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Article

From Aspiration to Reality: Understanding the Psychological Barriers to AI Adoption in Enterprise Management

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Abstract: A significant "aspiration-reality" gap universally exists in enterprise AI adoption processes, with a substantial disparity between management's technology empowerment vision and frontline employees' actual adoption willingness. This study aims to explain the formation mechanism of this phenomenon from a psychological barriers perspective. The study employed a cross-sectional survey design to collect valid samples from three enterprises at different stages of AI application, examining through structural equation modeling and multi-group comparison analysis the influence mechanisms of four psychological barrier dimensions, including perceived threat, technology anxiety, job insecurity, and perceived complexity, on AI adoption intention. Research findings reveal that perceived threat constitutes the strongest psychological barrier impeding AI adoption, with job insecurity playing a partial mediation role between perceived threat and adoption intention, uncovering the complete psychological transmission chain from threat cognition to affective response to behavioral intention, and the influence intensity of psychological barriers exhibits significant heterogeneity across different enterprise sizes, industry types, and employee AI experience backgrounds. The four-dimensional integrated model constructed by this study addresses the fragmentation in existing research and deepens the application of innovation resistance theory in enterprise AI contexts. The study provides enterprise managers with a strategic path shifting from pure technology promotion to dual-wheel driving of technology and psychology, effectively alleviating employee psychological barriers through implementing differentiated psychological intervention measures tailored to different contexts, facilitating the transformation of AI technology from management vision to practical application.

Keywords: artificial intelligence adoption; psychological barriers; perceived threat; job insecurity; enterprise management

1. Introduction

Artificial intelligence technology is reshaping enterprise management paradigms at an unprecedented pace, and enterprise managers universally regard AI as a strategic tool for enhancing competitive advantage, ranging from production process optimization to decision support systems [1]. However, there has been an interesting phenomenon in the sense that, despite the high hopes that artificial intelligence can bring, the adoption rate has been lower than anticipated, yet investment in artificial intelligence in business environments is on the increase [2]. The major challenges that characterize this phenomenon of "an ambitious vision yet harsh reality" are not in terms of technical or organizational feasibility. The main challenge lies in the psychological state of employees, as this represents the biggest "psychological chasm" that must be overcome in order to take artificial intelligence from strategic vision to practical application [3]. For instance, as managers in various business environments express their hopes and visions for the future, in which artificial intelligence can empower their business, employees may perceive this as a threat to their future, may worry about the technical capabilities that artificial intelligence can bring, and may also worry about their future career prospects [4]. The artificial intelligence adoption curve indicates that there are differences between various business environments, depending on their size [5], and that the challenges to artificial intelligence adoption in business environments are varied and intricate [6].

Existing research in technology acceptance has offered important theoretical foundations for understanding the adoption of innovations, as the Technology Acceptance Model has shown the positive impact of perceived usefulness and perceived ease of use on intention to use [7], while the emergence of generative AI has encouraged researchers to explore the applicability of existing TAMs in new technology contexts [8]. The Unified Theory of Acceptance and Use of Technology has extended existing research by considering external factors, such as social influences and facilitating conditions, in the technology acceptance process [9], and has also extended existing research by considering the differences of adopter types from the analytical perspective [10]. Although existing research has offered important theoretical foundations in the traditional information systems field, it has shown insufficient explanatory power in the AI field, as existing research has over-focused on the positive driving factors while systematically neglecting the exploration of negative psychological barriers.

Innovation Resistance Theory takes a different view in the approach to technology adoption by considering individuals' defensive reactions to new technologies and the psychological processes behind these reactions [11]. Although this theory has been validated in public sector innovation environments [12], it is still necessary to examine the mechanisms by which this theory operates in AI management environments. Of particular interest in this theory is that technology acceptance and resistance do not simply operate as opposing constructs but as complex patterns that change over time in response to individuals' experiences [13], with these pattern changes being interactively affected by functional, risk-related, and socio-legal factors [14].

Research on the role of psychological barriers in the context of AI has gradually gained attention in recent years and has developed into a multi-dimensional knowledge accumulation process. The dimension of the perceived threat of AI is the concern of employees that AI may replace their job roles [15]. The formation of employee willingness to collaborate with AI is significantly influenced by the levels of threats perceived by the employee and the moderating effect of the employee's own career orientations [16]. Technology anxiety is the concern of employees regarding their own capabilities of using AI technology, as the perception of skill gaps by individuals generates significant psychological pressure on the employee that influences the employee's self-efficacy [17] and subsequently the employee's trust in AI technology [18]. Job insecurity is the concern of employees regarding their job security, as the changes introduced by AI technology in the organization may induce employee depression due to the lack of psychological safety and ethical leadership in the organization [19]; corporate social responsibility can buffer the effect of AI adoption on employee mental health to a certain extent [20]. The dimension of the perceived complexity of AI is the cognitive perception of the cost of learning AI technology for the employee, as the occurrence of complexity barriers in the technology adoption process may manifest differently at different stages of the technology adoption process [21]; if the technology is considered too complex for the employee to learn, the motivation for adopting the technology is significantly reduced [22]. Trust is a significant psychological factor that plays a critical role in the adoption of AI technology by the employee, as the role of trust in the adoption of AI technology has been empirically examined in the context of the influence of various factors on human trust in AI technology [23]; the degree of information presentation [24] and the communication strategies of the leadership [25] significantly influence the employee's initial trust in AI technology.

