Cómo referenciar este artículo / How to cite this article

Mou, L., Chaveesuk, S., Vanitchatchavan, P., & Chaiyasoonthorn, W. (2026). Artificial Intelligence and Human Resource Performance in Higher Education: An Integrated UTAUT-TTF-TOE Model with Nonlinear Adoption Effects. *Espacio, Tiempo y Educación, 13*(2), pp. 499-521. doi: http://dx.doi.org/10.14516/ete.13225

Artificial Intelligence and Human Resource Performance in Higher Education: An Integrated UTAUT-TTF-TOE Model with Nonlinear Adoption Effects

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Abstract: This study investigates how artificial intelligence (AI) affects human resource (HR) performance in Chinese higher education institutions by integrating the Unified Theory of Acceptance and Use of Technology (UTAUT), Task-Technology Fit (TTF), and Technology-Organization-Environment (TOE) frameworks. It examines the inverted U-shaped moderating effect of AI adoption intensity on the usage–performance relationship. A cross-sectional quantitative design was employed, with data collected through structured questionnaires from 385 respondents across 32 higher education institutions in Guangdong Province, China. Structural equation modeling (SEM) tested the hypothesized relationships, while polynomial regression with quadratic interaction terms examined the curvilinear moderation. All hypothesized paths were supported. Performance expectancy, effort expectancy, and task-technology fit significantly predicted behavioral intention, while technology characteristics, task characteristics, organizational support, and environmental factors significantly predicted TTF. Actual AI Usage and TTF independently predicted HR Performance. AI adoption intensity showed an inverted U-shaped moderating effect, indicating that moderate rather than maximum adoption produces the strongest performance gains. The study contributes by integrating UTAUT, TTF, and TOE; extending TTF by positioning organizational and environmental factors as antecedents of fit; providing evidence of nonlinear AI adoption effects in

higher education; and demonstrating differential AI effectiveness across HR functions, with structured, data-intensive functions showing stronger technology–performance relationships.

Keywords: Artificial Intelligence, Human Resource Performance, UTAUT, Task-Technology Fit, TOE Framework, Adoption Intensity,

Received: 10-03-2026
Accepted: 02-09-2026

1. Introduction

Artificial intelligence (AI) is rapidly transforming human resource management (HRM) across all organizational sectors, including higher education (Muda & Erlina, 2020; Tambe et al., 2019; Vardarlier, 2020). Universities worldwide are deploying AI-powered tools for resume screening, adaptive learning, performance analytics, and workforce planning (Popenici & Kerr, 2017; Zawacki-Richter et al., 2019). China's higher education system, the world's largest with over 3,000 institutions and 47 million enrolled students is undergoing particularly rapid AI transformation following the State Council's New Generation AI Development Plan, which designated AI as a strategic national priority.

In this fast-changing environment, higher education institutions are challenged in a different way with HR management. In contrast to corporate organizations, universities have to deal with a variety of workforce categories, such as tenured faculty, contract lecturers, administrative staff, and researchers, with different policies and cultural expectations (Aljumah et al., 2026; Whitchurch, 2008). Examples of AI use in these areas include automated resume screening for faculty hiring, predictive analytics for employee retention, adaptive professional development systems, and intelligent workload allocation tools (Tambe et al., 2019; Zawacki-Richter et al., 2019). But how effective these applications are, empirically, in improving performance is another question.

Although the adoption of AI is rapidly expanding, the connection between AI use and higher education HR outcomes is still not fully understood. There are three gaps in the literature that need to be addressed. First, most of the previous technology adoption studies focus on individual acceptance factors and do not consider task-technology alignment and organizational-environmental contexts, which are crucial to understand the complex organizational adoption process (Dwivedi et al., 2019; Oliveira et al., 2014). This one lens perspective does not account for the inconsistent performance results of AI technologies across organizations and tasks.

Secondly, the literature assumes that the higher the level of technology adoption, the higher the level of performance (Delone & McLean, 2003). Recent studies, however, indicate that adoption intensity (the number, variety, and extent of the use of technology) may have nonlinear relationships with organizational outcomes (Hwang et al., 2009). However, the overuse of AI can lead to complexity, dependency, clashes with company culture, and diminishing returns (Mikalef & Gupta, 2021; Raisch & Krakowski, 2021). In the context of AI in HRM, this "more-is-better" notion has not been extensively tested, and there is no clear guidance for HRM practitioners regarding the optimal level of AI adoption.

Third, higher education institutions have unique features that distinguish them from the corporate environment in which most research on technology adoption has been carried out: complex governance structures, academic autonomy norms, multiple stakeholder interests, and different organizational cultures (Whitchurch, 2008). It is

not clear to date how well existing theories of technology adoption can be applied to the HR context in higher education and if the effectiveness of AI is different across HR functional areas in universities (Bond et al., 2019).

Importantly, it is imperative to consider the university as an educational and institutional environment, rather than a mere organizational environment when considering the role of AI in higher education. Educational missions, complex administrative structures, professional communities, academic autonomy and public responsibilities are combined in universities (Arthur & Bohlin, 2005). As such, HR changes can affect more than administrative efficiency (Worapongpat et al., 2025) as they can impact the way academic and professional work are organized, coordinated institutional knowledge, and the distribution of governance responsibilities. The study of AI in higher education also shows that the use of AI goes beyond teaching and learning to academic support and institutional and administrative services, which underscores the need to consider the implications for AI in the broader context of institutional transformation (Crompton & Burke, 2023; Zawacki-Richter et al., 2019). Recent studies also highlight the need for institutional support (Razzaq et al., 2026), institutional structures and governance (Mah & Groß, 2024), professional development, and coordinated organizational responses, rather than just technological adoption, when implementing AI in higher education. The study of AI adoption in university HR is an opportunity to explore the current technological transformation that is now part of the organisation and development of higher education institutions.

To fill this gap, this study develops and tests a combined UTAUT-TTF-TOE theoretical framework which covers individual acceptance factors (UTAUT), task-technology alignment (Goodhue & Thompson, 1995), and organizational-environmental contexts (Tornatzky & Fleischer, 1990). Importantly, the study adds the concept of AI adoption intensity as a moderating variable and examines the hypothesized inverted U-shaped relationship between the usage–performance relationship. The data are analyzed by using structural equation modelling and polynomial regression from 385 respondents from 32 higher education institutions in Guangdong Province, China.

Guangdong Province is very suitable to investigate, due to its empirical background. The study area chosen is the most economically relevant region in China (GDP, technological infrastructure) but the findings of this economically advanced region might not be transferable to the rest of China. The province has 67 qualified higher education institutions, including various institutions, comprehensive universities, research universities, applied universities and vocational colleges, and it has a rich institutional background for the analysis of the patterns of AI application. In addition, the higher education institutions in Guangdong are under the influence of the Greater Bay Area technology hub, and their implementation of AI is affected by the environment, which makes it an ideal place for studying the interaction between organizational and environmental factors in technology implementation.

In this research, four specific contributions are made. First, it shows that the combination of UTAUT, TTF, and TOE frameworks explains AI adoption and performance better than single-theory approaches, offering a more holistic view of AI adoption and performance in complex organizational contexts (Goodhue & Thompson, 1995; Oliveira & Martins, 2011; Tornatzky & Fleischer, 1990). Second, it extends TTF theory by positioning organizational support and environmental factors from the TOE framework

Espacio, Tiempo y Educación, v. 13, n. 2, July-December / Julio-Diciembre 2026, pp. 499-521.
ISSN: 2340-7263

as antecedents of task-technology fit, offering a more expansive conceptualization aligned with sociotechnical perspectives (Leonardi, 2013). Third, it provides empirical evidence that AI adoption intensity moderates the usage–performance relationship in an inverted U-shaped pattern within higher education, identifying an approximate optimal adoption threshold (Laursen & Salter, 2006). Fourth, it reveals significant differential AI effectiveness across HR functional areas, showing that structured, data-intensive functions (e.g., recruitment) yield substantially stronger technology–performance relationships than complex, relationship-intensive functions (e.g., talent planning), echoing prior research on task analysability and automation suitability (Autor et al., 2003; Davenport & Ronanki, 2018).

