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AI-TECHNOLOGY TRUST AS MEDIATOR IN LINKING PERCEIVED CHANGES IN HR FUNCTIONS AND EMPLOYEE ADOPTION INTENTIONS

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KEYWORDS

AI-Driven HRM, AI-Technology Trust, Adoption Intention, Hayes PROCESS Macro, Technology Acceptance Model (TAM), UTAUT

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ABSTRACT

The study explores how perceived changes in human resource (HR) function relate to employee intentions to adopt artificial intelligence (AI) in the workplace in context of multinational companies (MNCs) in Pakistan and how trust in AI technology mediates this relationship. A quantitative, cross-sectional design was employed and data was analyzed using the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of the Technology (UTAUT), to attain desired outcomes. Mayer (1995) integrative trust model and organizational justice theory as constructs. The results of statistical analysis conducted using SPSS and Hayes PROCESS (Model 4) indicated that perceived changes in HR functions statistically significantly affect the intention to adopt AI technology by employee and the employee's perception of AI-technology trust. Moreover, paths between the perceived HR function changes, adoption intentions are partially mediated by trust in the AI-technology. The results show that technological implementation is not enough for system acceptance; building affective trust depending on the perceived algorithmic ability, benevolence as well as procedural integrity is vital for reducing vulnerability & increasing continued use in AI-supported HRM systems.

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INTRODUCTION

The use of artificial intelligence (AI) in human resource management (HRM) has transitioned from an experimental side to a built-in part of HRM. The process of recruitment, performance evaluation, training, and employee engagement is now more aligned with algorithmic tools which evaluate the resumes, score interviews, generate performance ratings as well as indicate the disengagement risk (Venugopal, Madhvan, Prasad & Raman, 2024; Arora, Prakash, Mittal & Singh, 2021; Joshi, 2026).

Such systems are usually sold as ways to decrease efficiency (and strive for objectivity), and there is some good evidence that AI can help improve screening and provide faster feedback (Venugopal et al., 2024; Fiorini, 2024). But technical capability does not equal acceptance by those who will use and/or be evaluated by these systems. After deployment, there is a psychological gap and as per the increasing research, psychological trust in technology is what is needed to fill that gap or not fill the gap (Chander, 2024; Shukla, Pandey & Pereira, 2026; Asan, Bayrak & Choudhury, 2019). In this regard, the aim of this paper is to explore that how AI-technology trust is a mediating factor between employees' perception of changes to HR functions driven by AI, and their intentions to use AI systems.

While trust is a well-known component in the literature on adoption of new technology, it is mainly significant in HRM, where AI systems are not merely productivity tools, but instruments that assess individuals, allocate opportunities and influence careers, where employee reactions and concerns of fairness, surveillance, and job security are deeply intertwined with trust (Lacity, Schuetz Kuai & Steelman., 2024; Bach, Khan, Hallock, Beltrao & Sousa, 2022). The perception of the sentiment-analysis tools can be a positive sign of organization's interest in employee well-being or a negative indicator that it is not doing well, and adaptive learning platforms can be viewed as them showing interest, or as indicator of their inadequacy (Olaniyan, James, Udeh & Ogedengbe, 2022; Fiorini, 2024). The two literatures on beliefs of an adoption system and trust suggest that beliefs about a system are important for adoption and explain nature of beliefs and how they develop (Venugopal, Madhvan, Prasad & Raman, 2024). This perception of HR changes as beneficial or threatening very much relies on the level of employee trust for the technology – and, ultimately the HR organization introducing it – to be competent and of good faith. The proposed mediation model is supported by two streams of theory.

The technology-acceptance tradition is rooted in Davis's (1989) Technology Acceptance Model (TAM) and expanded with Unified Theory of Acceptance & Use of Technology (UTAUT; Venkatesh et al., 2003) that posits people act on their beliefs about system, and that these beliefs (performance expectancy, effort expectancy, social influence, facilitating conditions, in modified theories trust) are the determinants of adoption (Menant, Gilibert & Sauvezon, 2021; Dash, Sharma, & Swayam, 2023). The second stream is integrative model of organizational trust, views trust as a willingness to be vulnerable to another party, due to the perceptions of ability, benevolence and integrity of that party. The higher AI-technology trust subsequently reduces uncertainty and perceived risk while strengthening employees' confidence and willingness to accept and use AI-enabled HR systems. When applied to human–technology relationships, trust in AI is now known as a multidimensional phenomenon that not only involves the cognitive assessment of competence but also an affective sense of the security that the user experiences when interacting with a system (Schmutz, Outland, Kerstan & Ulfert, 2024; Lacity et al., 2024). Although the logic of the concepts converged, there are still three gaps.