However, the existing research is found to have evident shortcomings. For example, at the theoretical level, the research on psychological barriers is mostly fragmented and focuses on a single dimension, with a lack of systematic theory that integrates the cognitive and affective dimensions [26], and the research on organizational behavior is in urgent need of the integration of the theory and the challenges that are emerging [27]. At the empirical level, the research is mostly descriptive analysis with a lack of quantitative verification of the internal mechanism through which the psychological barriers affect the intention of adopting AI [28]. Based on the above analysis, the present research proposes a four-dimensional integrated model of psychological barriers that includes perceived threat, technology anxiety, job insecurity, and perceived complexity, aiming to explore the role of the psychological barriers in the transformation process from "aspiration" to "reality" of enterprise AI adoption.

This study proposes the following research hypotheses:

H1: Perceived threat has a significant negative effect on AI adoption intention.

H2: Technology anxiety has a significant negative effect on AI adoption intention.

H3: Job insecurity has a significant negative effect on AI adoption intention.

H4: Perceived complexity has a significant negative effect on AI adoption intention.

H5: Job insecurity mediates the relationship between perceived threat and AI adoption intention.

To intuitively present the hypothesized relationships and their theoretical logic, the conceptual model constructed by this study is illustrated in Figure 1. This model integrates cognitive-level psychological barriers of perceived threat and perceived complexity, affective-level psychological barriers of technology anxiety and job insecurity, and positions AI adoption intention as the ultimate outcome variable, while particularly incorporating job insecurity as a mediating mechanism through which perceived threat influences adoption intention.

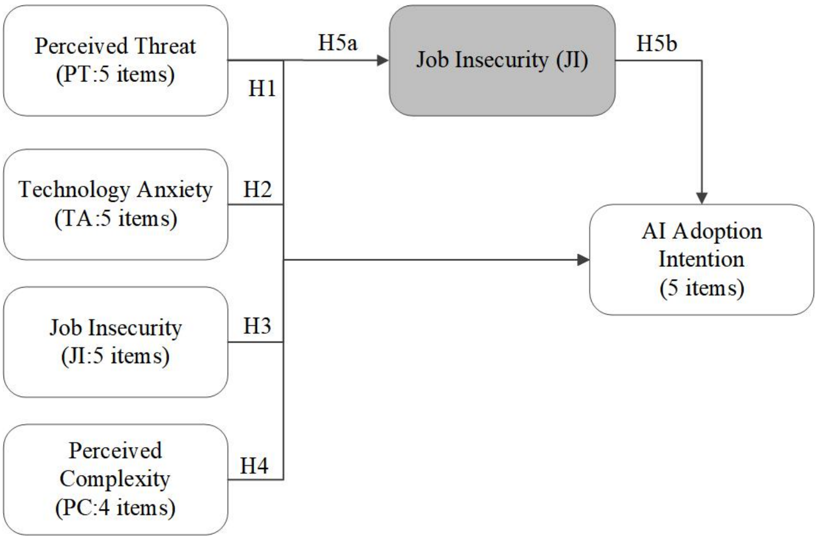


Figure 1. Conceptual Model of Psychological Barriers to AI Adoption in Enterprise Management

Figure 1 shows the multi-level routes of the impact of psychological barriers on the intention of adopting AI in organizations. The direct impacts of the four dimensions of psychological barriers on the intention of adopting AI in organizations are indicated by the solid arrows, which correspond to H1, H2, H3, and H4, respectively. The routes of mediation can be divided into two sections, H5a and H5b, which represent the routes from perceived threat to job insecurity and from job insecurity to the intention of adopting AI, respectively. This model indicates that the four dimensions of psychological barriers do not act independently, but their combined impacts on the behavioral decisions of employees can be transmitted by a mechanism in which cognitive evaluations evoke affective responses. This model provides a human-centered psychological theory of explaining the "aspiration-reality" gap in the adoption of AI in organizations.

This study, using structural equation modeling to examine the direct impacts of the four dimensions of psychological barriers on the intention of adopting AI in organizations, as well as the mediation role of job insecurity, and using multi-group comparisons to identify the boundaries of the impacts of psychological barriers, is expected to contribute to providing theoretical explanations and practice suggestions from a psychological point of view to bridge the "aspiration-reality" gap in the adoption of AI in organizations, as well as providing evidence for enterprise managers to guide the development of psychological intervention strategies.

2. Methodology

2.1. Research Design and Sample

The research design employed in this study was the cross-sectional survey design, which was used to examine the mechanisms through which psychological barriers influence the intention to adopt AI in an enterprise setting, where the psychological state and intention of employees can be evaluated at critical points in the enterprise's AI transformation process. The survey population was composed of enterprise managers and employees who had direct experience with AI technologies in their work processes or had decision-making authority in the adoption of AI technologies. Samples were drawn from three enterprises at different stages of AI transformation, specifically a large-scale manufacturing enterprise (employee size 1000+, having initiated smart manufacturing pilot programs, target 140 questionnaires), a medium-sized financial technology enterprise (employee size 500+, currently promoting AI-driven risk assessment tools, target 120 questionnaires), and a medium-sized service and retail enterprise (employee size 300+, planning to introduce AI customer service systems, target 90 questionnaires), with a total target sample size of 350.

The theoretical basis for enterprise selection lies in the potential for diverse industry characteristics and application contexts of AI to create heterogeneous forms of employees' psychological barriers. For instance, employees in the manufacturing industry may experience higher levels of work role threat due to machine automation in production lines. In contrast, employees in the financial technology industry may experience higher levels of technology anxiety due to the complexity of algorithmic decision-making. Similarly, employees in service and retail industries may experience higher levels of complexity burden due to learning requirements for human-machine interaction. The diverse application contexts provide a natural experiment to test the boundaries of psychological barriers [29]. The sampling method used in the study was based on stratified random sampling.