2. Theoretical Background and Hypotheses Development

2.1. UTAUT and Individual AI Acceptance

The UTAUT (Venkatesh et al., 2003) combine eight existing models into a simple framework consisting of four technology adoption factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. The concept of performance expectancy, the extent to which users perceive that technology will help them be more effective at their work is constantly found to be the most powerful predictor of behavioural intention in a variety of contexts. Effort expectancy, the ease of use of technology can be especially important in the early stages of adoption and with users who have less technical ability. Performance expectancy in higher education HRM with AI relates to HR managers' perceptions that using AI tools will enhance their efficiency, decision-making abilities, and service quality. Previous studies on organizational AI adoption have been consistent in outlining performance-related beliefs as key factors to address organizational inertia. Effort expectancy captures the perceived complexity of interacting with AI systems, which is highly relevant given the varying technical backgrounds of university HR staff. Higher education HR departments typically include professionals with administrative expertise but limited data science skills, making user-friendliness a critical adoption factor. Therefore:

H1. Performance Expectancy has a significant positive effect on Behavioral Intention to use AI.
H2. Effort Expectancy has a significant positive effect on Behavioral Intention to use AI.

2.2. TTF Theory and Technology–Task Alignment

While TTF focuses on the appropriateness of the technology, acceptance models focus on the reasons for the user's decisions to use technology. Therefore, if a technology is accepted, but does not meet the needs of a task, it will not enhance performance. On the other hand, a technology that is well fit for use can be underutilized if it is not perceived as being useful or easy to use (Balcerzak et al., 2025; Goodhue, 1995). AI-HRM's Task Characteristics are data requirements, data time sensitivity, data complexity, and procedural standardization, and its Technology Characteristics are functionality, data-processing capability, reliability, and adaptability. Therefore:

H3. Technology Characteristics have a significant positive effect on Task-Technology Fit.
H4. Task Characteristics have a significant positive effect on Task-Technology Fit.

2.3. TOE Framework and Contextual Influences on TTF

Tornatzky and Fleischer (1990) describe technological, organizational and environmental contexts as important influences on technology adoption within the TOE framework. The framework is extended by proposing that Organizational Support and Environmental Factors directly influence task-technology fit in this study. Organizational Support consists of leadership commitment, resource allocation, training and technical infrastructure, and Environmental Factors consist of competitive pressures, government policies, and industry trends.

Supportive organizational conditions can support technology–task alignment by offering resources for customization, integration, and learning. Likewise, external pressures can also increase awareness, legitimacy and resource allocation for implementing AI (Baker, 2012; Oliveira et al., 2014; Zhu et al., 2006). These contextual factors are added to the traditional TTF research that has mainly focused on technology and task characteristics, and recognizes that technology–task perceptions are socially and organizationally situated (D'Ambra et al., 2013; Leonardi, 2013). Therefore:

H5. Organizational Support has a significant positive effect on Task-Technology Fit.
H6. Environmental Factors have a significant positive effect on Task-Technology Fit.

2.4. Integration of UTAUT and TTF

The combination of UTAUT and TTF takes care of complementary aspects of technology adoption. UTAUT is used to predict the intention of using technology, while TTF is used to predict technology fit for work requirements (Lin & Wang, 2012). Both dimensions are crucial in the context of higher education HRM, as HR professionals need to see AI as useful and manageable, and also understand that AI capabilities align to certain HR tasks. TTF can impact on intentions and actual use. A good fit can lead to more positive perceptions of technology, less effort needed to use it and easier integration into workflow (Dishaw & Strong, 1999; Goodhue & Thompson, 1995). TF may also directly contribute to performance improvement due to technologies that are well-suited to the tasks improving the quality of the output, minimizing errors, and aiding better decisions. Therefore:

H7. Task-Technology Fit has a significant positive effect on Behavioral Intention to use AI.
H8. Behavioral Intention has a significant positive effect on Actual AI Usage.
H9. Task-Technology Fit has a significant positive effect on Actual AI Usage.
H10. Actual AI Usage has a significant positive effect on HR Performance.
H12. Task-Technology Fit has a significant direct positive effect on HR Performance.

2.5. AI Adoption Intensity: The Inverted U-Shaped Moderation

AI adoption is not a simple binary adopted/not adopted phenomenon; it is also a measure of the extent, depth and diversity of AI adoption (Fichman, 2001; Kot et al., 2021). AI has the potential to be utilized in higher education HRM in a few ways, such as screening resumes, and on a broader scale, in recruitment, training, performance management, compensation, employee relations, and workforce planning.

According to this study, the correlation between Actual AI Usage and HR Performance is u-shaped, with a peak intensity at a certain point. Although AI can have great value when it is first implemented, for example, by automating tasks and using data to make

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ISSN: 2340-7263

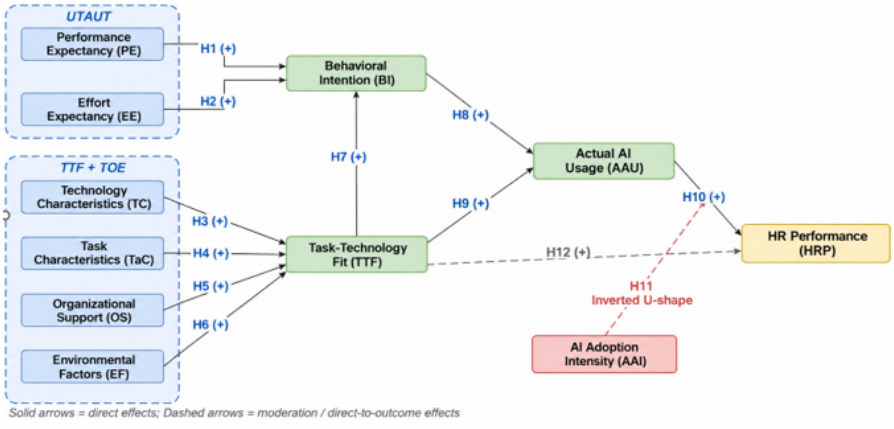
decisions, as it is used more and more, the benefits may grow smaller, and it can become more complex, reliant, and even culturally problematic if incorporated into multiple systems, which can also lead to diminishing returns (Mikalef & Gupta, 2021; Raisch & Krakowski, 2021). Implementing AI in a fragmented way can reduce its transformative impact at low intensity. While moderate adoption can ensure technological benefits and organizational manageability and human–AI complementarity, excessive adoption can lead to complexity and diminish the benefits of marginal performance (Hwang et al., 2009; Ransbotham et al., 2017). Therefore:

H11. AI Adoption Intensity moderates the relationship between Actual AI Usage and HR Performance in an inverted U-shaped pattern, such that the positive effect of usage on performance increases from low to moderate adoption intensity and decreases from moderate to high adoption intensity.

When the adoption is low and medium, the positive impact of AI on HR Performance is increasing, but when the adoption is moderate to high, the positive influence of AI on HR Performance is decreasing.

The conceptual framework (figure 1) integrates all the hypothesized relationships. Note that the solid arrows in Figure 1 and Figure 2 indicate direct paths between the core UTAUT and TTF constructs (H1–H10), while the dashed arrow from H12 (TTF → HRP) highlights this direct path between constructs from different frameworks, reflecting the different theoretical explanations of the role of this path as a fit-driven performance pathway that bypasses the intention-usage sequence.

