Employee Adoption of AI-Driven HR Tools: An Extended Theory of Planned Behavior Approach

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Abstract

Artificial intelligence (AI) is increasingly utilized in human resource management (HRM) for tasks such as recruitment, performance management, and e-learning. While AI-driven HR technologies offer the potential for greater efficiency and fairness, employee adoption remains limited due to concerns regarding trust, fairness, and transparency. This study applies the Theory of Planned Behavior (TPB), incorporating trust in technology and perceived fairness, to examine factors influencing employees' intentions to adopt AI-driven HR technologies. Partial least squares structural equation modeling (PLS-SEM) was used to analyze survey data from 260 employees at King Khalid University in Saudi Arabia. Results demonstrate that attitude, subjective norms, perceived behavioral control, trust, and fairness each positively influence intention, collectively explaining 53% of its variance. Trust was identified as the most influential factor. This research extends the TPB by integrating fairness and trust in high-stakes HR contexts, providing practical recommendations for the ethical implementation of AI, including transparency initiatives and the assurance of procedural and distributive justice.

***Key words**: artificial intelligence, human resource management, acceptance, trust, equity, theory of planned behavior*

Jel Codes Classification : M12,M15, O33,J24

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تبنّي الموظفين لأدوات الموارد البشرية المدعومة بالذكاء الاصطناعي: مقاربة موسّعة لنظرية السلوك المخطط

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الملخص

تُستخدم تقنيات الذكاء الاصطناعي (AI) بشكل متزايد في إدارة الموارد البشرية (HRM) لأداء مهام مثل التوظيف، وإدارة الأداء، والتعلّم الإلكتروني. ورغم أن التقنيات المدعومة بالذكاء الاصطناعي في إدارة الموارد البشرية تُوفر إمكانات كبيرة لتعزيز الكفاءة والعدالة، إلا أن تبنّي الموظفين لها لا يزال محدوداً بسبب مخاوف تتعلق بالثقة والإنصاف والشفافية. تهدف هذه الدراسة إلى تطبيق نظرية السلوك المخطط (TPB) من خلال دمج متغيري الثقة في التكنولوجيا والإحساس بالعدالة، وذلك لفحص العوامل المؤثرة في نية الموظفين لتبنّي تقنيات الذكاء الاصطناعي في إدارة الموارد البشرية. تم استخدام أسلوب النمذجة بالمعادلات الهيكلية الجزئية (PLS-SEM) لتحليل بيانات استبانة شملت 260 موظفاً في جامعة الملك خالد بالمملكة العربية السعودية. أظهرت النتائج أن الاتجاهات، والمعايير الذاتية، والتحكم السلوكي المدرك، والثقة، والعدالة تؤثر إيجابياً في نية التبني، وقد فسّرت هذه المتغيرات مجتمعةً ما نسبته 53% من التباين في النية. كما تبين أن الثقة هي العامل الأكثر تأثيراً. تسهم هذه الدراسة في توسيع نظرية السلوك المخطط من خلال دمج مفهومي العدالة والثقة في سياقات إدارة الموارد البشرية الحساسة، وتقدم توصيات عملية للتطبيق الأخلاقي لتقنيات الذكاء الاصطناعي، تشمل تعزيز الشفافية وضمان العدالة الإجرائية والتوزيعية.

الكلمات المفتاحية: الذكاء الاصطناعي، إدارة الموارد البشرية، القبول، الثقة، العدالة، نظرية السلوك المخطط

التصنيف: *M12,M15, O33,J24*

I- Introduction

Artificial intelligence (AI) is increasingly integrated into human resource management (HRM), automating and enhancing processes across the employee lifecycle. In recruitment, AI streamlines resume screening, chatbot interactions, and video interview analysis. In performance management, it enables continuous feedback and data-driven evaluations, while in e-learning, AI delivers personalized and adaptive training content. Despite these benefits, employee adoption remains uncertain due to concerns regarding surveillance, algorithmic bias, and data protection.