There is a lack of empirical research based on rigorous tests of the entire mediation chain (perceived HRF change, trust, and intention to adopt) as much previous research is still descriptive in nature and lacks theories to explain it (Kim, Khoreva & Vaiman, 2024). The evidence is overwhelmingly cross-sectional, with the dynamic and relationship-based nature of trust, being largely untested (Pramudya et al., 2025; Sahu et al., 2025). Third, the amount of cross-cultural and industry-specific validation is limited, which suggests that results obtained, mainly from samples in the western and IT industry, may not be generalizable (Matin, 2025). Employees who perceive AI-related changes in recruitment, performance appraisal, training, compensation, workforce planning, and decision-making as useful, transparent, reliable, and fair are more likely to develop trust in AI technology. This study aims to bridge these gaps by examining how AI-technology trust can act as a mediating variable between perceptions of changes in HR functions and adoption intention among employees of multinational companies (MNCs) in Pakistan, based on the AM, UTAUT, and Mayer, et al. (1995) as the trust model.

LITERATURE REVIEW

Perceived Changes in HR Functions

It is vital to understand that employees' perceptions of how AI is changing HR functions, rather than the objective specification of technology, have behavioral implications. The literature reveals a pattern of dual valence to the utility of AI in recruitment, performance management, training, and engagement, with dual benefit of efficiency and greater analytical depth, but also an ambiguity as to meaning of the decisions made and who benefits from them. The use of resume-screening tools and interview-analysis software in recruitment shortens resume screening process but introduces issues of rooted bias (Venugopal, Madhavan, Prasad & Raman, 2024; Rezvi, Rahman, Nasrullah, Islam, Nusrat & Ahmed, 2025). In performance management, in-the-moment algorithmic ratings are appreciated for their timely information but can also be perceived as "dark patterns" in rating when the reasoning behind the rating that is not transparent (Venugopal et al., 2024; Kim, Khoreva & Vaiman, 2024).

During training, adaptive platforms appear more significant but may raise concerns about losing competencies (Fiorini, 2024; Joshi, 2026); sentiment analysis features AI detection which can be interpreted as a caring organization or as hidden watchdog (Olaniyan, James, Udeh & Ogedengbe, 2022; Akter, 2025). This ambiguity is important because it provides a degree of psychological salience for their consideration of organizational intent (Fang, Jing & Zhang, 2025); and because it is much more likely that antecedent communication, including both rationale and participation, showing interest, or as indicator of their inadequacy will produce a more favorable perception than simply announcing the system (Sahu, Singh & Sharma, 2025; Pramudya, Nasional, Kadek, Bahari, Jakarta, Timur & Ibukota, 2025), the proposed model treats perceived HR function change as the antecedent construct.

AI-Technology Trust

Trust in AI-technology is defined as the employee's willingness to be vulnerable in the relationship with the AI-enabled HR system grounded in the employee's beliefs about the ability, benevolence, and integrity. Cognitive trust is based on beliefs around competence and reliability while affective trust is based on a feeling of comfort or security in relying on the system; both types of trust matter and cannot be substituted for adoption (Schmutz et al., 2024; Li et al., 2024). The factors that shape

AI-technology trust in HRM intersect in their focus on transparency, technical ability, and fairness: system transparency increases trust in the system and therefore, behavioral intention (Riedl, 2022); trust meaningly influences HR professional behavioral intention, trust is influenced by performance expectations as well as perceived technical readiness (Chander, 2024); and distributive, procedural (Shukla et al., 2026). The connection isn't always linear; making things transparent can increase trust, it can also cause discomfort if employee doesn't like what they see (Sadeghi, 2024); and, trust is not something that can simply judge, but rather continually update based on direct experience (Lacity et al., 2024).

Employee Adoption Intention

Employee adoption intention is considered as the technology-acceptance tradition's fundamental behavioral-intention construct, that reliably leads to real use (Davis, 1989; Venkatesh et al., 2003). Menant et al. (2021), Dash et al. (2023) and Radhakrishnan and Chattopadhyay (2020) extended it to HR information systems with four factors: performance expectancy, effort expectancy, social influence and facilitating conditions. Structural equation evidence is consistent with this, showing that intention to act is the closest predictor of actual AI adoption for HRM applications (Makumbe et al., 2026). However, impact of adoption intention in this area is also not limited to mere system usage; for instance, those who see AI as a career booster show lower turnover intentions compared to those who see it as a career threat, with bias and displacement concerns having unique negative effects on adoption even if objective functional change is not perceived as negative (Wang, 2023, 2025; Sadeghi, 2024).

