SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 2.1, (2026), pp. 15602-15612
Open Access. Online & Print

DOI: 10.5281/zenodo.20593354

ARTIFICIAL INTELLIGENCE ACCEPTANCE AND AI LITERACY IN HIGHER EDUCATION ADMINISTRATION: THE MEDIATING ROLE OF AI-ENABLED JOB CHARACTERISTICS

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Received: 04/04/2026
Accepted: 20/05/2026

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ABSTRACT

Artificial intelligence (AI) is being applied to higher education administration in recent years, but fewer studies have investigated how administrators use these AI tools to enhance their own AI literacy. This paper investigates whether AI-enabled job characteristics mediate the effect of AI acceptance on AI literacy for university administrative staff. A total of 687 administrators in Tianjin were surveyed, and then structural equation modelling was performed on this data. Based on the results, it can be seen that AI acceptance is positively related to AI literacy and more positive perceptions of AI-enhanced job attributes. AI-enabled job characteristics were also positively associated with AI literacy and partially mediated the relationship between AI acceptance and AI literacy. Based on the above results, the development of AI literacy among staff cannot be based solely on whether they find AI convenient and simple to use; rather, changes in their sense of autonomy, skill application and professional purpose after being exposed to AI in their work should also be considered. This paper extends the research on technology acceptance by linking it to capability development and identifies job characteristics as a crucial work-design mechanism for higher education administration.

KEYWORDS: AI Acceptance; AI Literacy; Higher Education Administration; AI-Enabled Job Characteristics; Structural Equation Modelling; Work Design; Administrative Personnel.

1. INTRODUCTION

At present, many applications of artificial intelligence (AI) have appeared in higher education, such as student evaluation and performance analysis, support for school management, and other services. Although there are more opportunities for efficiency now due to the above changes, problems such as ethical leadership and professional boundaries have also emerged (Bond et al., 2024; Crompton & Burke, 2023; Zawacki-Richter et al., 2019), along with changes in the function of people in schools. Recently, researchers have also pointed out that generative AI may change how knowledge is generated, shared and assessed in academia; moreover, issues such as algorithmic bias and the transparency of scholarly communication are also emerging problems (Kumar & Bhuvaneswari, 2026). Therefore, the application of artificial intelligence in higher education should be regarded as both a change in technology and a modification of organisation and psychology (Vrontis et al., 2022).

Compared with academic staff, university administrators face distinct challenges when integrating AI into their work environments. Administrative responsibilities frequently involve compliance monitoring, policy implementation, resource allocation, student services, institutional reporting, and operational decision-making. Consequently, administrators must balance the efficiency benefits offered by AI with accountability, procedural consistency, transparency, and ethical responsibility. These unique role requirements make AI literacy particularly important for administrative personnel, as they must critically evaluate AI-supported recommendations while ensuring alignment with institutional policies and governance standards (Ng et al., 2021; UNESCO, 2024).

The staff at the university are directly responsible for this work. They support faculty and students, as well as institutional management, and many of their daily tasks can now be helped by or changed through AI systems. Technology acceptance research has provided the foundation for exploring why employees are willing to use new-hire systems. Perceived usefulness and perceived ease of use continue to be significant determinants of technology acceptance (Granic & Marangunic, 2019; Scherer et al., 2019), and other studies in higher education have also identified institutional trust, self-efficacy and perceived support as predictors (Al Darayseh, 2023; Chatterjee & Bhattacharjee, 2020). Acceptance does not guarantee that staff will gain the necessary knowledge, skills and values for the use of AI in daily life at the appropriate time.

In recent years, the concept of AI literacy has expanded in academic research to include several components, such as the basic comprehension of AI systems, critical analysis of algorithmic results, ethical reasoning in AI use, and adaptability to different environments. Carolus et al. (2023) and Lintner (2024) have also distinguished among the cognitive, behavioural and meta-level competencies in other frameworks. AI literacy for administrators is not about knowing how to operate the tool. Acknowledge data deficiencies, dispute the AI's recommendations, and ensure that decisions made by means of AI align with institutional policies and professional values.