Figure 1: Proposed Conceptual Model: Integrated UTAUT-TTF-TOE Framework with AI Adoption Intensity Moderation.



3. Research Methodology

3.1. Research Design and Sample

A cross-sectional quantitative design evaluated the proposed model using data from Guangdong Province, China. The target population comprised HR professionals, IT personnel, university administrators, and university management personnel who were involved in or familiar with AI-related HR practices within higher education institutions.

A stratified purposive sampling strategy was employed to ensure representation across different institutional types and geographic areas. Institutions were classified as comprehensive, research, applied and vocational institutions, and as being located in the Pearl River Delta or in peripheral areas. The study involved 32 higher education institutions, which comprised 10 comprehensive universities, 7 research-intensive universities, 8 applied universities and 7 vocational institutions. The 24 participating institutions were geographically distributed in the Pearl River Delta, and 8 in the peripheral areas of Guangdong Province. This distribution was developed to reflect the institutional diversity and variation in organizational and technological environments throughout the province.

The participating institutions were required to meet three criteria: (1) have an enrollment of more than 5,000 students; (2) have implemented AI in at least one HR-related application for over a year; and (3) have expressed their support for the study. In each of the participating institutions, the respondents were purposefully selected in the appropriate HR departments, administrative units, IT or technology units, and university management offices. The questionnaire was sent to the personnel who fit the criteria of the target respondents and had the necessary knowledge of the HR practices in the institution regarding the use of AI. Therefore, the recruitment process was structured to elicit feedback from those who had direct or informed exposure to the implementation of AI and its role in HR processes, not from members of the university who lacked such knowledge of the study context.

Table 1: Respondent (N=385).

Characteristic	n	%
Gender: Male	178	46.2
Female	207	53.8
Age: 25–30	67	17.4
31–40	124	32.2
41–50	136	35.3
Over 51	58	15.1
Education: Bachelor's	112	29.1
Master's	198	51.4
Doctoral	58	15.1
Role: HR Manager/Director	76	19.7
HR Specialist	128	33.2
College/Dept. Admin	68	17.7
IT Technical Staff	47	12.2
University Management	43	11.2
Other	23	6

The total number of questionnaires sent out was 450, which were sent to the 32 participating institutions, with about 14 questionnaires sent per institution, depending on the size of the institution and the number of eligible respondents. Questionnaires were conducted online and on paper. A total of 409 questionnaires were returned, with 385 questionnaires used for analysis after being screened for completeness and eligibility, giving a valid response rate of 94.1% of questionnaires returned. The final sample comprised HR managers/directors (N=76, 19.7%), HR specialists (N=128, 33.2%), college/department administrators (N=68, 17.7%), IT technical staff (N=47, 12.2%), university management personnel (N=43, 11.2%), and respondents

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classified as other (N=23, 6.0%). These respondent groups brought in the voices of HR professionals and those working with the technical, administrative, and managerial aspects of implementing AI. The data collection and follow-up took place for three months, from June to September 2025. Independent-samples t-tests between early and late respondents revealed no significant differences, suggesting that there was no significant nonresponse bias. The demographic data of the respondents is summarized in Table 1.

3.2. Measurement

This study employed 5-poin Likert scale for data collection. Performance Expectancy (10 items) and Effort Expectancy (5 items) were adapted from Venkatesh et al. (2003) and Pillai and Sivathanu (2020). Technology Characteristics (10 items) and Task Characteristics (10 items) were based on Goodhue and Thompson (1995) and D'Ambra et al. (2013), while Task-Technology Fit (5 items) was measured using Goodhue and Thompson's (1995) scales. Organizational Support (10 items) and Environmental Factors (5 items) drew on TOE operationalizations by Baker (2012) and Oliveira et al. (2014). Behavioral Intention and Actual AI Usage each comprised four items. AI Adoption Intensity was measured using 14 items covering breadth, depth, and diversity, while HR Performance comprised 15 items covering efficiency, decision quality, innovation capability, and service quality.

The instruments underwent English–Chinese–English back-translation following Brislin (1970), with discrepancies resolved by three bilingual researchers. A pilot study involving 45 participants from five institutions outside the main sample confirmed acceptable reliability ($\alpha > 0.80$). Minor wording adjustments were made following pilot feedback. AI Adoption Intensity was operationalized as a second-order reflective construct comprising adoption breadth, depth, and diversity. Breadth captured AI deployment across HR functions; depth assessed the degree of process integration; and diversity reflected the range of AI technologies used. HR Performance was similarly considered as a second-order reflective construct comprising efficiency, decision quality, innovation capability, service quality, and strategic contribution.

3.3. Common Method Bias Assessment

Given the cross-sectional, self-reported data, CMB was assessed using several procedures. Harman's single-factor test showed that the first factor explained 24.56% of the variance, below the 50% criterion (Podsakoff et al., 2003). The one-factor CFA model also showed poorer fit ($\chi^2/df = 8.23$, CFI = 0.534, RMSEA = 0.142) than the 11-factor model ($\chi^2/df = 1.49$, CFI = 0.962, RMSEA = 0.038). In addition, VIF values ranged from 1.234 to 2.876, below the 3.3 threshold (Kock, 2015). Overall, these results indicate no substantial evidence of CMB, although its presence cannot be completely excluded due to the cross-sectional, self-reported design.

3.4. Analytical Strategy

Data analysis followed a two-stage SEM approach (Anderson & Gerbing, 1988)123}. The measurement model was first assessed reliability and validity. The structural model was then tested to examine direct hypothesized paths (H1–H10, H12). For the moderating effect (H11), polynomial regression with quadratic interaction terms was employed following the approach of Hwang et al. (2009), where the curvilinear

moderation is specified as:

$$HRP = b_0 + b_1 \cdot AAU + b_2 \cdot AAI + b_3 \cdot AAI^2 + b_4 \cdot AAU \times AAI + b_5 \cdot AAU \times AAI^2 + \varepsilon \quad (1)$$

A significant negative coefficient for b_5 (AAU × AAI²) indicates the hypothesized inverted U-shaped moderation. The optimal adoption intensity threshold was calculated by setting the first derivative of the moderation function to zero:

$$AAI_{optimal} = -\frac{b_4}{2 \times b_5} \quad (2)$$

All SEM analyses were conducted using AMOS 28.0 with maximum likelihood estimation. Bootstrapping with 5,000 resamples was employed to generate bias-corrected 95% confidence intervals.

4. Results

4.1. Measurement Model Assessment

The results of reliability and convergent validity are shown in TABLE 2. The internal consistency of the scales was satisfactory, with all Cronbach α values > 0.867 and all composite reliabilities (CR) values > 0.874, which are considered to denote excellent internal consistency (Hair et al., 2019; Tiana et al., 2024). Convergent validity was shown by all average variance extracted (AVE) values being greater than 0.50 (Fornell & Larcker, 1981). The measurement model achieved excellent fit: $\chi^2/df = 1.49$, CFI = 0.962, TLI = 0.958, RMSEA = 0.038, SRMR = 0.034.

Table 2: Reliability And Convergent Validity.

Construct	Items	α	CR	AVE
Performance Expectancy (PE)	10	0.923	0.928	0.637
Effort Expectancy (EE)	5	0.898	0.904	0.654
Technology Characteristics (TC)	10	0.912	0.918	0.612
Task Characteristics (TaC)	10	0.908	0.914	0.598
Task-Technology Fit (TTF)	5	0.891	0.897	0.636
Organizational Support (OS)	10	0.934	0.938	0.618
Environmental Factors (EF)	5	0.878	0.886	0.612
Behavioral Intention (BI)	4	0.912	0.918	0.736
Actual AI Usage (AAU)	4	0.896	0.904	0.702
AI Adoption Intensity (AAI)	14	0.938	0.942	0.582
HR Performance (HRP)	15	0.945	0.948	0.598

The Fornell-Larcker criterion was used to verify the discriminant validity, which is obtained by computing the square root of the AVE of each construct, and comparing it to the correlations of all other constructs. Further, the values of all the HTMT ratios were below 0.85, which added to the discriminant validity (Henseler et al., 2015).