To comply with research ethics standards, this study received approval from the Institutional Review Board (IRB Number: XXX-XXX-XXX-XXX), with all participants being thoroughly informed of research purposes, data usage, and confidentiality commitments before completing the questionnaire, signing informed consent electronically. The research process strictly adhered to anonymity principles, with the questionnaire system collecting no personally identifiable information, all data being encrypted for storage and used solely for academic research purposes. Particularly noteworthy is that given psychological barrier measurement involved employees' negative emotions and threat perceptions regarding AI technology, the questionnaire opening explicitly stated that survey results would not be used for enterprise performance evaluation or personnel decisions, thereby maximizing reduction of social desirability bias and encouraging honest responses.

2.2. Measurement

The measurement framework is based on a four-dimensional construct of psychological barriers to AI and the intention to adopt AI, with all the scales being based on well-established theoretical models. The dimension of perceived threat is based on five items that measure the employees' cognitive evaluation of AI as a potential threat to their work roles, as indicated by the following example: "AI technology will threaten my work role in the organization." The dimension of technology anxiety is based on five items that measure the employees' tension and uneasiness caused by AI technology, as indicated by the following example: "Using AI technology makes me feel nervous and uneasy." The dimension of job insecurity is based on five items that measure the employees' concerns about the risk of unemployment due to AI technology, as indicated by the following example: "I worry about losing my current job due to the introduction of AI technology." The dimension of perceived complexity is based on four items that measure the employees' subjective judgment of the learning difficulty of AI technology, as indicated by the following example: "AI technology is too complex for me to understand." The dependent variable of AI adoption intention is based on five items, as indicated by the following example: "I am willing to proactively use AI tools in my daily work." The formulation of the items for the psychological barrier dimensions is intended to measure the psychological level of cognitive evaluation or emotional response rather than the objective level of the technology itself, as indicated by the theoretical positioning of the study [30].

All scales used seven-point Likert scales for measurement. The range of the scales is from 1 (strongly disagree) to 7 (strongly agree). Such scales have enough discriminatory power and can capture the intensity differences of psychological barriers. Moreover, such scales can avoid measurement errors caused by excessive subdivision. In order to ensure the semantic equivalence and cultural appropriateness of the scales for the Chinese enterprise context, the research team employed a rigorous translation and back-translation method. In the translation and back-translation process, two translators conducted the mutual translation between Chinese and English. Then, a professional researcher conducted the semantic consistency verification and made necessary adjustments for expressions with significant cultural differences. Pre-testing the scales involved collecting feedback from 30 employees from different enterprises and positions. Cognitive interview methods were employed. Some minor adjustments were made for the expressions of individual items according to the feedback from the pre-test.

The design of the control variable included two major categories, namely, the demographic characteristics and the experience in AI, where the demographic characteristics included the age, gender, education level, and hierarchy of the job, while the experience in AI included the experience in using AI (existence or absence of experience in using AI) and the receipt of training in AI, and these variables allowed the control of the impact of the individual characteristics on the intention to adopt AI, especially considering the finding in the prior study that the level of technology familiarity had a significant impact on the intensity of the psychological barrier.

2.3. Data Analysis Strategy

The approach for data collection was through an online questionnaire tool named Wenjuanxing, where the human resources departments of the enterprises helped in facilitating the dissemination of the questionnaire links to the target employees through their internal email systems. The entire duration for the data collection was three weeks. To ensure the quality of the collected data, the questionnaire tool has integrated several mechanisms for quality control, including the monitoring of response time, attention checks, and logical consistency checks. The cleaning of the collected data was done in a very strict manner, where the criteria for cleaning were response times too short (less than 3 minutes), the presence of a straight-lining response pattern (standard deviation less than 0.5), failure to pass attention checks, and logical contradictions. The cleaning was done at an expected rate of 15%-20%.

To clearly present the workflow of the methodologies employed in the current study, the entire flow of the research procedures from sample selection to data analysis is shown in Figure 2. This flowchart presents the logical progression relationships between the five key stages in the research workflow, including sample selection and ethics, questionnaire construction and pretest, data collection and quality control, data cleaning and preparation, and statistical analysis and hypothesis testing. The key operational steps and quality assurance for each stage have been marked in the flowchart.