The change in AI acceptance to AI literacy may be determined by how staff experience their AI-enabled work. Research on work design has shown that automated and algorithmic systems can reduce autonomy, lower task complexity, reduce the quantity of information, limit feedback and diminish skill diversity (Parent-Rocheleau & Parker, 2022; Parker & Grote, 2022). These changes are considered a loss of employees' self-efficacy, a sense of powerlessness, or other decreases in their sense of purpose for living in terms of work (Berretta et al., 2023; Verma & Singh, 2022). AI-enabled job features are thus considered to be a potential psychological and work-design route for converting acceptance into literacy development in this study.

Recent governance frameworks and organizational adaptation studies have emphasized that successful AI integration in higher education administration depends not only on individual acceptance but also on institutional policies, digital competencies, and ethical oversight mechanisms (UNESCO, 2024; Vrontis et al., 2022). Although AI in higher education has received more attention from scholars recently, university administrative staff are still relatively understudied. Most of the current acceptance models only reach behavioural intention or use, and do not follow the path of capability development. To address the above problem, this paper examines whether AI-enabled job characteristics mediate the impact of AI acceptance on AI literacy for administrative staff at universities in Tianjin, China. This study adds to previous research by connecting AI acceptance with capability-oriented results, expanding AI literacy research to administrative staff, and examining job characteristics as a pathway for psychological adjustment under AI-related organisational change.

2. THEORETICAL BACKGROUND AND HYPOTHESES

2.1. AI Acceptance and AI Literacy

AI acceptance in this study refers to a person's favorable assessment of intelligent technology, which includes the perceived usefulness, ease of use, general attitude, and intention to use AI in the future. Based on research on technology acceptance, it has been shown that beliefs about the usefulness and ease of use of technology are closely related to people's use of technology in education (Granic & Marangunic, 2019). Acceptance will also affect whether employees in the office are willing to learn new functions and participate in training for using AI tools in their daily work voluntarily (Scherer et al., 2019). AI literacy is, on the other hand, a wider range of skills. Learning the functions of AI, judging the results produced by machines, identifying ethical risks, and determining whether to be guided by these suggestions (Ng et al., 2021; Carolus et al., 2023). Because the staff who are willing to learn about AI are more likely to see AI-related tasks as learnable and relevant to their work, they will also be more inclined to acquire these skills (Al Darayseh, 2023; Chatterjee & Bhattacharjee, 2020).

Recent studies have increasingly emphasized AI literacy development among non-academic employees in higher education institutions. Administrative personnel often engage with AI systems in student services, institutional planning, resource management, and operational support functions (Bond et al., 2024). Therefore, their AI literacy extends beyond technical competence and includes ethical judgment, critical evaluation of algorithmic outputs, and responsible organizational decision-making (UNESCO, 2024). Despite the growing adoption of AI across higher education administration, empirical evidence focusing specifically on administrative personnel remains limited. This study addresses this gap by examining how AI acceptance contributes to AI literacy development among university administrative staff (Ng et al., 2021; Carolus et al., 2023). Based on the above, the following hypothesis is proposed.

H1: AI Acceptance positively affects AI Literacy.

2.2. AI Acceptance And AI-Enabled Job Characteristics

AI Systems will change how employees work. Automate repetitive operations, assist in analyzing data, and reduce the requirement for manual decision-making. Work-design studies have gradually described intelligent technologies as systems capable of changing the complexity of tasks, autonomy, monitoring and feedback, as well as skill requirements (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2022).

Not all the staff are aware of these changes in the same way. Staff with a high acceptance of AI may consider using AI tools for work as a form of support, training and professional development. Staff with low acceptance may perceive the same changes as increased supervision, role replacement or reduced autonomy. Thus, the acceptance of AI may serve as an index for changes in the work environment for employees.

Although there is still a lack of direct evidence from higher education administration, related studies indicate that people's initial attitudes towards AI affect their response to changes in education and organization brought about by AI (Hashemi et al., 2026; Qahtan & Alwan, 2025). In line with the work on organizational adaptation and professional identity (Vrontis et al., 2022), we anticipate that administrative staff with a higher acceptance of AI will report more positive characteristics of AI-enabled jobs.