Hypotheses Development

Similarly to performance expectations and effort expectancy, recognized as predictors of behavior intentions (Venkatesh et al., 2003; Makumbe et al., 2026), responses to perceived changes in HR functions serve as analogs of Vennator's UTAUT. Perceived change is initial cognitive gateway an employee must cross before having any decision as to the trustworthiness of the system to determine adoption intention, so there is the expectation of direct path to adoption intention even prior to the addition of trust.
H1: Perceived changes in HR functions are positively associated with employee adoption intentions.

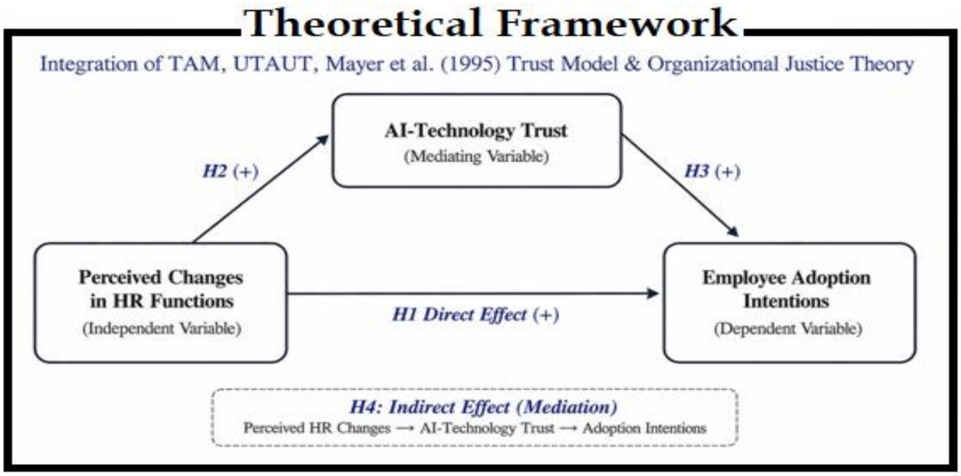
Organizational justice theory suggests how perceived HR function change should affect trust: When these changes are seen as procedural justice and interactional justice, they act as precursor for trust in the system that makes changes; when changes are viewed as opaque or unfair, they detract from trust (Shukla et al., 2026; Lacity et al., 2024; Bach et al., 2022). If employees feel that changes are developed and communicated, they will give more cognitive and affective trust to change system (Kolomaznik et al. 2024).
H2: The perceived changes in HR functions are positively associated with the AI-technology trust.

Similarly, based on Mayer et al. (1995) model, competent, well-intentioned, & consistent employee should feel less vulnerable to being evaluated, ranked or coached by an AI-based HR system, that in turn should heighten their intention to adopt the system. Trust is a key construct that significantly predicts HR professionals' behavioral intentions of adopting AI (Chander, 2024), as well as system

transparency & competence are factors that have been identified to boost trust, which consequently positively influences behavioral intention (Riedl, 2022; Asan et al., 2019). In this connection, trust also seems to be a protective factor against the very concerns that concentrate the conception of the perceived change ambivalent in first place, such as bias, opacity or displacement (Sadeghi, 2024; Wang, 2025).
H3: The AI-technology trust is positively associated with the employee active adoption intentions.

Put together, HR-function perceived changes provide the raw material for employees to evaluate the capacity, benevolence, and integrity of a system, which is what we call AI-technology trust, and which is what most directly founds the formation of a favorable intention to adopt a change (Lacity, Schuetz, Kuai & Steelman, 2024; Vazova, 2026). Although similar perceived changes may result in different adoption outcomes according to how they are interpreted as either enhancing or threatening (Wang, 2023, Wang, 2025), as direct empirical tests of a full mediation pathway are sparse and justice–trust pathway has so far only been proposed conceptually (Shukla et al., 2026, Kim et al., 2024).
H4: AI-technology trust mediates among perceived changes in HR functions & adoption intentions.