4.2. Structural Model and Hypotheses Testing

To confirm the adequacy of the measurement model, the two-stage SEM approach was applied, the structural model was estimated. The structural model demonstrated excellent fit to the data: $\chi^2/df = 1.58$, CFI = 0.956, TLI = 0.952, RMSEA = 0.041, SRMR = 0.048. All fit indices met or exceeded the recommended thresholds ($\chi^2/df < 3.0$, CFI > 0.95, TLI > 0.95, RMSEA < 0.06, SRMR < 0.08) (Hu & Bentler, 1999). Additionally,

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the hypothesized model was compared against three alternative structural models: a direct-effects-only model, a fully mediated model, and a partial mediation model without the TTF→HRP direct path. The hypothesized model demonstrated superior fit by both AIC and BIC criteria ($\Delta\chi^2$ tests all significant at $p < 0.001$), confirming the proposed theoretical structure. All direct path hypotheses (H1–H10, H12) were supported at $p < 0.001$. Table 3 summarizes the results.

Table 3: Structural Model Path Analysis Results.

Hypothesis	β	95% CI	C.R.	p	Result
H1: PE → BI	0.342	[0.278, 0.406]	9.87	< 0.001	Supported
H2: EE → BI	0.267	[0.198, 0.336]	7.23	< 0.001	Supported
H3: TC → TTF	0.356	[0.294, 0.418]	10.45	< 0.001	Supported
H4: TaC → TTF	0.298	[0.232, 0.364]	8.56	< 0.001	Supported
H5: OS → TTF	0.234	[0.162, 0.306]	6.78	< 0.001	Supported
H6: EF → TTF	0.187	[0.112, 0.262]	5.12	< 0.001	Supported
H7: TTF → BI	0.289	[0.221, 0.357]	8.12	< 0.001	Supported
H8: BI → AAU	0.467	[0.408, 0.526]	14.23	< 0.001	Supported
H9: TTF → AAU	0.278	[0.208, 0.348]	7.67	< 0.001	Supported
H10: AAU → HRP	0.398	[0.334, 0.462]	11.56	< 0.001	Supported
H12: TTF → HRP	0.312	[0.245, 0.379]	8.89	< 0.001	Supported

Note: β = standardized path coefficient; CI = bias-corrected bootstrap confidence interval (5,000 resamples); C.R. = critical ratio. All paths significant at $p < 0.001$. H11 (the inverted U-shaped moderation of AI Adoption Intensity) is not included in this table as it represents a nonlinear moderating effect rather than a direct structural path; it is tested separately via polynomial regression in Table 4.

The model explained substantial variance in all endogenous constructs: R^2(TTF) = 0.512, R^2(BI) = 0.554, R^2(AAU) = 0.498, and R^2(HRP) = 0.472. These values are within the range of values observed in previous technology adoption studies (e.g., Venkatesh et al., 2003). The HR Performance R^2 of 0.472 is similar to or higher than those found in related studies, indicating that the integrated framework offers reasonable explanatory power in the context of higher education, although caution should be exercised in making direct comparisons across studies because of variation in samples, measures and contexts. The relatively high R^2 values in all endogenous constructs also suggest that the model does not explain the variance in a single pathway but is spread across the nomological network, which further validates the holistic nature of the integrated model.

The path of behavioural intention to actual AI Usage was the largest standardized coefficient in the model with an effect size of $f^2 = 0.312$ (Cohen, 1988). The Actual AI Usage to HR Performance path (β = 0.398) had a medium effect size ($f^2 = 0.234$), suggesting that the use of AI has meaningful real-world impacts on HR outcomes, not just statistically. The Organizational Support and Environmental Factors paths to TTF were statistically significant, but with small effect size ($f^2 = 0.076$ and 0.048, respectively), indicating that these contextual factors are statistically significant, but have a relatively small magnitude compared to technology and task characteristics.

4.3. Inverted U-Shaped Moderation Analysis (H11)

To test the hypothesized inverted U-shaped moderating effect of AI Adoption Intensity, hierarchical polynomial regression was conducted. TABLE 4 presents the results.

Figure 2: Structural Model with Standardized Path Coefficients and R^2 Values.

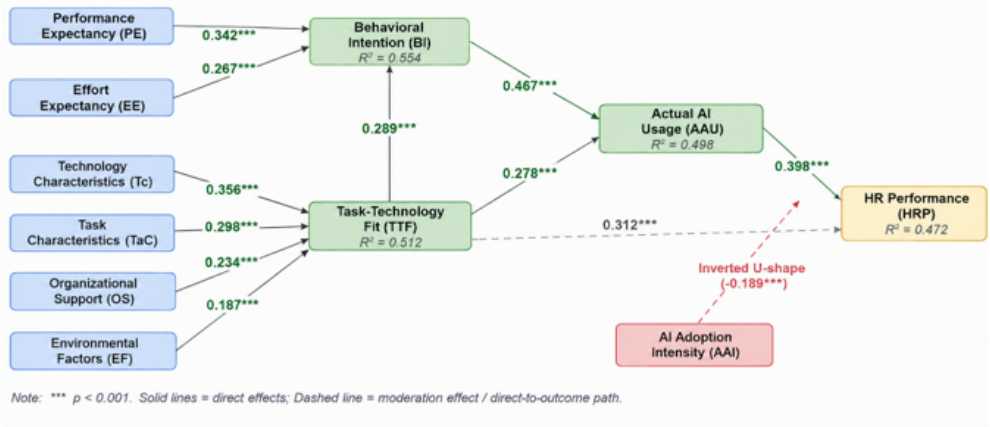


Table 4: Polynomial Regression Results for Inverted U-Shaped Moderation.

Variable	Model 1	Model 2	Model 3
Actual AI Usage (AAU)	0.398***	0.398***	0.398***
AI Adoption Intensity (AAI)		0.287***	0.312***
AAI^2			0.087*
AAU × AAI		0.134***	0.267***
AAU × AAI^2			−0.189***
R^2	0.486	0.512	0.534
ΔR^2	—	0.026***	0.022***
F for ΔR^2	—	18.67***	15.89***

Note: *** p < 0.001; * p < 0.05. Standardized coefficients (β) reported. Model 1 = direct effect only; Model 2 = linear moderation; Model 3 = quadratic moderation. R^2 values represent the variance explained by the polynomial regression models for HRP. The optimal threshold calculation in Equation (3) uses unstandardized coefficients (B).

The quadratic interaction term (AAU × AAI^2) was negative and highly significant (β = −0.189, p < 0.001), providing strong support for H11. To determine the optimal adoption intensity, Equation (2) was applied using the unstandardized regression coefficients: B = 0.524 for the linear interaction term (AAU × AAI) and B = −0.0706 for the quadratic interaction term (AAU × AAI^2):

$$AAI_{optimal} = -B_4 / (2 \times B_5) = -0.524 / (2 \times (-0.0706)) = -0.524 / (-0.1412) \approx 3.71 \quad (3)$$

Simple slopes analysis at three levels of adoption intensity confirmed the inverted U-shaped pattern (Table 5).

Table 5: Simple Slopes Analysis at Different Levels of AI Adoption Intensity.