The Theory of Planned Behavior (TPB) provides a robust framework for predicting behavioral intention, emphasizing the influence of attitude, subjective norms, and perceived behavioral control (Ajzen, 1991). However, traditional TPB applications in technology adoption often overlook crucial factors in the context of AI in HR, particularly **trust** and **perceived fairness**. Employees are unlikely to adopt AI-driven HR technologies unless they perceive these systems as **reliable**, **secure**, and **equitable** (Glikson & Woolley, 2020). These omissions highlight a theoretical and empirical gap in understanding employees' acceptance of AI in high-stakes HR contexts.

To address this gap, the present study augments the TPB framework with two additional predictors—**trust in technology** and **perceived fairness**—to examine the determinants of employees' intention to adopt AI-driven HR tools. By integrating these variables, the study

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provides a more comprehensive explanation of behavioral intention, particularly within the **cultural and institutional context of Saudi Arabia**. Moreover, it contributes practical insights for HR leaders seeking ethical and effective AI implementation strategies, emphasizing transparency, procedural justice, and accountability (Bondarouk & Brewster, 2022; Dwivedi et al., 2023).

I-1- Research Problem and Questions

Despite the growing integration of AI into HR practices, employee adoption remains inconsistent. Many employees express concerns about the **trustworthiness**, **fairness**, and **transparency** of AI systems—factors that can undermine successful implementation. Understanding the behavioral drivers of AI acceptance in HRM is therefore critical, especially in settings where HR decisions directly influence employees' careers and wellbeing.

I-2- Main Research Question:

What are the key factors influencing employees' intention to adopt AI-driven HR technologies within King Khalid University?

I-3- Subquestions:

1. How do **attitude**, **subjective norms**, and **perceived behavioral control** (as defined by the TPB) affect employees' intention to adopt AI-driven HR tools?
2. To what extent does **trust in technology** predict employees' adoption intention beyond the traditional TPB variables?
3. How does **perceived fairness** (procedural and distributive) influence employees' willingness to accept AI-driven HR tools?
4. Which of these factors—attitude, norms, control, trust, or fairness—has the strongest influence on employees' intention to adopt AI in HR?

I-4- Importance of the Study

This study is significant in several respects. **Theoretically**, it advances the Theory of Planned Behavior by incorporating trust and perceived fairness—two constructs that are essential but often neglected in AI adoption research. This integrated model provides a richer understanding of the psychological mechanisms underlying employee acceptance of AI-based HR technologies. **Empirically**, the study contributes to the emerging literature on AI adoption within developing and non-Western contexts by focusing on the Saudi higher education sector, represented by King Khalid University. **Practically**, the findings offer actionable recommendations for HR leaders and policymakers to enhance employees' trust and perceptions of fairness through transparent communication, ethical data governance, and inclusive AI design. These insights can guide organizations toward responsible and effective AI integration that supports both organizational performance and employee wellbeing.

II- Literature Review

II-1- AI in Human Resource Management

AI is transforming human resource management (HRM) by automating recruitment, enabling predictive analytics for employee performance, and developing personalized learning platforms. While these tools offer increased efficiency, they also raise concerns regarding algorithmic bias and data privacy (Meijerink et al., 2021; Tambe et al., 2019).

Amazon discontinued an AI recruitment tool due to gender bias, illustrating the potential negative consequences of poorly designed AI systems.

Recent studies (Bondarouk & Brewster, 2022; Dwivedi et al., 2023) emphasize that acceptance hinges on factors beyond mere functionality; it must also embody fairness, transparency, and alignment with cultural norms.

II-2- The Theory of Planned Behavior (TPB)

TPB states that intention is influenced by attitude, subjective norms, and perceived behavioral control. It is widely used in technology adoption research. In HR, attitudes reflect perceived utility, subjective norms represent societal expectations, and perceived behavioral control indicates confidence in using AI solutions. However, critics argue that TPB may be insufficient for technologies involving ethical considerations.