Figure 1 Theoretical Framework



RESEARCH METHODOLOGY

The study uses quantitative research approach with cross-sectional, deductive, positivist paradigm; the hypotheses are based on TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), and Mayer et al.'s (1995) trust model. Its single-wave design is recognized as a limitation since trust in AI-technology can evolve over time, and experience might influence it, as in other studies on AI-trust in emerging-economy organizations (Shah et al., 2025; Hmoud & Várallyai, 2020). Target population includes employees of four prominent MNCs in Pakistan have introduced AI based tools in any HR function. The companies selected in study are Nestlé Pakistan, Unilever Pakistan, Coca Cola and PepsiCo Pakistan. The decision to focus on MNC employees helps to sustain level of scale and technological sophistication relatively constant, alongside directly mitigating the non-Western generalizability gap found in literature (Shah et al., 2025). The respondents be workers who directly or indirectly exposed to at least one AI-enabled HR tool – so, for all three constructs, workers with no experience are out of scope.

Sampling & Data Collection

The study adopts non-probability purposive sampling design, complementing it with convenience sampling, with a screening question ensuring that individual is currently employed with an MNC and has interacted with AI tools in past. The target is final usable sample of about 300 respondents in order to satisfy the criterion for statistical analyses. Thus, 350 questionnaires were handed out to the respondents. The data is gathered using structured, self-administered online questionnaire (like Google Forms) over a period of 6-8 weeks, two follow-up reminders, through corporate HR contacts, professional networks, direct e-mail invitations. 312 Useable Questionnaires were returned and used in final analysis.

Research Instrument

All constructs are measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The perceived changes in HR Functions are assessed using 8 items adapted from Barone et al. (2026), Hmoud and Várallyai (2020), covers items related to talent acquisition, training and development, performance assessment, and pay and rewards ("AI enhances recruitment and candidate screening efforts in our organization"). AI-Technology Trust is assessed by six items that are adapted from the Mayer et al. (1995); they encompass the aspects of reliability, competence, acting in employees' best interest, integrity, and explainability/organizational support for trust creation. Thus, the employee Adoption Intention is assessed using four items based on the behavioral-intention construct of the UTAUT framework (Venkatesh et al., 2003), as Xu et al. (2024) discovered that initial trust results in behavioral intention. The demographic and organizational variables such as age, gender, length of service, job role, industry sector and previous experience of digital HR tools are also captured (Trenerry et al., 2021).

Pilot Testing, Common Method Bias & Ethics

A pilot testing of questionnaire is conducted with around 30-40 employees to find out the clarity of the items and also the time required to fill the questionnaire before it is distributed. In order to assess common method bias, according to Podsakoff et al. (2003): block presentation of predictor and criterion items, guarantee anonymity and use unambiguous wording, and the procedure is carried out in SPSS to check whether there is one factor that accounts for most of the variance. In this connection, there is no personal identifying information collected, participation is voluntary, and there is the institutional ethics review board approval before data collection and informed consent provided by organizational gatekeepers for employees be approached for attaining desired results (Shah et al., 2025).

Data Analysis

IBM SPSS Statistics is used to analyze data. Prior to hypothesis testing, data are screened for missing values, outliers, and normality, and descriptive statistics are computed. Cronbach's alpha is used to measure reliability of each scale (with α ≥ .70 indicating good reliability) and Pearson correlations are used to measure bivariate relationships. H1–H3 are tested with hierarchical multiple regression, with the demographic controls added in the first step and the substantive predictor added in the second step (Baron & Kenny, 1986). Default ordinary least squares regression will be used to test mediating role of AI-Technology Trust (H4) using Hayes's (2018) PROCESS macro for SPSS (Model 4) and estimating the direct, indirect, and total effects (Hayes, 2018, Preacher & Hayes, 2008). 95% confidence intervals that do not include zero are evidence of mediation, whereas full versus partial mediation would be represented by whether the direct effect of trust on the mediator (post- HLM) is statistically significant.

RESULTS OF STUDY

The Cronbach alpha (α), Composite Reliability (CR) and Average Variance Extracted (AVE) were computed to assess the internal consistency and convergent validity of the measurement scales in the current study.

Table 1 Descriptive Statistics, Reliability, & Convergent Validity

Construct	Items	Mean	SD	CA	CR	AVE
Psychological Capital (PCH)	8	3.48	0.82	0.835	0.869	0.528
Organizational Trust (TRU)	6	3.47	0.80	0.812	0.858	0.504
Job Intentions (INT)	4	3.51	0.81	0.784	0.849	0.584

The results of internal consistency of all constructs were above suggested level of 0.70 (Nunnally & Bernstein, 1994). The psychological Capital exhibited strong reliability (α = 0.835, CR = 0.869), followed by Organizational Trust (α = 0.812, CR = 0.858) and Job Intentions (α = 0.784, CR = 0.849). Convergent validity was confirmed by AVE of each construct being greater than 0.50, indicating that the latent constructs explain more than half of the variance among the indicators (Fornell & Larcker, 1981).