AAI Level	Slope (β)	S.E.	t	p
Low (M – 1 SD = 2.59)	0.234	0.052	4.50	< 0.001
Moderate (M = 3.48)	0.412	0.038	10.84	< 0.001
High (M + 1 SD = 4.37)	0.287	0.048	5.98	< 0.001

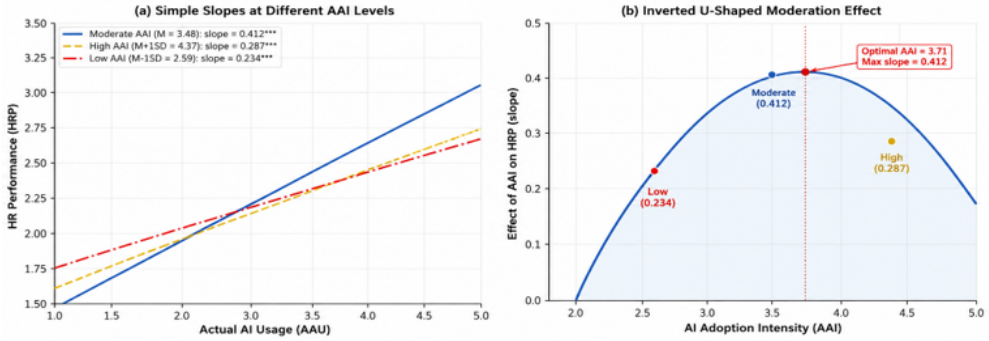
Note: Simple slopes represent the effect of AAU on HRP at each level of AAI.

At low adoption intensity, the usage–performance effect was positive but modest (β = 0.234); at moderate intensity, it reached its maximum (β = 0.412); and at high intensity,

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it diminished significantly (β = 0.287). Group-based validation further confirmed this pattern: institutions with adoption intensity near the optimal range (3.5–4.0) showed the strongest usage–performance relationship (β = 0.456), significantly exceeding both below-optimal (β = 0.312; z = 2.89, p = 0.004) and above-optimal groups (β = 0.298; z = 3.12, p = 0.002). Figure 3 illustrates the inverted U-shaped moderation effect.

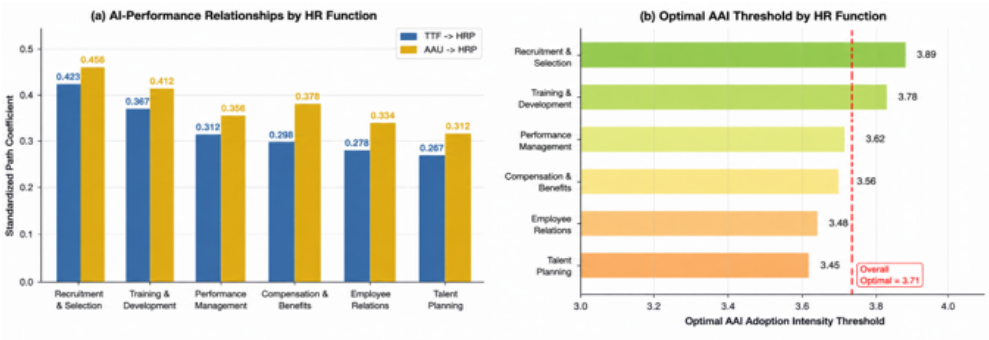
Figure 3: Inverted U-Shaped Moderation of AI Adoption Intensity on the AAU–HRP Relationship.



4.4. Additional Analyses: Multi-Group Comparison Across HR Functions

Multi-group SEM revealed significant variations in the TTF–HRP relationship across HR functional areas ($\Delta\chi^2 = 67.89$, $\Delta df = 10$, $p < 0.001$): Recruitment and Selection (β = 0.423), Training and Development (β = 0.367), Performance Management (β = 0.312), Compensation and Benefits (β = 0.298), Employee Relations (β = 0.278), and Talent Planning (β = 0.267). The optimal adoption intensity threshold also varied, ranging from 3.89 (Recruitment) to 3.45 (Talent Planning), suggesting that structured, data-intensive functions support higher adoption intensity before experiencing diminishing returns. Figure 4 presents these multi-group results.

Figure 4: Multi-Group Comparison of AI–Performance Relationships and Optimal Adoption Intensity Thresholds Across HR Functional Area.



4.5. Mediation Analysis

Indirect effect pathways were identified using bootstrapping-based mediation analysis. Behavioral Intention fully mediated the Effort Expectancy–Actual AI Usage relationship

(indirect effect = 0.125, 95% CI [0.091, 0.164], $p < 0.001$; direct effect = 0.034, n.s.), while partially mediating the Performance Expectancy–Usage relationship (indirect = 0.160, 95% CI [0.124, 0.201]; direct = 0.089, $p < 0.05$). Task-Technology Fit fully mediated the impact of Technology Characteristics and Task Characteristics on Behavioral Intention, suggesting that the impact of both technology and task factors on adoption is mediated by fit perceptions. Actual AI Usage partially mediated the relationship between TTF and HRP (indirect = 0.111, 95% CI [0.079, 0.149]; direct = 0.312, $p < 0.001$), suggesting that TTF has a direct effect on performance, as well as an indirect effect mediated by increased usage of AI.

Additionally, serial mediation chains were found: Performance Expectancy was related to HR Performance through the sequence PE → BI → AAU → HRP (indirect = 0.064, 95% CI [0.045, 0.087], $p < 0.001$); and Technology Characteristics was related to Performance through the sequence TC → TTF → AAU → HRP (indirect = 0.039, 95% CI [0.026, 0.056], $p < 0.001$). These multi-step pathways show the complicated causal structures between distal antecedent factors and ultimate performance outcomes.

4.6. Robustness Checks

A number of robustness checks were performed. Second, the main structural relationships did not significantly change after the control variables (gender, age, education, work experience, institution type, institution size, geographic region, and duration of implementation of the AI) were introduced; all path coefficients remained within 0.05 of their original values, demonstrating the robustness of the model. Of the control variables, AI implementation duration had the greatest effects ($\beta = 0.112–0.156$, $p < 0.001$), and institution type had significant effects, with vocational colleges having significantly lower values across outcomes compared to the reference category of research universities. Second, multi-group analysis by institution type confirmed structural invariance, with all hypothesized paths remaining significant across comprehensive, research, applied, and vocational institutions, though with varying magnitudes, research universities showing the strongest usage–performance relationships ($\beta = 0.456$) and vocational colleges showing the weakest ($\beta = 0.334$).

5. Discussion

5.1. Key Findings

This study offers empirical evidence supporting an integrated UTAUT-TTF-TOE framework for understanding the relationship between AI adoption and HR performance in higher education. Three sets of findings merit particular attention. Given the cross-sectional, self-report design, all reported relationships should be understood as associational rather than causal. This study brings together the data from various angles, and creates a deeper understanding of the role of AI in HRM, especially in higher education. The model combines three major theories: UTAUT, TTF, and TOE that look at individual cognition, task-technology fit, and organizational and environmental conditions. The model demonstrates the functioning of AI in complex offline environments. The multi-layered, cross-dimensional integrated analysis of the impacts of AI applications has a higher level of explanatory power in the context of the stakeholders of universities and the complex rules (Zawacki-Richter et al., 2019).

The first is that the integrated framework was more explanatory ($R^2 = 0.472–0.554$ for

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endogenous constructs) than most single-theory applications. In the UTAUT components, Performance Expectancy (β = 0.342) was the most significant predictor of adoption intention, supporting the meta-analytic results on the different contexts of technology adoption (Dwivedi et al., 2019). Effort Expectancy, although with a smaller effect (β = 0.267), was still significant, suggesting that usability issues continue to be a problem in the higher education HR setting where the technical proficiency of staff members can vary. Given that the relative magnitudes of these two effects are consistent with the classic pattern found in applications across UTAUT (Venkatesh et al., 2003), HR professionals in Chinese universities, similar to other organizational settings, should focus on perceived usefulness over perceived ease of use in forming their intentions to adopt.