Although AI-enabled job characteristics are conceptually related to traditional work-design theories, the construct reflects a distinct phenomenon. Traditional job characteristics describe relatively stable aspects of work, including autonomy, skill variety, task significance, and feedback (Hackman & Oldham, 1976). In contrast, AI-enabled job characteristics capture employees' perceptions of how these work attributes are reshaped through interactions with intelligent technologies (Parker & Grote, 2022). AI systems may alter decision-making processes, information access, task complexity, learning opportunities, monitoring mechanisms, and perceptions of professional purpose. Consequently, AI-enabled job characteristics represent an AI-specific extension of traditional work-design constructs and provide a useful framework for understanding employee adaptation during digital transformation (Parker & Grote, 2022; Parent-Rocheleau & Parker, 2022). Hence, the hypothesis two is proposed below.

H2: AI acceptance is positively correlated with AI-enabled job attributes. -

2.3. AI-Enabled Job Characteristics and AI Literacy.

The way employees view changes in their work due to AI may also affect their desire to learn about AI. According to the theory of job design, autonomy, purpose and the opportunity to learn all help employees gain experience in their work (Hackman & Oldham, 1976). Employees who think that AI can help them improve in learning and in their daily work are more likely to learn how to use the new AI tool (Scherer et al., 2019). Baashirah (2025) proposes a policy-driven framework for academic governance and performance management in higher education that links the attributes of AI-enabled work with institutional accountability mechanisms to determine how staff view the significance of AI literacy.

Previously, some research has linked AI-enabled job attributes, such as expanded information processing, skill demands and autonomy, to adaptive behaviour and innovation at work (Verma & Singh, 2022). At the same time, AI literacy is also being regarded as a combination of technical knowledge, ethical awareness, self-reflection and adaptive problem-solving (Carolus et al., 2023). As human-AI collaboration requires continuous learning and adaptation (Kolbjørnsrud, 2024), employees who feel that their AI-enhanced work will improve their own abilities are expected to have a higher level of AI literacy. Accordingly, the hypothesis three is proposed below.

H3: AI-enabled job attributes positively affect AI literacy.

2.4. Mediating Role Of AI-Enabled Job Characteristics

Based on the above reasons, it can be concluded that the acceptance of AI may affect AI literacy in two ways. The direct path is motivated by motivation and engagement; thus, employees who are more willing to learn about AI are more likely to try using AI tools in their work and participate in training (Scherer et al., 2019). Indirect path based on work interpretation: acceptance determines whether AI-related changes are perceived as supportive or threatening, and this interpretation can affect the effort employees invest in learning (Parker & Grote, 2022).

The design of work will be affected to some extent by whether employees believe that new technologies will increase or reduce their sense of control over their work, competence, and professional purpose (Parker & Grote, 2022). If AI is to be used to enhance the living conditions of employees, then they will be eager to learn how to operate it well (Kolbjørnsrud, 2024). Therefore, the study considers the features of AI-enabled jobs as a mediator between the degree of AI acceptance and AI literacy. The hypothesis four is portrayed below.

H4. AI-enabled job characteristics mediate the relationship between AI acceptance and AI literacy.

3. METHODS

3.1. Participants

A cross-sectional study was conducted to test the above model. Online distribution of questionnaires used convenience sampling to administrators of higher education institutions in Tianjin China. A total of 703 were collected. After excluding responses that were either in a pattern or had an unreasonably short completion time, 687 valid questionnaires were finally available for analysis; the effective response rate was 97.7%.

The demographic features of the sample are as follows: Table 1. The two genders were males, at a rate of 47.5% (n=326), and females, at a rate of 52.5% (n=361). Job Rank: 199 respondents were junior staff (29.0%), 386 were intermediate staff (56.2%), and 102 were senior staff (14.8%). Educational backgrounds: 346 people had a college degree (50.4%), 278 people had a master's degree (40.5%), and 63 people had a doctoral degree (9.2%).

Table 1: Demographic Characteristics of Participants (N = 687).