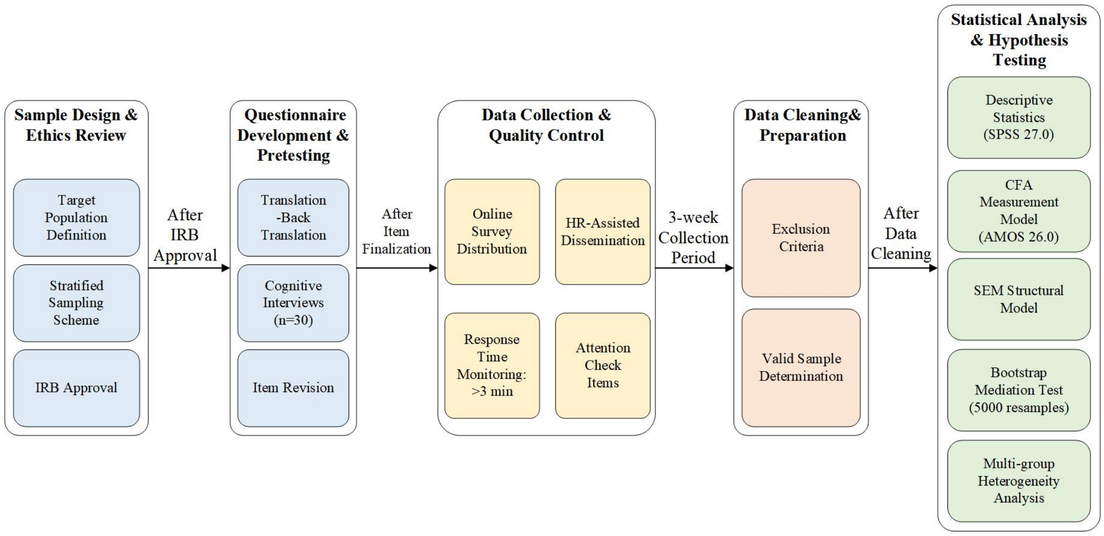


Figure 2. Research Procedure and Data Collection Process

Figure 2 outlines the methodological pathway along which the research design progresses through five stages of sequential research activities. The first stage involves the definition of the target population, stratified sampling, and obtaining approval from the IRB. The second stage involves the development of the questionnaire, which includes translation and back-translation, and cognitive interviews with 30 participants. The third stage involves the execution of the online distribution of the survey, with quality control maintained during a three-week period. The fourth stage involves data cleaning using exclusion criteria. The fifth stage involves the application of descriptive statistics using SPSS 27.0, CFA measurement model testing using AMOS 26.0, SEM, Bootstrap mediation analysis using 5,000 bootstrap resamples, and multi-group heterogeneity analysis.

Data analysis employed multi-level statistical methods to comprehensively examine the mechanisms through which psychological barriers influence AI adoption intention. Descriptive statistical analysis was completed through SPSS 27.0 software, calculating means, standard deviations, skewness, and kurtosis for each variable to assess data distribution characteristics, and generating Pearson correlation coefficient matrices to preliminarily examine relationships between variables. Measurement model testing employed confirmatory factor analysis techniques, evaluating through AMOS 26.0 software the goodness-of-fit of the five-factor model (perceived threat, technology anxiety, job insecurity, perceived complexity, and AI adoption intention), with key fit indices including chi-square to degrees of freedom ratio (χ^2 / df), comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR), with all indices needing to simultaneously satisfy established thresholds ($\chi^2 / df < 3$, $CFI > 0.90$, $TLI > 0.90$, $RMSEA < 0.08$, $SRMR < 0.08$) for measurement model acceptance [31]. Reliability testing employed dual indicators of Cronbach's α coefficient and composite reliability (CR), while validity testing included convergent validity (assessed through average variance extracted AVE, requiring $AVE > 0.50$) and discriminant validity (employing the Fornell-Larcker criterion, requiring the square root of each latent variable's AVE to be greater than that latent variable's correlations with other latent variables).

Structural equation modeling was used as the primary methodology for testing the hypotheses. Structural equation modeling allows for the simultaneous estimation of path coefficients from perceived threat, technology anxiety, job insecurity, and perceived complexity to AI adoption intention while controlling for measurement error. Maximum likelihood estimation methods were used for the estimation of the model. Critical ratios (C.R.) and p-values were used for testing the significance of the path coefficients. In addition, control variables such as age, gender, level of education, job hierarchy, AI usage experience, and AI training experience were included in the model as exogenous variables. In the context of testing the mediation model for the role of job insecurity between the relationship between perceived threat and AI adoption intention, the standard Bootstrap procedures were followed. In this context, the three basic paths that need to be estimated include the path from perceived threat to job insecurity, the path from job insecurity to AI adoption intention, and the direct path from perceived threat to AI adoption intention. In addition, the indirect effect between the two variables was also tested using the Bootstrap method and the 95% confidence interval. In this context, the null hypothesis is rejected if both the upper and lower bounds of the confidence interval do not include zero. The Bootstrap method has more statistical power than other methods and thus ensures methodological rigor in testing Hypothesis H5.

Heterogeneity analysis was carried out using multi-group structural equation modeling. The sample groups were differentiated based on enterprise size (large vs. small and medium), industry type (manufacturing, financial technology, and service/retail), and AI usage experience (experienced vs. inexperienced). It was checked whether the path coefficients of the relationship between psychological barriers and AI adoption intention differed significantly among the groups. The key to multi-group analysis lies in chi-square difference testing ($\Delta\chi^2$), judging the significance of cross-group differences in path coefficients by comparing chi-square value differences between constrained models and unconstrained models, with this analysis capable of revealing contextual boundary conditions of psychological barrier influences.

Common method bias is considered a potential threat for cross-sectional self-report research; therefore, effective control is necessary. Procedural controls for common method bias involved the incorporation of questionnaire anonymity to avoid social desirability bias, randomized item order to avoid order effects, reverse scoring to identify careless responding, and the insertion of an opening statement that asserts: “This survey has no right or wrong answers; please respond according to your true feelings.” Statistical controls for common method bias involved the implementation of Harman’s single-factor test. All items of the measurement study were included in the analysis of an unrotated exploratory factor analysis. The rationale behind the test is that if common method bias is not a significant problem for the study, the variance explained by the first factor should be below 50%. The data analysis procedure employed in the current study effectively integrates procedural controls with statistical controls to provide reliable data regarding the research question of how psychological barriers affect the transformation mechanism of enterprise AI adoption from “aspiration” to “reality.”