The effect of TTF on both Behavioral Intention (β = 0.289) and direct HR Performance (β = 0.312) shows that the technology-task alignment is an independent and significant explanatory variable other than the individual acceptance variables. Furthermore, the TTF effect (β = 0.289) was similar in magnitude to the Effort Expectancy effect (β = 0.267), suggesting that HR professionals pay as much attention to functional alignment as they do to usability when making adoption decisions. This result is in line with Dishaw and Strong (1999) who integrated TTF-TAM, indicating that similar dynamics might be at work in the more comprehensive UTAUT framework.

The four antecedents of Task-Technology Fit led to an informative pattern. Technology Characteristics (β = 0.356) was the strongest predictor followed by Task Characteristics (β = 0.298), Organizational Support (β = 0.234), and Environmental Factors (β = 0.187). The pattern suggests that the perceptions of fit of the current sample may be more related to what the AI system can do (functionality, reliability, adaptability) and what tasks require (data analysis requirements, time sensitivity, complexity); and that contextual factors may be important but secondary enablers. Beyond supporting the adoption process, the role organizational support plays in perceptions of fit suggests that organizational support can be enhanced by providing supportive infrastructure, training, and organizational leadership commitment to the technology-task fit. Second, the inverted U-shaped moderation of adoption intensity (optimal threshold ≈ 3.71) is the most novel finding of the study. This is in line with the possibility of a non-linear relationship, which is emerging from manufacturing contexts (Hwang et al., 2009). This is because of the increasing complexity of integration at high levels of adoption, increased reliance on automated processes that reduces human expertise, conflicts with academic autonomy norms, and declining marginal value of peripheral applications.

This finding is interesting for its practical implications. The simple slopes analysis showed the usage–performance effect (β = 0.412) was 76% higher than at low intensity (β = 0.234) and 44% higher than at high intensity (β = 0.287). This significant difference highlights the fact that the performance impact of AI adoption differs significantly based on the context of overall AI adoption intensity. The results of the group-based validation demonstrate that the usage–performance effect for institutions in the near-optimal range (AAI = 3.5–4.0) is β = 0.456, which is significantly higher than for below-optimal and above-optimal institutions (β = 0.312 and 0.298, respectively), further supporting the inverted U-shaped relationship with statistically significant differences between the groups.

The theoretical mechanisms behind this pattern should be considered, however, we note that the specific threshold of 3.71 is sample specific and should not be used as a universal threshold. This is due to the specific institutional setting, scales of measurement and sampling of the current study and could vary in other settings. When AI is adopted in just

one or two HR processes, they do not have enough critical mass to create a transformative impact (Ransbotham et al., 2017). There are no cross-functional synergies for the users, limited data sharing between AI systems and a lack of support for the organizational learning curve in becoming proficient with AI. However, at moderate intensity of adoption, comprehensiveness and manageability allow for effective human-AI complementation, which are what Raisch and Krakowski (2021) call the "augmentation zone" where AI takes over repetitive, data-driven tasks, and humans take over tasks involving judgment and context. As AI systems become more prevalent in nearly every aspect of the business, at high adoption intensity, there is a risk of "capability overload" where the complexity of managing, integrating and maintaining multiple AI systems consumes resources that could otherwise be used to create value (Mikalef & Gupta, 2021).

The other is that the moderating role of the intensity of AI use in HRM is inverted U shape. In other words, the more the AI is used, the more it improves the performance of HRM at the beginning, which decreases over time. This trend forms an ideal range of adoption of the model. However, when the adoption intensity is above a threshold, the effect of performance improvement gets reduced. That is, there is no direct correlation between increased technology investment and improved outcomes. Excessive dependency on technology can overload people, create overly complicated systems and lead to organizational lag and coordination (Laursen & Salter, 2006). In higher education, the operations of the organization are constrained under certain conditions and have a degree of professional autonomy. Overuse of AI could have a negative impact on established governance logic and workflows that exist offline. This is a society of personal relationships and there are many reasons for problems. When used in an inappropriate way, AI could actually have a negative impact (Selwyn, 2016).

Third, the differential effectiveness across HR functional areas is consistent with the core tenet of the TTF theory: AI is most valuable when its capabilities are aligned with the characteristics of the task. The technology–performance relationship was strongest for Recruitment and Selection ($\beta = 0.423$), and weakest for Talent Planning ($\beta = 0.267$), which required complex, long-term, strategic judgments, where tacit knowledge plays a role. This picture is further enriched by the fact that optimal adoption intensity thresholds vary between functions from 3.89 for Recruitment to 3.45 for Talent Planning. Presumably, those functions with a higher degree of technology-task fit can tolerate more AI adoption without diminishing returns because the technology is adding value in more aspects of those functions (Li, 2021). Conversely, those functions that are less aligned hit their sweet spot sooner, as more and more AI is deployed in areas where the technology is less capable. Theoretically, this research adds new insights to the Task-Technology Fit Theory (TTF). The initial theory was mainly about the match of the characteristics of the task and the function of the technology. Based on the study, it can be inferred that, the task-technology fit is not only dependent on the technology itself, but also on the external environment and organizational resource allocation, which is indirectly demonstrated in this study.

Beyond its implications for technology adoption and human resource management, the findings can be understood in relation to the changing organization of higher education. Universities are not simply organizations that adopt technologies to improve administrative efficiency; they are educational institutions in which organizational arrangements, professional roles, academic practices, and governance structures jointly shape the conditions under which education is provided. The use of AI in higher education is becoming pervasive across all institutional and administrative tasks and in

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the classroom, and it should be addressed at the university level (Crompton & Burke, 2023; Zawacki-Richter et al., 2019). In this regard, the observed connection between using AI, task-technology fit, and HR performance indicates that the use of AI may affect the organization and coordination of educational activities in universities. Including AI in recruitment, training, performance management, workforce planning, and other HR-related tasks can impact the way administrative tasks, information sharing, and decision-making are distributed among HR stakeholders and academic activities. The results go beyond the HRM interpretation of the use of the technology, as they reveal the technology as part of the institutional structure of higher education.

The results also have implications for changing professional roles within universities. The relationships between technology and performance were stronger in structured functions (e.g., recruitment and selection) than in more relationship-oriented functions (e.g., talent planning), suggesting that AI does not impact all aspects of university work equally. Instead, the organizational value relies on the nature of professional activities and the level of technological capabilities that can replace human judgment. This distinction is important in the context of higher education, where there are clear norms of expertise, responsibility and professional autonomy for academic and professional staff. Recent studies on the role of AI in higher education also emphasize the significance of staff skills, professional development, and institutional support for successful implementation of AI in education (Mah & Groß, 2024). AI can reallocate simple information-processing tasks while boosting the need for human judgment, context interpretation, interpersonal interactions, and institutional accountability. This is not just about replacing human resources practices with AI, but about reshaping the interplay between technology and the humans that enable the university to function.

The results also underscore the governance aspect of technological change in higher education. The strong influence of organizational support and environmental factors on task-technology fit suggest that the effectiveness of AI is not only determined by the technology but also by the organizational environment. This interpretation aligns with recent higher education research which considers the integration of AI as an institutional governance problem of policy, accountability, human oversight, professional development, and organizational support (Crompton et al., 2026). When implementing AI in organizational processes, universities are faced with several questions regarding responsibility, supervision, professional autonomy, data utilization, and institutional accountability. The integration of AI in organizational processes raises a number of questions for universities regarding responsibility, supervision, professional autonomy, data use, and institutional accountability. This transformation can be understood as part of the broader process of the evolution of HEIs, where shifts in organizational structures, professional roles, technologies and relations to the wider society have constantly redefined the nature of university work. While this is not an historical study, the results of the present cross-sectional study offer empirical evidence to a current stage of this ongoing institutional transformation and illustrate the progress of the embedding of AI in the organization and governance of higher education.