Item	Variables	Number	Percentage (%)
Gender	Male	326	47.5
	Female	361	52.5
Job rank	Junior	199	29.0
	Intermediate	386	56.2
	Senior	102	14.8
Educational background	Bachelor's degree	346	50.4
	Master's degree	278	40.5
	Doctoral degree	63	9.2

Note: Percentages May Not Total 100 Due To Rounding

3.2. Measures

3.2.1. Questionnaire Adaptation and Validation

The measurement scales employed in this study were adapted from previously validated instruments reported in the literature. To ensure contextual suitability for higher education administration, the questionnaire items were reviewed and refined according to the research context of AI-assisted administrative work in Chinese universities. The questionnaire was translated into Chinese and subsequently back-translation into English by bilingual researchers to ensure semantic equivalence (Brislin, 1970).

Prior to the formal survey, a pilot study was conducted among university administrative personnel in Tianjin, China. A total of 160 questionnaires were distributed, and 151 valid responses were obtained, yielding a response rate of 94.38%. The pilot data were used to examine item quality, internal consistency, and overall questionnaire clarity. The results indicated satisfactory psychometric properties and supported the use of the instrument in the formal study. Minor wording refinements were subsequently incorporated based on participant feedback and preliminary statistical analyses.

The three scales are derived from existing studies and have been modified to suit the specific circumstances of AI-assisted university management. All the items were scored on a 5-point Likert scale, and 1 represented 'strongly disagree' and 5 represented 'strongly agree'. A high score suggests a relatively large degree of that factor.

3.2.2. AI Acceptance

The scale for AI acceptance includes perceived usefulness, perceived ease of use, attitude towards intelligent systems and behavioural intention to use in the future. The reasons for selecting these dimensions are that previous research has shown an association between them and the adoption of technology and artificial intelligence (AI) in education (Al Darayseh, 2023; Granic & Marangunic, 2019; Scherer et al., 2019).

3.2.3. AI-Enabled Job Characteristics

Items of the scale for AI-enabled job characteristics were adapted from work-design studies and modified for administrative work. The subjects of the survey were the administrative staff's perceptions of changes in their own sense of autonomy and learning ability after introducing artificial intelligence at work. Based on the previous studies, it can be expected that intelligent technologies will change both the meaning of work and the necessary skills for it (Berretta et al., 2023; Parker & Grote, 2022; Verma & Singh, 2022).

3.2.4. AI Literacy

The scale of AI literacy is divided into categories such as technology, ethics, management skills, etc. Almatrafi et al. (2024), Andoniou (2025), Carolus et al. (2023) and Laupichler et al. (2022) have all shown that the current view of AI literacy includes not only basic technical knowledge but also ethical awareness, critical thinking, adaptability to change, etc.

3.2.5. Procedure And Ethical Considerations

The research will use anonymous questionnaires ethically. Before completing the questionnaire, the purposes of this study and the right of free will in participation were disclosed to the participants; guarantees on data secrecy were provided, as well as information on withdrawal at any time. Consent was obtained before submission. No personally identifiable information was added to the final analysis set.

3.2.6. Data Analysis

The statistical analysis was used for data breakdown. The software of SPSS and AMOS was employed for data analysis. First, descriptive statistics and Pearson correlation coefficients were used to study the general trends of the data. Second, a confirmatory factor analysis (CFA) was performed on the measurement model. Cronbach's alpha and composite reliability (CR) were used to assess reliability, and average variance extracted (AVE) and standardized factor loadings were employed for convergent validity analysis.

Based on the above validation of the measurement model, structural equation modelling (SEM) was employed to examine the indirect paths in the presence of gender, educational background and administrative rank. Bootstrapping with 5,000 resamples was used to examine the indirect effect of AI-enabled job features. Model fit was assessed via the χ^2/df ratio, RMSEA, CFI, TLI and SRMR. As the study employed cross-sectional self-report data, Harman's single-factor test was also carried out after the main analysis to verify the absence of common method bias.

4. RESULTS

Descriptive Statistics and Correlation Analysis. The mean score of AI acceptance was 3.54 (SD = 0.58), the mean score of AI-enabled job characteristics was 3.31 (SD = 0.50), and the mean score of AI literacy was 3.45 (SD = 0.60). As shown in Table 2, the degree of acceptance of AI was positively correlated with AI-enabled job features ($r = .434$, $p < .001$) and AI literacy ($r = .527$, $p < .001$). AI-enabled job features were also positively correlated with AI literacy ($r = .415$, $p < .001$). These correlations provide preliminary support for the proposed model.