II-3- Having faith in technology

Trust is essential when using complex or opaque systems. Individuals base trust on perceptions of reliability, integrity, and security. In HR, employees must be confident that AI systems are fair and protect confidential information. Research indicates that explainability and accountability significantly enhance trust in AI.

Fairness, as delineated in organizational justice literature (Colquitt, 2001), has gained prominence in algorithmic systems. Binns (2018) distinguishes between individual fairness, which involves treating similar situations consistently, and group fairness, which ensures equity among demographic categories. To enhance the clarity of our operationalization, this study utilized a fairness scale that captures both individual and group fairness, as well as procedural justice. Procedural justice focuses on the processes that lead to outcomes, ensuring they are transparent and just. This comprehensive approach aligns with the justice concerns we raise and strengthens the validity of our fairness construct. Employees are more likely to accept AI in HR when the steps are clear and the outcomes are fair.

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II-4- Different Ways to Adopt

TAM and UTAUT are adoption models that emphasize perceived usefulness, ease of use, and facilitating conditions. However, they do not explicitly address justice or trust, underscoring the need for an enhanced TPB model. For instance, if an AI-driven HR tool produces biased evaluations, TAM and UTAUT may overlook fairness concerns. By integrating fairness and trust, the extended TPB framework better explains employee resistance to adopting efficient but potentially inequitable HR technologies.

II-5- Hypotheses

H1: A positive attitude toward AI-driven HR tools affects intention.

H2: Subjective norms have a positive effect on intention.

H3: Perceived behavioral control has a positive effect on intention.

H4: Having faith in technology has a positive effect on intention.

H5: The belief that things are fair has a positive effect on intention.

III- Methodology

This study was conducted at King Khalid University, Saudi Arabia.A cross-sectional survey was administered to 260 employees, who selected their most relevant HR domain (recruitment, performance, or e-learning).

Measures: We used established scales, such as Colquitt (2001) for fairness and McKnight et al. (2002) for trust.All items were assessed using 7-point Likert scales.

Validity and Reliability: Cronbach's alpha ranged from 0.80 to 0.89, composite reliability from 0.87 to 0.92, and AVE from 0.62 to 0.75. The Fornellâ€“Larcker criterion confirmed discriminant validity. Harman's single-factor test was used to assess common method bias.

IIII- Results

IIII-1- Descriptive Statistics

Of the 260 respondents, 60.4% were male and 39.6% were female. The sample included participants from E-Learning (34.6%), Recruitment (33.1%), and Performance Management (32.3%). Additionally, 21.2% had less than two years of experience, and 10% had more than fifteen years.

IIII-2- Measurement Model

The measurement model demonstrated adequate reliability and validity. Cronbach’s alpha values ranged from 0.80 to 0.89, composite reliability (CR) values ranged from 0.87 to 0.92, and average variance extracted (AVE) values ranged from 0.62 to 0.75. All values exceeded the recommended thresholds, indicating strong convergent validity. The Fornell–Larcker criterion confirmed the presence of discriminant validity.

Table n°1: Reliability and Validity of Constructs

Construct	Cronbach Alpha	Composite Reliability (CR)	AVE
Attitude (ATT)	0.82	0.87	0.65
Subjective Norms (SN)	0.80	0.88	0.63
Perceived Behavioral Control (PBC)	0.83	0.87	0.62
Trust (TRU)	0.89	0.92	0.75
Fairness (FAI)	0.85	0.90	0.68
Intention (INT)	0.88	0.91	0.71

Note. Cronbach's alpha (α) values above .70 indicate acceptable internal consistency (≥ .80 preferred for established scales). Composite Reliability (CR) values between .70 and .95 confirm internal consistency reliability, and Average Variance Extracted (AVE) values above .50 demonstrate adequate convergent validity.

IIII-3- Structural Model

The extended TPB model explained 53% of the variance in intention. All proposed pathways were statistically significant. Trust was the strongest predictor, followed by subjective norms and attitude.