5.2. Theoretical Implications

This study makes five theoretical contributions. First, it advances multi-theoretical integration by demonstrating that the UTAUT–TTF–TOE framework captures multi-level determinants of AI adoption, individual, task, organizational, and environmental, and

provides stronger explanatory power for technology adoption in knowledge-intensive organizations (Oliveira et al., 2014; Venkatesh et al., 2016). Second, it extends TTF theory by positioning organizational support and environmental factors as antecedents of task–technology fit. This moves TTF beyond its traditional emphasis on technology and task characteristics and supports a sociotechnical view in which effective fit is shaped by contextual conditions that enable or constrain technology–task alignment (Goodhue & Thompson, 1995; Leonardi, 2013).

Third, the study validates the inverted U-shaped moderating effect in the adoption intensity theory for the first time in an empirical study. Building on the multidimensional conceptualization presented by Fichman (2001), the results cast doubt on the notion of monotonic technology–performance relationships and indicate that there is an optimum range for adoption intensity. Fourth, the study situates the theory of adoption in higher education by finding institutional heterogeneity. The research universities exhibited higher usage–performance relationships ($\beta = 0.456$) than the vocational colleges ($\beta = 0.334$), indicating that the benefits of AI usage are influenced by institutional capacity, infrastructure, data culture and analytics capabilities. Finally, the results show that two performance pathways, namely Actual AI Usage ($\beta = 0.398$) and TTF ($\beta = 0.312$) independently predict HR performance. AI thus generates value both in terms of its usage and the quality of the technology–task fit. This is in addition to the Delone and McLean (2003) IS Success Model, which differentiates utilization and fit as two complementary mechanisms by which AI can impact on organizational performance.

5.3. Practical Implications

Institutions should target moderate rather than maximum AI adoption intensity. The optimal threshold of approximately AAI ≈ 3.71 suggests substantial but not exhaustive deployment, covering 4–5 major HR functions at meaningful integration depth while avoiding complexity and diminishing returns. Implementation needs to be flexible for HR function as well. AI could be applied to a moderate extent to Recruitment and Selection, Training and Development, and to a cautious extent to Talent Planning and Employee Relations and Performance Management and Compensation.

It should be an institution's priority to align its technology, rather than how much it uses. The effect of TTF on HR performance ($\beta = 0.312$) is similar to that of Actual AI Usage ($\beta = 0.398$). Regular fit assessments, solution customization and systematic task analysis can help to keep things aligned as technology and tasks change. Institutions need to build up enablers of the organization and environment before scaling AI. Organizational Support ($\beta = 0.234$) indicates that leadership commitment, training, technical capacity, and implementation plans are important; Environmental Factors ($\beta = 0.187$) indicates that policy monitoring and competitive pressures and external adoption trends are important. The most powerful predictor of adoption intention is Performance Expectancy ($\beta = 0.342$), and it is crucial that the institutions are made aware of concrete performance benefits. Lastly, the intention–usage gap needs to be addressed: intention was a powerful predictor of actual usage ($\beta = 0.467$), but the mean intention (3.82) was higher than the mean actual usage (3.56). Programmes focused on targeted change management, HR AI champions, learning time and technical support can help bring intentions to fruition.

5.4. Limitations and Future Research

This study has few limitations which could be the future directions. First of all, the

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geographic concentration in Guangdong prevents the generalizability of the findings, since institutions in less developed regions might be subject to different resource constraints and adoption dynamics. Cultural factors can also affect AI use in different contexts, which facilitates cross-cultural comparisons (Hofstede, 2001). Secondly, the cross-sectional design restricts causal conclusions. The relationships observed are associational and reverse causation or feedback effects cannot be ruled out. Longitudinal studies would support causal interpretation. Third, self-reported measures for predictors and outcomes may lead to same-source bias. While the results of the CMB tests showed there was no significant concern, more future research should include objective measures like time-to-hire, training completion, and cost efficiency. Fourth, although an inverted U-shaped relationship was found, it was not directly measured and should be tested explicitly, as it might be explained by the mechanisms of complexity, over-reliance, cultural conflict, and diminishing marginal utility. Fifth, the composite measure of AI adoption intensity may not fully reflect the qualitative differences in deployment; thus, the threshold of 3.71 should be interpreted as an approximate and context-specific figure. Sixth, institutional choice might be biased. Seventh, the adoption of AI could shift and the best threshold may change over time, necessitating periodic review. Finally, objective technology-use and performance measures could be used to reinforce reliance on perceptual TTF and HR performance measures. Complementary evidence could be provided from mixed methods research, which is a combination of surveys and institutional administrative records (Tagaev & Bilan, 2026).

6. Conclusion

This research extends the research on the effect of AI on HR performance in HE by creating and testing an integrated UTAUT–TTF–TOE model that includes the moderating effect of the AI adoption intensity. All hypothesized relationships were supported based on the 385 responses received from 32 Chinese higher education institutions, which led to three conclusions: The integrated framework offers a full and empirically supported explanation of AI adoption and HR performance, highlighting the benefits of multi-level theoretical integration for complex technology adoption phenomena (Venkatesh et al., 2012). Second, the intensity of AI adoption has an inverted U-shape moderating effect, with an optimal score of 3.71 on a five-point scale. This implies that strategic optimization, rather than maximum adoption, could create more performance benefits, but that could be context dependent due to the cross sectional, single region design of the study. Third, the difference in effectiveness of AI across the HR functions further highlights the importance of aligning technology with task and the need for function-specific implementation strategies.

Institutions should invest in technology task fit, with a focus on substantial adoption of AI, moderate to high intensity, and invest in fit quality, not just quantity, for practitioners. The approximate 3.71 threshold is used to inform implementation planning, and the different functional thresholds allow for differentiated deployment approaches, with increased deployment in data-intensive functions and less deployment in relationship intensive functions, such as employee relations and talent planning. The results offer a foundation for longitudinal and cross-cultural research, mixed methods research based on objective performance measures, and research on the causes of the declining returns. As generative AI and LLM continue to evolve at a fast pace, it is also crucial to periodically review the relationships between AI adoption and performance.

Acknowledgment

The authors would like to thank all participants for their support and cooperation during the data collection process. Special appreciation is extended to the supervisor, Singha, for valuable guidance and continuous support throughout the study. The authors also acknowledge the King Mongkut's Institute of Technology in Thailand for providing a supportive academic environment and necessary resources. In addition, the authors are grateful to the anonymous reviewers and editors for their constructive comments, which have significantly improved the quality and clarity of this paper.

References

Aljumah, A. I., Nuseir, M. T., Hameed, W. U., AlShawabkeh, A., & Fararah, F. S. (2026). Reconfiguring higher education for digital transformation through artificial intelligence and entrepreneurial education in developing sustainable marketing capabilities. *Discover Sustainability, 7*(1), 1106. https://doi.org/10.1007/s43621-026-03367-7

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Arthur, J., & Bohlin, K. (2005). *Citizenship and Higher Education: The Role of Universities in Communities and Society.* Routledge. https://doi.org/10.4324/9780203415931

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics, 118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Baker, J. (2012). The Technology–Organization–Environment Framework. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), *Information Systems Theory: Explaining and Predicting Our Digital Society, Vol. 1* (pp. 231–245). Springer New York. https://doi.org/10.1007/978-1-4419-6108-2_12

Balcerzak, A. P., Zinecker, M., & Mičánek, J. (2025). The impact of artificial intelligence on task performance and decision-making: Empirical evidence on generation Z. *Human Technology, 21*(3), 620–639. https://doi.org/10.14254/1795-6889.2025.21-3.7

