influences employees' AI Perceived Ease of Use, AI Perceived Usefulness, and Hypotheses H4a, H4b hold.

2) Perceived Ease of Use and Behavioral Intention of AI for Automation, Behavioral Intention of AI for Knowledge Creation. The standard path coefficients of AI perceived ease of use (PE) to behavioral intention of AI for knowledge creation (KBI), and behavioral intention of AI for automation (ABI) are 0.296 ($P=0.001<0.01$), 0.163 ($P=0.013<0.05$), respectively, which suggests that the employees' perceived ease of use of AI positively affects their behavioral intention to use AI for knowledge creation and automation behavioral intention, and hypotheses H5a and H5b are valid.

3) Perceived usefulness and behavioral intention to use AI for automation and AI for knowledge creation. The standard path coefficients of AI perceived usefulness (PU) to behavioral intention of AI for knowledge creation (KBI), and behavioral intention of AI for automation (ABI) are 0.514 ($p=0.001<0.01$), 0.844 ($p=0.001<0.01$), respectively, which suggests that at the significance level of 0.001, employees' AI perceived usefulness positively influences their behavioral intention to use AI for knowledge creation and automation, and hypotheses H6a, H6b hold.

4) Behavioral intention of AI for knowledge creation and knowledge creation behavior. The standard

path coefficient of behavioral intention of AI for knowledge creation (KBI) to behavior of AI for knowledge creation (KUB) is 0.834 (P=0.001 < 0.01), which indicates that employees' behavioral intention to use AI for knowledge creation will have a significant positive effect on behavior of AI for knowledge creation. Hypothesis H7a is valid.

5) Behavioral intention of AI for automation and automation behavior. The standard path coefficient of behavioral intention of AI for automation (ABI) to behavior of AI for automation (AUB) is 0.839 (p=0.001 < 0.01), which suggests that employees' behavioral intention to use AI for automation will have a significant positive effect on behavior of AI for automation, and Hypothesis H7b is valid.

Table 7. Path test of structural equation model

Relation path	Nonnormalized coefficient	S.E.	C.R.	P	Normalized coefficient
H1a: PE←TI	0.426	0.115	3.345	0.002	0.426
H1b: PU←TI	0.435	0.103	3.725	0.001	0.485
H2a: PE←OS	-0.123	0.128	-0.879	0.405	-0.135
H2b: PE←OS	-0.087	0.136	-0.648	0.468	-0.092
H3a: PE←EM	0.194	0.091	1.986	0.042	0.208
H3b: PE←EM	0.203	0.089	2.425	0.018	0.248
H4a: PE←KT	0.423	0.112	3.945	0.001	0.428
H4b: PE←KT	0.281	0.092	2.904	0.007	0.306
H5a: KBI←PE	0.268	0.076	3.728	0.001	0.295
H5b: ABI←PE	0.143	0.058	2.715	0.013	0.163
H6a: KBI←PU	0.492	0.083	6.231	0.001	0.514
H6b: ABI←PU	0.784	0.075	11.824	0.001	0.844
H7a: KUB←KBI	1.134	0.097	12.695	0.001	0.834
H7b: AUB←ABI	0.996	0.091	11.726	0.001	0.839

Taking the above results together, all the hypotheses we have proposed are argued and therefore it can be argued that organizational training can positively influence employees' acceptance of AI technology and thus reduce resistance to AI technology.

5. Conclusion

In order to understand the impact of organizational training on employees' AI technology resistance behavior, the article constructs a structural equation model of the two from the moderating role of organizational training on employees' AI acceptance. Based on the research on organizational training and employees' perceived awareness of AI, research hypotheses are proposed. Improve the structural equations to test the hypotheses. Training investment, employee motivation and knowledge training all have a significant positive effect on both employees' AI perceived ease of use and AI perceived usefulness (p<0.05). Organizational support, on the other hand, did not have a positive effect. Employee AI perceived ease of use and AI perceived usefulness had a positive effect on employee behavioral intention to use AI for knowledge creation and automation (p<0.05). Employees' behavioral intention to use AI for knowledge creation would have a positive effect on AI for knowledge creation (p<0.05), and behavioral intention to use AI for automation would have a positive effect on AI for automation (p<0.05).

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