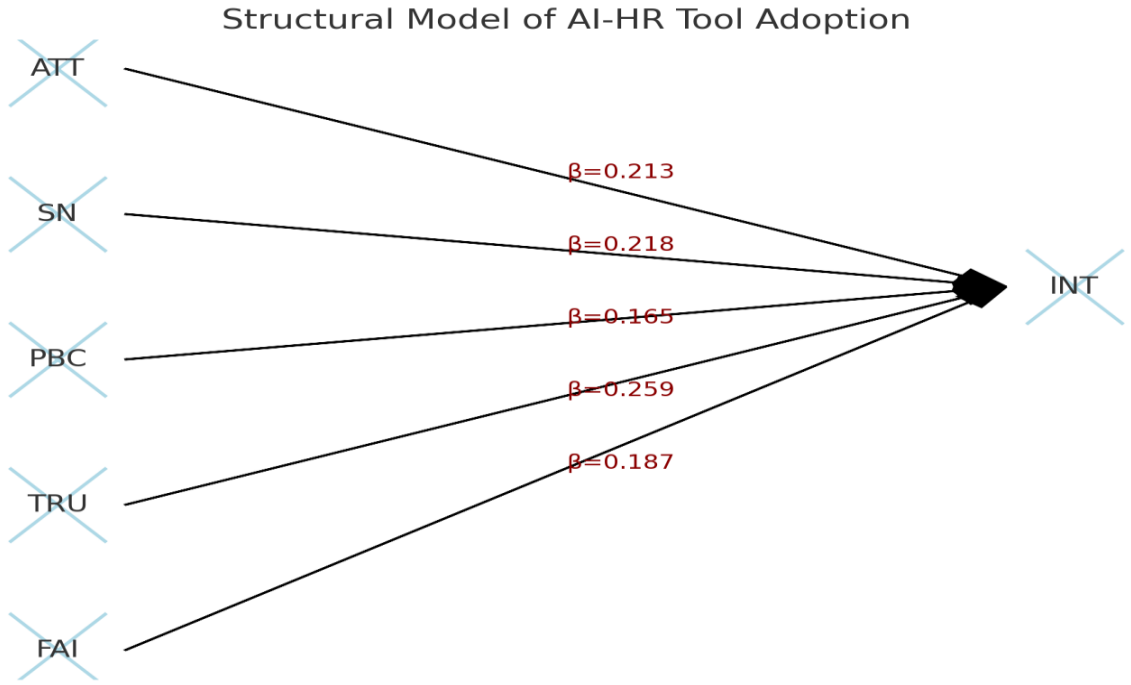
Table n°2: Structural Model Results

Path	(Standardized)	p-value	Effect Size
ATT → INT	0.213	< .01	0.05
SN → INT	0.218	< .01	0.06
PBC → INT	0.165	< .05	0.04
TRU → INT	0.259	< .001	0.09
FAI → INT	0.187	< .01	0.07

Note. Effect sizes interpreted as small = 0.02, medium = 0.15, and large = 0.35 (Cohen, 1988). All paths significant at $p < .05$.

The Stone–Geisser's Q^2 values, obtained via blindfolding, were all above zero, confirming adequate predictive relevance of the model.

Figure n°1: Structural Model of AI-HR Tool Adoption



Note. All path coefficients are significant at $p < .05$. R^2 for Intention = .53.

IIIII- Discussion

This research substantiates the predictive efficacy of the Theory of Planned Behavior (TPB) regarding the adoption of AI-HR, identifying trust and fairness as principal explanatory variables. Trust was identified as the most significant factor, underscoring the importance of transparency, data security, and dependability in promoting acceptance (Glikson & Woolley, 2020).Fairness is also important: workers are more likely to use AI technologies that they think are fair and follow the right steps (Binns, 2018).