Bond, M., Zawacki-Richter, O., & Nichols, M. (2019). Revisiting five decades of educational technology research: A content and authorship analysis of the British Journal of Educational Technology. *British Journal of Educational Technology, 50*(1), 12–63. https://doi.org/10.1111/bjet.12730

Brislin, R. W. (1970). Back-Translation for Cross-Cultural Research. *Journal of Cross-Cultural Psychology, 1*(3), 185–216. https://doi.org/10.1177/135910457000100301

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Lawrence Erlbaum Associates. https://doi.org/10.4324/9780203771587

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: the state of the

field. *International Journal of Educational Technology in Higher Education, 20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Crompton, H., Burke, D., Nickel, C., Bozkurt, A., Miao, F., Sharples, M., Greene, J. A., et al. (2026). Governing generative AI in higher education: a global Delphi study on policy and practice. *International Journal of Educational Technology in Higher Education, 23*(1), 21. https://doi.org/10.1186/s41239-026-00602-z

D'Ambra, J., Wilson, C. S., & Akter, S. (2013). Application of the task-technology fit model to structure and evaluate the adoption of E-books by Academics. *Journal of the American Society for Information Science and Technology, 64*(1), 48–64. https://doi.org/10.1002/asi.22757

Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the Real World. *Harvard Business Review, 96*(1), 108–116. https://hbr.org/2018/01/artificial-intelligence-for-the-real-world

Delone, W. H., & McLean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems, 19*(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with task–technology fit constructs. *Information & Management, 36*(1), 9–21. https://doi.org/10.1016/S0378-7206(98)00101-3

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model. *Information Systems Frontiers, 21*(3), 719–734. https://doi.org/10.1007/s10796-017-9774-y

Fichman, R. G. (2001). The Role of Aggregation in the Measurement of It–Related Organizational Innovation1. *Management Information Systems Quarterly, 25*(4), 427–455. https://doi.org/10.2307/3250990

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Goodhue, D. L. (1995). Understanding User Evaluations of Information Systems. *Management Science, 41*(12), 1827–1844. https://doi.org/10.1287/mnsc.41.12.1827

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *Management Information Systems Quarterly, 19*(2), 213–236. https://doi.org/10.2307/249689

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis* (8th ed.). Cengage.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hofstede, G. (2001). *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations* (2nd ed.). Sage.

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Hwang, G.-J., Yang, T.-C., Tsai, C.-C., & Yang, S. J. H. (2009). A context-aware ubiquitous learning environment for conducting complex science experiments. *Computers & Education, 53*(2), 402–413. https://doi.org/10.1016/j.compedu.2009.02.016

Kock, N. (2015). Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach. *International Journal of e-Collaboration (IJeC), 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kot, S., Hussain, H. I., Bilan, S., Haseeb, M., & Mihardjo, L. W. W. (2021). The role of artificial intelligence recruitment and quality to explain the phenomenon of employer reputation. *Journal of Business Economics and Management (JBEM), 22*(4), 867–883. https://doi.org/10.3846/jbem.2021.14606

Laursen, K., & Salter, A. (2006). Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms. *Strategic Management Journal, 27*(2), 131–150. https://doi.org/10.1002/smj.507

Leonardi, P. M. (2013). When Does Technology Use Enable Network Change in organizations? A comparative Study of Feature Use and Shared Affordances. *Management Information Systems Quarterly, 37*(3), 749–775. https://doi.org/10.25300/misq/2013/37.3.04

Li, X. Q. (2021). *Intelligent Transformation: Evolution of Artificial Intelligence Technology and Value Creation*. Tsinghua University Press.

Lin, W.-S., & Wang, C.-H. (2012). Antecedences to continued intentions of adopting e-learning system in blended learning instruction: A contingency framework based on models of information system success and task-technology fit. *Computers & Education, 58*(1), 88–99. https://doi.org/10.1016/j.compedu.2011.07.008

Mah, D.-K., & Groß, N. (2024). Artificial intelligence in higher education: exploring faculty use, self-efficacy, distinct profiles, and professional development needs. *International Journal of Educational Technology in Higher Education, 21*(1), 58. https://doi.org/10.1186/s41239-024-00490-1

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Muda, I., & Erlina, E. (2020). Sustainable HR Development to Support Successful Implementation of Offline Accounting Apps by Rural Enterprises in Indonesia. *Journal of International Studies, 13*(4), 70–88. https://doi.org/10.14254/2071-8330.2020/13-4/5

Oliveira, T., & Martins, M. F. (2011). Literature Review of Information Technology Adoption Models at Firm Level. *The Electronic Journal Information Systems Evaluation, 14*(1), 110–121. https://academic-publishing.org/index.php/ejise/article/view/389

Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management, 51*(5), 497–510. https://doi.org/10.1016/j.im.2014.03.006

Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. *Benchmarking: An International Journal, 27*(9), 2599–2629. https://doi.org/10.1108/bij-04-2020-0186

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning, 12*(1), 22. https://doi.org/10.1186/s41039-017-0062-8

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping Business With Artificial Intelligence: Closing the Gap Between Ambition and Action. *MIT Sloan Management Review, 59*(1). https://sloanreview.mit.edu/projects/scholars/reshaping-business-with-artificial-intelligence

Razzaq, S., McCarthy, P. M., & El-Soussi, A. (2026). AI-driven pathways to improve writing performance of ESL learners to drive innovation and sustainability in higher education. *Discover Sustainability, 7*(1), 1110. https://doi.org/10.1007/s43621-026-03464-7

Selwyn, N. (2016). *Education and Technology: Key Issues and Debates*. Bloomsbury Academic. https://doi.org/10.5040/9781474235952

Tagaev, B., & Bilan, Y. (2026). AI adoption and human capital development in transition economies: Evidence from Uzbekistan. Polish Journal of Management Studies, 33(2), 250-280. https://doi.org/10.17512/pjms.2026.33.2.16.

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *California Management Review, 61*(4), 15–42. https://doi.org/10.1177/0008125619867910

Tiana, Y., Batool, Z., & Abbasi, M. (2024). Digital Information and Brand Loyalty in China: An Emerging Perspective of Metaverse Users in Online Businesses. *Journal of Metaverse Business Designs, 5*(1), 39–49. https://doi.org/10.70890/JMBD.2024.5104

Tornatzky, L. G., & Fleischer, M. (1990). *The Processes of Technological Innovation*. Lexington

Books.

Vardarlier, P. (2020). Digital Transformation of Human Resource Management: Digital Applications and Strategic Tools in HRM. In U. Hacioglu (Ed.), *Digital Business Strategies in Blockchain Ecosystems: Transformational Design and Future of Global Business* (pp. 239–264). Springer International Publishing. https://doi.org/10.1007/978-3-030-29739-8_11

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward A Unified View1. *Management Information Systems Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology1. *Management Information Systems Quarterly, 36*(1), 157–178. https://doi.org/10.2307/41410412

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead. *Journal of the Association for Information Systems, 17*(5), 328–376. https://doi.org/10.17705/1jais.00428

Whitchurch, C. (2008). Shifting Identities and Blurring Boundaries: the Emergence of Third Space Professionals in UK Higher Education. *Higher Education Quarterly, 62*(4), 377–396. https://doi.org/10.1111/j.1468-2273.2008.00387.x

Worapongpat, N., Arunyakanon, P., & Rianwilairat, W. (2025). Modern Human Resource Management that Affects Academic Work Efficiency at Rajabhat University in Bangkok. *Journal of Education and Learning Reviews, 2*(3), 57–72. https://doi.org/10.60027/jelr.2025.949

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0

Zhu, K., Dong, S., Xu, S. X., & Kraemer, K. L. (2006). Innovation diffusion in global contexts: determinants of post-adoption digital transformation of European companies. *European Journal of Information Systems, 15*(6), 601–616. https://doi.org/10.1057/palgrave.ejis.3000650