Table 2: Descriptive Statistics and Correlations Among Study Variables.

Variable	M	SD	1	2	3

AI acceptance	3.54	0.58	-		
AI-enabled job characteristics	3.31	0.50	.434***	-	
AI literacy	3.45	0.60	.527***	.415***	-

Note: ***P < .001.

Common method bias. Harman conducted a single-factor test at the top and thus ruled out common method bias. The unrotated principal component analysis had 11 factors with eigenvalues greater than 1. The first factor explained 7.742 per cent of the total variance and did not meet the general requirement of 40 per cent. Thus, it is unlikely that the common method bias will be the reason for the results.

Reliability and validity. The CFA results supported the measurement model. Standardized factor loadings ranged from .642 to .844. Composite reliability (CR) values ranged from .770 to .845, while average variance extracted (AVE) values ranged from .508 to .604. Cronbach's alpha coefficients were .944 for AI acceptance, .865 for AI-enabled job characteristics, and .888 for AI literacy.

All standardized factor loadings exceeded the recommended threshold of .60, while CR values were above .70 and AVE values exceeded .50. According to established criteria, these results indicate satisfactory internal consistency, construct reliability, and convergent validity (Fornell & Larcker, 1981). Therefore, the measurement model demonstrated acceptable psychometric properties and was considered suitable for subsequent hypothesis testing (Table 3).

Table 3: Reliability And Convergent Validity Summary.

Varialbes	Dimensions	Cronbach's alpha	Loading range	CR	AVE
AI acceptance	Usefulness; ease of use; attitude; behavioral intention	.944	.642-.844	.770-.845	.508-.604
AI-enabled job characteristics	Autonomy; skill diversity; professionalism	.865	.642-.844	.770-.845	.508-.604
AI literacy	Technological knowledge; management design; ethics; professional development	.888	.642-.844	.770-.845	.508-.604

Note: CR = Composite Reliability; AVE = Average Variance Extracted. CR And AVE Are Reported as Observed Ranges from the Available Measurement Output.

Structural Model and Hypothesis Testing. The structural model showed a good fit to the data: chi-square/df = 1.785, RMSEA = 0.034, CFI = 0.985, TLI = 0.980, and SRMR = 0.028.

The Path Coefficients are as follows: Table 4. AI acceptance has a positive impact on AI literacy (β = .715, p < .001) and supports H1. AI acceptance also positively affects AI-enabled job characteristics (β = .584, p < .001) and supports H2. AI-enabled job characteristics were positively correlated with AI literacy (β = .268, p < .01) and thus supported H3.

Table 4: Structural Model and Bootstrap Mediation Results.

Hypothesis / Effect	Path	β	95% CI	Result
H1	AI acceptance → AI literacy	.715***	-	Supported
H2	AI acceptance →AI-enabled job characteristics	.584***	-	Supported
H3	AI-enabled job characteristics → AI literacy	.268**	-	Supported
H4	AI acceptance →AI-enabled job characteristics→ AI literacy	.157***	[.063, .250]	Supported

Note: **P < .01; ***P < .001. Gender, Job Rank, And Educational Background Were Controlled in the Mediation Model. Model Fit: Chi-Square/Df = 1.785, Rmsea = .034, Cfi = .985, Tli = .980, Srmr = .028.

Mediation Analysis. Bootstrap analysis with 5,000 resamples shows that there is a significant indirect effect of AI acceptance on AI literacy through AI-enabled job characteristics (β = .157, 95% CI [.063, .250]). Because the direct path from AI acceptance to AI literacy was still large, it is expected to show partial mediation. Therefore, H4 is confirmed.