3. Results

3.1. Descriptive Statistics

Data collection resulted in 362 questionnaires, with 59 being excluded as a result of rigorous quality control, thereby leaving us with a valid data set of 303, representing an effective response rate of 83.7%. The data set was composed of 58.4% males and 41.6% females, with the majority being between the ages of 30-39, i.e., 42.9%. The most represented educational level was that of Bachelor’s, with 53.1% of the respondents. The job hierarchy was composed of 54.1% entry-level employees, 34.0% middle managers, and 11.9% senior managers, thereby covering various levels in the management of enterprises. On the other hand, in regard to the experience with AI, 48.2% claimed to have experience with AI tools, while only 37.6% had training in AI, thereby indicating that there was a gap in training initiatives and actual experience in the promotion of AI in enterprise settings.

Descriptive statistics and correlation analysis on the primary variables were conducted in order to examine the characteristics of the data set, thereby preliminarily exploring the associations between variables, providing foundational support for subsequent confirmatory factor analysis and structural equation modeling. The analysis provided quantitative data on the presence of psychological barriers, as determined by means and standard deviations, with the skewness and kurtosis tests being used to examine normality in multivariate data sets. The analysis also provided preliminary validation support for the directional relationships between variables in the proposed model, as well as providing prerequisite support for the proposed mediation hypotheses, as determined by the relationship between perceived threat and job insecurity, as presented in Table 1.

Table 1. Descriptive Statistics and Correlation Matrix of Main Variables

Variable	M	SD	Skewness	Kurtosis	1	2	3	4	5
1. PT	4.58	1.19	-0.63	0.18	—				
2. TA	4.13	1.42	-0.38	-0.52	0.48***	—			
3. JI	4.27	1.26	-0.41	-0.29	0.61***	0.43***	—		
4. PC	4.05	1.38	-0.29	-0.71	0.39***	0.57***	0.36***	—	
5. AAI	3.68	1.34	-0.14	-0.48	-0.52***	-0.39***	-0.46***	-0.33***	—

Note. *N = 303. PT = Perceived Threat; TA = Technology Anxiety; JI = Job Insecurity; PC = Perceived Complexity; AAI = AI Adoption Intention. M = Mean; SD = Standard Deviation. ***p < .001.*

As shown in Table 1, perceived threat has the highest mean value at 4.58 with the strongest negative correlation with adoption intention at -0.52. This implies that work role threat is the main factor influencing AI adoption in enterprise environments. Adoption intention has a value less than the midpoint at 3.68, thus proving the "aspiration-reality" gap. The strong correlation between perceived threat and job insecurity at 0.61 implies that threat perception leads to job insecurity, thus providing the required conditions for the proposed mediation model.

3.2. Measurement Model Testing

Moreover, confirmatory factor analysis was used to assess the construct validity of the scale by examining the congruence between the measurement models and observed data. In this study, three competing models were developed to assess the dimensional structure of psychological barriers. The five-factor model views perceived threat, technology anxiety, job insecurity, perceived complexity, and AI adoption intention as five different latent constructs, based on the assumptions that the four types of psychological barriers are theoretically distinct and can be measured separately. The single-factor model, on the other hand, integrates all the measurement items into a single latent construct to assess the severity of common method bias. The significantly lower model fit of the single-factor model compared to the five-factor model suggests that common method bias is not a major concern. The four-factor model integrates job insecurity and technology anxiety into a single latent construct for affective barriers to test if these two types of affective barriers can be combined. The model comparisons were performed using chi-square difference testing to assess if the five-factor model has a superior fit compared to the competing models, as shown in Table 2.

Table 2. Model Fit Indices and Comparison

Model	χ^2	df	X^2/df	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$	Δdf
Five-factor model	694.52	278	2.50	0.91	0.90	0.069	0.061	—	—
Four-factor model	881.76	282	3.13	0.87	0.86	0.083	0.072	187.24***	4
Single-factor model	1912.38	288	6.64	0.68	0.66	0.135	0.108	1217.86***	10

Note. *N = 303. ***p < 0.001.*

Moreover, as shown in Table 2, the five-factor model provides a good fit to the data, with χ^2/df = 2.50, CFI = 0.91, and RMSEA = 0.069, significantly outperforming the four-factor model, which has a CFI of only 0.87, and the single-factor model, which has a CFI of only 0.68. The chi-square differences, $\Delta\chi^2$ = 187.24 and $\Delta\chi^2$ = 1,217.86, are statistically significant, indicating that the combination of job insecurity and technology anxiety or the aggregation of all barriers into a single factor would result in theoretically untenable solutions, as the four psychological barriers are thought to tap distinct cognitive and emotional mechanisms.

To establish the level at which each of the observed items contributes to its corresponding latent variable, standardized assessment of factor loadings in relation to the five-factor model was conducted. The factor loadings are a measure of the degree of relationship between items and latent variables. Higher factor loadings imply a more effective measurement of the desired constructs. In line with established academic standards, it is imperative that all factor loadings are statistically significant and exceed a threshold value of 0.60. Any item with factor loadings less than 0.60 may not have a high enough level of measurement validity and may be considered for deletion. In this study, all factor loadings were retained in order to illustrate the completeness of the measurement system, as well as to investigate the level of consistency in items measuring similar constructs through an analysis of variation in factor loadings. Excessive variation in factor loadings may be an indication of differential item comprehension. The findings in this regard are illustrated in Table 3.