IIIII-1- Comparison with Previous Studies

TAM and UTAUT focus on perceived usefulness and ease of use. However, our findings show that in high-stakes HR contexts, ethical and social factors, especially trust and fairness, are equally important. This is consistent with evidence from healthcare and finance, where ethical considerations significantly impact AI adoption.

IIIII-2- Consequences for Theory

This research extends the Theory of Planned Behavior (TPB), demonstrating that behavioral models should incorporate the ethical and emotional aspects of artificial intelligence. It shows that intention is shaped not only by cognition but also by perceptions of justice and reliability.

IIIII-3- Real-Life Trade-Offs

Organizations must balance transparency and efficiency in AI implementation. Highly accurate but opaque AI systems may not engender trust, whereas more interpretable systems may be less efficient. HR leaders should prioritize approaches that enhance comprehensibility, fairness, and employee engagement to mitigate these trade-offs. To operationalize this balance, organizations can track transparency through specific metrics such as explanation

accuracy and audit frequency. By routinely assessing these indicators, HR leaders can ensure that AI systems are both transparent and efficient, making the implementation process more actionable and trustworthy.

IIIII-4- Directions for Future Research

Future research should examine trust and fairness as mediators or moderators within the TPB framework, conduct cross-cultural comparisons, and use longitudinal designs to track changes in perceptions over time.

IIIIII- Practical Implications

Promote transparency to build trust by offering user-friendly AI dashboards and ensuring employees understand decision-making processes. In Saudi Arabia, dashboards should highlight group achievements and shared progress to reflect collectivist values. Address power distance by clarifying decisions at various organizational levels and the role of AI. These cultural adaptations will enhance employee trust and engagement.

Ensure fairness by conducting regular audits and gathering employee feedback on AI-driven HR systems.

Enhance organizational readiness by providing training programs that increase employees' understanding of AI and promote empowerment.

Align HR practices with cultural norms by emphasizing fairness and social legitimacy, especially in environments with high collectivism and power distance.

IIIIIII- Limitations and Future Research

This study advances understanding of AI implementation in HRM but has several limitations. First, the cross-sectional design limits causal inference. Longitudinal or experimental research is needed to examine how trust and fairness perceptions develop over time and influence actual adoption. For example, tracking changes in AI tool usage over six months could provide valuable insights into sustained adoption and the evolving impact of trust and fairness and institutional context of Saudi Arabia may limit generalizability. Cultural traits such as collectivism and power distance may elevate the significance of subjective norms like fairness. Subsequent research should conduct comparative studies in diverse geographical contexts (e.g., Western, Asian, and Middle Eastern settings) to assess the robustness of the extended Theory of Planned Behavior (TPB) model.

Third, reliance on self-reported survey data raises concerns about social desirability bias and common method variance. Future studies should incorporate multiple data sources, such as HR performance records and system usage logs, to validate findings.

FourthFourth, the model considered trust and fairness only as direct determinants. Future research should explore these variables as mediators or moderators within the TPB framework. Additionally, domain-specific analyses may reveal important contextual differences, since AI technologies in HRM are changing quickly, future research should look into new issues like how to make algorithms easier to understand, how to hold people accountable, and how to follow the rules. These factors may affect adoption in ways that aren't shown in the current paradigm.

Conclusion

This study shows that employees' willingness to adopt AI-driven HR technologies is influenced by TPB constructs, trust, and perceptions of justice. Trust was the most significant factor, highlighting its importance in high-stakes HR settings. By integrating trust and fairness, this research enhances the TPB framework and demonstrates that ethical and socio-emotional factors are as important as cognitive evaluations in technology adoption.

From a managerial perspective, these findings highlight the importance of promoting transparency, ensuring algorithmic fairness, and building employee trust through clear communication. Organizations should implement AI systems alongside ethical policies, regular audits, and targeted training programs to address concerns related to fairness and trust. Such initiatives will foster more effective and responsible AI adoption in human resource management. As AI increasingly shapes organizational decision-making, HR leaders and researchers must continue to balance efficiency with fairness, transparency, and employee wellbeing.

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