Group differences. Exploratory Analysis of

Gender, Job Rank and Education Level. The levels of acceptance for AI and the characteristics of AI-enabled jobs were all the same across all job ranks. Only AI literacy showed a gender difference, and males scored higher than females (M = 3.526 and 3.384, t = 3.137, p = .002). There were no gender differences in AI acceptance or AI-enabled job characteristics. Educational background was related to a deficiency in AI literacy; doctoral degree holders had higher levels of AI literacy than those with master's or bachelor's degrees (F = 5.315, p = .005). There were also different degrees of perceived usefulness, skill diversity, professionalism and the overall measure of AI-enabled job characteristics among them.

Based on the above exploration, it is proposed that AI-related changes will differ according to previous education and access to technological learning resources. They should be taken lightly, but they show that specialised training and support are needed.

5. DISCUSSION

This study examined the correlations among AI acceptance, AI-enabled job characteristics, and AI literacy. The results indicate that AI acceptance is directly and indirectly related to perceptions of AI-enabled work through the mediator of AI literacy. Acceptance is not to be considered the conclusion of technology adoption, but rather it is related to subsequent development of capabilities.

5.1. AI Acceptance and AI Literacy

The positive relationship between AI acceptance and AI literacy is consistent with the research on technology acceptance; that is to say, perceived usefulness and ease of use motivate people to use digital tools (Granic & Marangunic, 2019; Scherer et al., 2019). The results of this study are the intention to use AI and AI literacy. Therefore, it is expected that administrative staff with a favourable view of AI will be more inclined to learn how AI systems operate and to assess the results as well as their ethical issues. In line with recent frameworks for AI literacy that consider all kinds of literacies as multi-dimensional abilities rather than only technical knowledge (Almatrafi et al., 2024; Andoniou, 2025; Laupichler et al., 2022; Lintner, 2024), the above results have also been observed. Andoniou (2025) thinks that AI literacy should include critical AI reasoning, digital ethics, human-AI collaboration and curriculum integration; therefore, it is in line with our view that administrative AI literacy should also cover evaluative and ethical judgment in addition to tool operation.

5.2. AI Acceptance And AI-Enabled Job Characteristics

AI acceptance also predicted the perceived features of AI-enabled jobs. Therefore, the attitudes of the staff towards artificial intelligence will likely change how they understand the changes in work. Some administrators believe that the application of AI will help manage daily life more conveniently and enjoy rich information and powerful functions. Others may be subject to monitoring, role ambiguity, or reduced autonomy. Our results indicate that employees who are more open to AI are more likely to view changes in work due to AI positively. According to the work-design model for algorithmic management and digital labour (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2022; Parker & Grote, 2022), it should be understood this way.

5.3. AI-Enabled Job Characteristics and AI Literacy

AI-enabled job features were positively correlated with AI literacy and also served as a partial mediator. Therefore, we believe this will help us understand the underlying reasons for the above results. When the staff feel that AI-assisted work offers them greater autonomy and variety in skills, or a sense of purpose in their work, they will be more willing to learn about the technology and use it responsibly. According to the above analysis, more empowering AI-related job characteristics are associated with adaptable and novel work behaviour (Verma & Singh, 2022). Baashirah (2025) also indicated that, under the governance of higher education, policy-driven systems integrating smart technology for performance management may affect employees' sense of purpose in AI-assisted work. The positive evaluation of job characteristics in our study was directly associated with higher AI literacy; thus, institutional governance designs that support AI application more proactively (rather than focusing solely on supervision) may encourage the growth of people's AI skills.

The partial mediation effect identified in this study has important theoretical implications. The findings suggest that AI acceptance alone does not fully explain the development of AI literacy among university administrators. While positive attitudes toward AI directly encourage learning behaviors and engagement with intelligent technologies, administrative staff’s perceptions of AI-related changes in their work environment provide an additional pathway through which literacy develops.

From an organizational change perspective, administrators respond not only to technology itself but also to how technology reshapes their professional experiences, responsibilities, and opportunities for development. Consequently, effective AI transformation strategies should simultaneously address both psychological acceptance and AI-enabled work design (Parker & Grote, 2022; Vrontis et al., 2022).

5.4. Cultural And Institutional Implications of the Mediation

The Mediating effects are also institutional in nature. The Structure of University Administration Generally includes policies, service responsibilities and formal procedures. At the same time, we will also pay more attention to the benefits for people. It should also be in line with the institution's standards and improve the efficiency of administrative work. Positive perceptions of the attributes of AI-enabled jobs may help promote individual acceptance to foster more stable and responsible development of AI literacy in the company (Vrontis et al., 2022).