Table 3. Standardized Factor Loadings of Five-Factor Model

Item	PT	TA	JI	PC	AAI
Item 1	0.79	0.78	0.74	0.79	0.77
Item 2	0.76	0.73	0.79	0.73	0.72
Item 3	0.82	0.81	0.71	0.68	0.83
Item 4	0.73	0.76	0.82	0.81	0.69
Item 5	0.81	0.84	0.76	—	0.80

Note. *N = 303. PT = Perceived Threat; TA = Technology Anxiety; JI = Job Insecurity; PC = Perceived Complexity; AAI = AI Adoption Intention. All factor loadings are significant at p < 0.001.*

As presented in Table 3, the factor loadings range from 0.68 to 0.84, with all loadings well above the minimum of 0.60. These results support the validity of the measurement model. The moderate variation in the factor loadings suggests that the items measure distinct aspects of each construct. It is interesting to note that the item for perceived complexity 3 has the lowest loading of 0.68, possibly due to the individual differences in the perception of the difficulty of the learning process. In contrast, the item for technology anxiety 5 has the highest loading of 0.84, possibly because technology anxiety is likely to be a more direct expression of emotions.

To assess the reliability and validity of the measurement system comprehensively, reliability and validity analysis was conducted to ensure that the hypothesis testing was underpinned by a reliable and valid measurement system. The reliability analysis was conducted using two measures of internal reliability: Cronbach's alpha and composite reliability. Both measures require a value of 0.80 or above for the reliability to be considered satisfactory. The validity analysis was conducted to assess the convergent validity and discriminant validity of the measurement system. Convergent validity was assessed using the average variance extracted (AVE). AVE values of 0.50 or above are considered acceptable since they indicate that the latent variables explain more than 50 percent of the variance in the measured variables. The discriminant validity of the measurement system was assessed using the Fornell-Larcker criterion. The square root of the AVE of each latent variable should be higher than its correlations with the other latent variables for the discriminant validity of the measurement dimensions of the psychological barriers to be assured. Common method bias was assessed using Harman's single-factor test. The test is considered non-problematic if the first factor accounts for less than 50 percent of the variance, as presented in Table 4.

Table 4. Reliability and Validity Assessment

Construct	Cronbach's α	CR	AVE	√AVE	PT	TA	JI	PC	AAI
PT	0.87	0.88	0.61	0.781	0.781				
TA	0.86	0.87	0.62	0.787	0.48	0.787			
JI	0.82	0.83	0.59	0.768	0.61	0.43	0.768		
PC	0.80	0.81	0.57	0.755	0.39	0.57	0.36	0.755	
AAI	0.85	0.86	0.58	0.762	0.52	0.39	0.46	0.33	0.762

Note. *N = 303. CR = Composite Reliability; AVE = Average Variance Extracted. Bold diagonal elements represent √AVE; off-diagonal elements represent inter-construct correlations. Harman's single-factor test: 38.6% variance explained.*

Table 4 shows that the reliability of the model is good, with Cronbach's alpha values ranging from 0.80 to 0.87, while composite reliability ranges from 0.81 to 0.88. Average Variance Extracted (AVE) ranges from 0.57 to 0.62, all of which are above the critical value of 0.50, thus establishing convergent validity. Moreover, the square root of AVE for each construct is higher than the correlations between the constructs, thus establishing discriminant validity. Common method bias is also not a major problem since the test for Harman's single factor accounts for only 38.6% of the variance.

3.3. Hypothesis Testing

The direct effect testing model adopted structural equation modeling to estimate the path coefficients of the four dimensions of psychological barriers to AI adoption intention at one time. This model is capable of reducing measurement errors and allowing correlations between independent variables. The model was estimated with age, gender, education level, job hierarchy, AI usage experience, and AI training experience as control variables to reduce the confounding influences of demographic characteristics and technical background knowledge. Critical ratios and p-values were used to evaluate the significance of path coefficients, and the standardized coefficient values were used as an indication of the relative degree of influence among the four dimensions of psychological barriers in hindering AI adoption intention, as shown in Table 5.

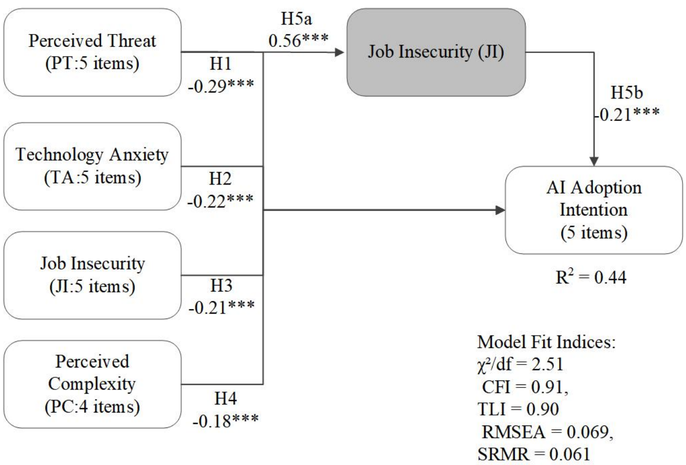
Table 5. Direct Effects of Psychological Barriers on AI Adoption Intention (H1-H4)