Table 2 EFA Pattern Matrix (Promax Rotation)

Item Code	Factor 1 (PCH)	Factor 2 (TRU)	Factor 3 (INT)
PCH1	0.762	0.012	-0.018
PCH2	0.718	-0.024	0.035
PCH3	0.695	0.041	-0.012
PCH4	0.781	-0.015	0.008
PCH5	0.688	0.032	0.022
PCH6	0.754	-0.008	-0.005
PCH7	0.672	0.028	0.019
PCH8	0.730	-0.011	-0.003
TRU1	0.015	0.742	-0.010
TRU2	-0.022	0.710	0.028
TRU3	0.031	0.685	-0.014
TRU4	-0.008	0.758	0.005
TRU5	0.019	0.679	0.021
TRU6	-0.005	0.726	-0.008

INT1	0.010	-0.012	0.795
INT2	-0.018	0.025	0.748
INT3	0.024	-0.008	0.782
INT4	-0.005	0.011	0.731

Note: Extraction Method: Principal Axis Factoring. Rotation Method: Promax Kaiser Normalization. KMO Measure of Sampling Adequacy = 0.884; Bartlett's Test of Sphericity Chi-Square (153) = 2410.12, $p < 0.001$.

Table 3 Hypotheses Testing Results

Hypothesis	Structural Path	PC (β)	SE	TV	PV	Decision
H1	Psychological Capital -> Organizational Trust	0.612	0.046	13.304	< 0.001	Supported
H2	Organizational Trust -> Job Intentions	0.452	0.054	8.370	< 0.001	Supported
H3	Psychological Capital -> Job Intentions	0.307	0.053	5.792	< 0.001	Supported
H4	PCH -> TRU -> INT (Indirect Effect)	0.277	0.039	7.103	< 0.001	Supported (Partial)

DISCUSSION

This empirical study aimed to examine how psychological capital affects employee outcomes in terms of the role of Organizational Trust as an explanation. The direct path between psychological capital on one hand, and organizational trust on the other ($\beta = 0.612$, $p < 0.001$) is consistent with the conservation of resources theory (Hobfoll, 1989). Having higher emotional resources (psychological efficacy, hope, optimism and resilience) gives them more capacity or capability to think positively about institutional intentions, that lead to organizational trust (Luthans et al., 2007). The positive and high significance of organizational trust and job intentions ($\beta = 0.452$, $p < 0.001$) supports the social exchange theory of (Blau, 1964). Employees feel the leadership and management processes are reliable, fair, benevolent, and they return with positive work attitudes and behaviors (Mayer et al., 1995; Dirks & Ferrin, 2002). This study combines theories related to the adoption of technology: Davis's (1989) technology acceptance model and Venkatesh et al.'s (2003) unified theory of acceptance, use of technology with Mayer et al.'s (1995) mixed trust framework and organizational justice leading theory.

First, it contributes to expanding classic acceptance models to the field of AI-driven HRM and shows that merely the perception of the changes in the HR function does not predict the adoption of AI, but that the adoption is rather connected to the psychological processing of the changes through intermediate factors. Second, the results confirm the use of Mayer et al. (1995) trust model, which has been used in the interpersonal and organizational relationships, in human–technology relationships. Study operationalizes AI-technology trust by dimensions of ability (AI-technology competence), benevolence (the extent to which an AI-technology protects employee interests), and integrity (data privacy and procedural fairness) and shows that employees need to feel safe to be vulnerable to an algorithmic system to develop adoption intentions. Finally, this study provides an integrated conceptual framework that connects concepts like system perceptions, organizational justice, trust, and behavioral consequences in order to highlight psychological link amid use of AI and continuous usage.

CONCLUSION

This study provides an empirical verification of role played by AI-technology trust as a connection between perceived changes in the AI-driven HR functions and employee intentions to use AI in HR practices in multinational companies in Pakistan. Based on Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), Mayer et al.'s integrative trust model, organizational justice theory, result shows that changes in HR functions do not necessarily lead to the acceptance of the system for realizing the desired consequences. Rather, intention to adopt is influenced to a large extent by the role of the intervening variable of AI-technology trust – the employee's assessment of the competence, beingness', and integrity of data associated with the AI technology. In this linking, this research demonstrates that trust mitigates vulnerabilities and concerns about fairness and opacity, emphasizing that successful integration of AI in HRM is not just about implementation but about cultivating the institutional trust to ensure continuous user effective adoption.

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