5.5. Group Differences

Exploratory group comparisons provided additional insights into AI-related adaptation among university administrators. Administrative rank did not show significant differences across the main study variables, suggesting that AI-related adaptation may not be strongly associated with formal organizational hierarchy.

The educational differences observed in this study may reflect unequal opportunities for advanced digital learning and varying levels of exposure to emerging technologies. Individuals with doctoral-level education often engage in research-intensive activities and therefore may have more frequent interactions with AI-related applications. Similarly, the gender differences identified in AI literacy should not be interpreted as inherent differences in capability. Prior research suggests that disparities may be associated with technology self-efficacy, previous experience, access to training opportunities, and organizational support structures (Carolus et al., 2023). These findings underscore the importance of inclusive AI literacy initiatives that provide equitable learning opportunities for all administrative personnel. Universities should therefore avoid relying on a one-size-fits-all training approach and instead provide diverse learning opportunities that accommodate the needs of different employee groups.

6. PRACTICAL IMPLICATIONS

The above research results have some implications for university leadership and administrative personnel training.

6.1. AI Literacy as Psychological and Professional Development

AI literacy should be regarded as both a professional qualification and a set of ethics, not merely as technical training. The training programme will also teach the application of relevant practical instruments, as well as how to recognize bias and limitations in the data, accountability, etc. Provide the staff with opportunities to learn how to use AI systems and, at the same time, how to question and evaluate them. Andoniou (2025) has put forward the multi-dimensional literacy framework of critical thinking, digital ethics and human-AI cooperation, and offers this training as a practical blueprint.

Universities may consider establishing a tiered AI literacy development framework. At the foundational level, training programs should focus on AI concepts, system functionality, and responsible use principles. Intermediate-level training should emphasize critical evaluation of AI-generated outputs, identification of algorithmic bias, and interpretation of AI-supported recommendations. Advanced-level programs can focus on AI governance, ethical decision-making, data stewardship, and organizational implementation strategies. Such a progressive framework would allow institutions to align AI literacy development with employees' professional responsibilities and career progression (Ng et al., 2021; UNESCO, 2024).

6.2. Boosting AI Acceptance as a Starting Point

Improve the Acceptance of AI as a way to start. Universities can reduce the uncertainty of AI by providing specific cases relevant to administrative work and showing how AI can reduce repetitive labour. At the same time, it should not be mistaken for a simple hope. Training should also cover the deficiencies and risks of AI-assisted decisions.

6.3. Redesigning AI-Enabled Work

Design AI-assisted work processes carefully. If AI is only employed for expanded monitoring and efficiency improvements at a high speed, the staff will feel threatened. If it is used as a resource for supporting judgment, reduce low-value tasks, and extend the scope of skill application, staff will be more willing to learn about and properly use AI technology. Baashirah (2025) has put forward that a policy-driven framework can be built to integrate artificial intelligence (AI) with sustainable academic governance, thus boosting the sense of purpose for employees in their work and advancing learning.

To operationalize AI-enabled job redesign, universities may conduct workflow analyses to identify administrative activities that can be augmented rather than replaced by AI systems. Routine tasks such as scheduling, information retrieval, document classification, and report generation can be automated, enabling employees to devote greater attention to judgment-intensive, strategic, and service-oriented responsibilities. Such redesign efforts may strengthen employees' perceptions of autonomy, skill variety, and professional meaning, thereby supporting the development of AI literacy.

6.4. Differentiated Support

Differentiation in support. Given that staff have varying levels of education, prior knowledge and self-confidence, and training requirements, multiple routes to AI learning need to be established by the university. Peer support, a low-pressure practice environment, and targeted training can all help prevent the expansion of the AI-related transformation in existing inequalities.

Beyond formal training programs, universities should establish institutional support mechanisms that encourage continuous AI learning. These mechanisms may include AI learning communities, peer mentoring programs, online resource repositories, consultation services, and opportunities for cross-departmental collaboration. Such support structures can facilitate knowledge sharing and reduce uncertainty associated with AI adoption (Bond et al., 2024).