Path	**β**	**SE**	**C.R.**	**p**	**Hypothesis**	**Result**
Main Effects						
PT → AAI	-0.29	0.053	-5.47	< 0.001	H1	Supported
TA → AAI	-0.22	0.048	-4.58	< 0.001	H2	Supported
JI → AAI	-0.21	0.049	-4.29	< 0.001	H3	Supported
PC → AAI	-0.18	0.046	-3.91	< 0.001	H4	Supported
Control Variables						
Age → AAI	0.04	0.038	1.05	0.294	—	—
Gender → AAI	-0.03	0.042	-0.71	0.478	—	—
Education → AAI	0.08	0.041	1.95	0.051	—	—
Job Hierarchy → AAI	0.06	0.039	1.54	0.124	—	—
AI Experience → AAI	0.17	0.045	3.78	< 0.001	—	—
AI Training → AAI	0.07	0.044	1.59	0.112	—	—

Note. *N = 303. PT = Perceived Threat; TA = Technology Anxiety; JI = Job Insecurity; PC = Perceived Complexity; AAI = AI Adoption Intention. β = Standardized path coefficient; SE = Standard error; C.R. = Critical ratio.*

As shown in Table 5, perceived threat has the strongest negative impact on resistance, followed by technology anxiety, job insecurity, and perceived complexity, where the coefficients vary between β = -0.18 and -0.22. All these effects are significant at $p < 0.001$, thus validating the importance of work-role threat as the major resistance barrier. As for the control variables, AI usage experience has a significant impact on resistance, whereas formal training is again found to be nonsignificant, implying that experience is more important than training in overcoming psychological resistance.

The path diagram of the structural equation model shows the relationships between the four dimensions of the psychological barrier and the intention to adopt AI, along with the standardized coefficients. It shows the dual effect of the perceived threat, which influences the intention to adopt AI directly and indirectly through job insecurity. The model fit indices and the explanatory power of the model on the intention to adopt AI, based on the R^2 values, are shown in the figure, as depicted in Figure 3.



Note. ****p < 0.001*

Figure 3. Structural Equation Model with Standardized Path Coefficients

Figure 3 illustrates the full structural equation model with all the hypothesized paths being statistically significant. The goodness of fit of the model is satisfactory: $\chi^2/df = 2.51$, CFI = 0.91, TLI = 0.90, RMSEA = 0.069, and SRMR = 0.061, with 44% variance explained for AI adoption intention. The direct effect of perceived threat is the strongest among the paths, while the mediation effect of job insecurity is shown through paths H5a and H5b.

To test whether the perceived threat indirectly influences the intention of adopting AI by evoking concerns regarding job security, mediation analysis was carried out. The analysis involved a bootstrap resampling test with 5,000 resamples to estimate the three primary paths: path a, the effect of the perceived threat on job insecurity; path b, the effect of job insecurity on the intention of adopting AI; and path c', the direct effect of the perceived threat on the intention of adopting AI. The indirect effect was considered significant if the 95% bias-corrected confidence interval did not contain zero, as shown in Table 6.

Table 6. Mediation Effect Testing Results of Job Insecurity (H5)

Path	β	SE	C.R.	p	95% CI
Mediation Paths					
Path a: PT → JI	0.56	0.057	9.82	< 0.001	—
Path b: JI → AAI	-0.21	0.049	-4.29	< 0.001	—
Effects on AI Adoption Intention					
Direct effect (c'): PT → AAI	-0.17	0.054	-3.15	0.002	—
Indirect effect (a×b)	-0.12	0.031	—	—	[-0.184, -0.063]
Total effect (c)	-0.29	—	—	—	—

Note. *N = 303. PT = Perceived Threat; JI = Job Insecurity; AAI = AI Adoption Intention. β = Standardized path coefficient; SE = Standard error; C.R. = Critical ratio; CI = Confidence interval based on 5000 bootstrap samples. The indirect effect is significant as the 95% confidence interval does not contain zero, indicating partial mediation.*

From Table 6, the perceived threat significantly influences job insecurity ($\beta = 0.56$, $p < 0.001$), which in turn negatively affects the intention to adopt ($\beta = -0.21$). The indirect effect is also significant (β = -0.12, 95% CI [-0.184, -0.063] excluding zero). The direct effect is also significant ($\beta = -0.17$, $p = 0.002$), implying partial mediation. The results imply that the work role threat is mediated through two processes: direct negative influence on the intention to adopt and an indirect effect through increased resistance due to job insecurity concerns.

3.4. Heterogeneity Analysis

The multi-group comparison examined whether the path coefficients of the psychological barriers to AI adoption intention differed significantly across different enterprise sizes, types of industries, and AI usage experience background. Structural equation modeling was used to perform the multi-group analysis. The analysis compared the chi-square differences between the constrained models with equal path coefficients and the unconstrained models. The results showed significant differences in the chi-square values, as shown in Table 7.

Table 7. Multi-group Comparison Results of Path Coefficients

Path	Group 1	β_1	Group 2	β_2	$\Delta\chi^2$	p
Enterprise Size						
PT → AAI	Large (n=121)	-0.32	SME (n=182)	-0.27	1.24	0.265
TA → AAI	Large	-0.25	SME	-0.20	1.18	0.277
JI → AAI	Large	-0.29	SME	-0.16	5.17	0.023
PC → AAI	Large	-0.20	SME	-0.17	0.43	0.512
Industry Type						
PT → AAI	Mfg (n=121)	-0.38	Fin-Tech (n=104)	-0.24	6.83	0.009
PT → AAI	Mfg	-0.38	Service (n=78)	-0.22	8.12	0.004
TA → AAI	Mfg	-0.23	Fin-Tech	-0.20	0.47	0.493
JI → AAI	Mfg	-0.23	Fin-Tech	-0.19	0.82	0.365
PC → AAI	Mfg	-0.20	Fin-Tech	-0.17	0.41	0.522
AI Usage Experience						
PT → AAI	No Exp (n=157)	-0.32	Exp (n=146)	-0.26	1.87	0.171
TA → AAI	No Exp	-0.31	Exp	-0.14	6.24	0.013
JI → AAI	No Exp	-0.23	Exp	-0.19	0.84	0.359
PC → AAI	No Exp	-0.21	Exp	-0.16	1.29	0.256

Note. *N = 303. PT = Perceived Threat; TA = Technology Anxiety; JI = Job Insecurity; PC = Perceived Complexity; AAI = AI Adoption Intention. Mfg = Manufacturing; Fin-Tech = Financial Technology; SME = Small-and-Medium Enterprises; Exp = Experience. Bold rows indicate significant group differences. $\Delta\chi^2$ tests the difference in path coefficients between groups (df = 1).*

Table 7 demonstrates job insecurity exerting stronger negative effects in large enterprises at β = -0.29 versus small-medium enterprises at β = -0.16 with $\Delta\chi^2$ = 5.17. Manufacturing employees show intensified perceived threat at β = -0.38 compared to financial technology at β = -0.24 and service retail at β = -0.22 with $\Delta\chi^2$ = 6.83. Inexperienced employees exhibit amplified technology anxiety at β = -0.31 versus experienced employees at β = -0.14 with $\Delta\chi^2$ = 6.24.

4. Discussion

The empirical findings of this study indicate the fundamental mechanism by which psychological barriers shape the "aspiration-reality" gap in the adoption of enterprise AI technology, where threat perception has the strongest negative effect on AI adoption intention at β = -0.29, followed by technology anxiety at β = -0.22, job insecurity at β = -0.21, and perceived complexity at β = -0.18, which altogether explain 44% of the variance in AI adoption intention. Research on employee resistance to workplace AI technology has emphasized the necessity of systematic intervention at the organizational level [32]. However, this study has demonstrated the quantitative path coefficient results that indicate the dominance of threat perception at the individual psychological level. The dual structure of the cognitive and affective barriers identified in this study is consistent with the multidimensional features of employee resistance in the context of digital transformation [33]. However, the involvement of AI technology in threats related to the replacement of work roles differs from other digital technologies. Research on employee well-being in the context of digital transformation has emphasized that reducing the perception of complexity can reduce employee resistance [34]. However, the findings of this study indicate that even when controlling for the complexity barriers, threat perception and the affective barriers have independent strong effects. The mediation mechanism identified in this study has demonstrated the psychological chain by which threat perception indirectly affects AI adoption intention via the mechanism of job insecurity. The indirect effect is β = -0.12 and the direct effect is β = -0.17. However, this finding differs from the public sector perspective on AI change management [35] because the key role played by job insecurity as a transmission mechanism is more prominent in the context of enterprise than in the public sector.

The four-dimensional integrated model built by this study solves the problem of fragmentation in previous research, providing a complete picture of the AI organizational adoption theoretical model along with the macroscopic research of AI, which is transforming the work practices of organizations [36]. The results of the analysis of heterogeneity also provided support for the differentiated management of AI, where the impact of employees' job insecurity in large enterprises at the standardized coefficient β = -0.29 was higher than that of small and medium-sized enterprises at the standardized coefficient β = -0.16, the impact of employees' perceived threat in the manufacturing industry at the standardized coefficient β = -0.38 was higher than that of the financial technology industry at the standardized coefficient β = -0.24 and the service retail industry at the standardized coefficient β = -0.22, and the technology anxiety effect of employees without AI usage experience was higher than that of employees with AI usage experience at the standardized coefficient β = -0.31 compared to β = -0.14. The results of this study also resonate with the research on digital leadership [37] for the guidance of psychological intervention strategies under different contexts. The results of this study also show that AI usage experience has a significant positive effect on AI adoption intention at the standardized coefficient β = 0.17, while the formal AI training effect at the standardized coefficient β = 0.07 was not significant, which is consistent with the research conclusion on the application of AI in the field of HR management [38].

5. Conclusion

This study offers a fresh theoretical angle based on the psychological barriers perspective to understand the "aspiration-reality" gap in enterprise AI adoption, which shows how employees' cognitive judgments on the threat of work roles are transformed into behavioral resistance through the evoking of affective responses of career insecurity when the technology is technically feasible but not psychologically acceptable. This challenges the underlying assumption of technological determinism that enterprise AI adoption can be naturally accomplished by improving the functionality of AI technology, without considering employees' underlying psychological resistance mechanisms to technology adoption that may challenge their professional identities. When the enterprise develops AI adoption strategies to improve efficiency, employees are engaged in psychological negotiations on the value of their occupation and the space for survival, which is the underlying reason for the "aspiration-reality" gap being difficult to bridge. The contextual heterogeneity confirmed in this study suggests that there is no one-size-fits-all solution to the enterprise AI transformation, given the different underlying psychological vulnerabilities of large enterprises' hierarchical rigidity, the technology threat of automation in the manufacturing industry, and the cognitive unfamiliarity of AI technology resulting from the lack of exposure. Successful enterprise AI adoption is not only the implementation of technology but the reconstruction of the psychological contract in the change management process, requiring employees to change from passive acceptance to active engagement, which can be accomplished through transparent communication, capability building, and career security assurances. Future studies could extend to the dynamic evolution of the psychological barriers to AI adoption and the buffering effect of positive psychological capital on technology threat perception.

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