7. LIMITATIONS AND FUTURE RESEARCH

The research conducted the quantitative design to investigate that AI-enabled job characteristics mediate the impact of AI acceptance on AI literacy for administrative staff at universities in Tianjin, China. Although the study discovered meaningful finding, several limitations should be acknowledged.

7.1. Sampling Method

The use of convenience sampling may introduce selection bias because individuals with stronger interests in AI-related topics may have been more willing to participate in the survey. Consequently, the sample may not fully represent the broader population of higher education administrative personnel. Future studies should consider probability-based sampling approaches to improve representativeness and external validity.

7.2. Causal Inference

This study employed a cross-sectional design and thus could not determine causality. Although the proposed model was grounded in established theoretical perspectives, longitudinal studies are needed to examine whether AI acceptance influences changes in AI-enabled job characteristics and subsequent developments in AI literacy over time.

7.3. Generalizability

The sample consisted of university administrative personnel from Tianjin, China. Therefore, the findings may not be fully generalizable to other regions, institutional contexts, or cultural settings. Future studies should validate the proposed model across different countries, higher education systems, and organizational environments.

7.4. Self-Report Measurement

Only self-reported data were collected. Although the common method bias assessment did not indicate a serious problem, future studies may strengthen methodological rigor by incorporating behavioural indicators, training records, supervisor evaluations, or task-based assessments of AI literacy.

7.5. Scope Of Mechanisms Examined

The present study focused on the mediating role of AI-enabled job characteristics. Future research may extend the model by examining additional mediating mechanisms, including technostress, algorithmic trust, perceived risk, professional identity, and organizational readiness. Furthermore, potential moderating variables such as institutional support, leadership style, organizational culture, and prior digital experience warrant further investigation (Tarafdar et al., 2019).

Moreover, future studies should consider longitudinal designs to establish causal relationships, comparative institutional analyses across different higher education contexts, and additional mediating or moderating variables as noted above.

8. CONCLUSION

This study examined the relationships among AI acceptance, AI-enabled job characteristics, and AI literacy among higher education administrative personnel. The findings indicate that AI acceptance is positively associated with AI literacy both directly and indirectly through AI-enabled job characteristics. In addition, AI-enabled job characteristics were found to play a significant partial mediating role, suggesting that employees' perceptions of AI-related changes in their work environment contribute to the development of AI literacy.

The principal contribution of this study lies in demonstrating that AI literacy development among higher education administrators is not solely a consequence of technology acceptance. Rather, perceptions of AI-enabled job characteristics constitute a significant organizational mechanism linking acceptance to literacy development. By integrating technology acceptance theory, AI literacy scholarship, and work-design perspectives, this study provides a novel explanatory framework for understanding how universities can cultivate AI-capable administrative workforces during ongoing digital transformation.

The findings contribute to the growing literature on AI adoption in higher education while offering practical guidance for institutional leaders seeking to promote responsible and sustainable AI integration. Specifically, universities should not only encourage positive attitudes toward AI but also design supportive AI-enabled work environments that foster learning, autonomy, and professional development.

Declarations

Ethics approval and consent to participate: The study took the form of an anonymous online questionnaire. The reasons for the study, whether participation is required, the right to withdraw, and privacy will be protected have been explained to the participants. Obtained signed permission to distribute and collect questionnaires.

Funding: No particular grants were provided by any public, commercial or non-profit institutions for this study.

Author contributions: Weihan Liang: Conceptualisation, method and research, formal analysis, writing the original draft and manuscript revision. Kang Huo: Literature review, data curation, and writing-review and editing. Pengfei Chen: Supervision, validation and writing-review and editing. All the authors have read and approved the final version.

Data Availability: The data in this study can be obtained from the corresponding author upon reasonable request and in accordance with ethical and institutional regulations.

The authors have no conflicts of interest.

Generation of AI tools: Only for language polishing and grammar correction of the paper in the initial writing phase was a generative AI tool used. The design of the study, its main ideas, data analysis and interpretation, and conclusions are the results of this work. The authors have read the entire paper and take full responsibility for its contents.

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