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Artificial Intelligence Adoption in Human Resource Practices in Nepal: Trust, Performance, and Organizational Outcomes

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ABSTRACT

Artificial Intelligence (AI) is affecting human resource (HR) practices internationally, but little is known about AI adoption in Global South countries, such as Nepal. This research analyzes employees' attitudes towards AI implementation in HR processes and its consequences for trust, job performance, and organizational outcomes. For this research, the constructs were defined as: trust was operationalized as employees' beliefs about the reliability and integrity of AI-based HR decisions; fairness was conceptualized as justice and bias in AI-based processes; and transparency was conceptualized as the degree to which a user's perceptions of disclosure and openness of the mechanisms behind AI algorithms and decisions. These constructs were measured using a number of Likert-scale items adapted from validated scales. This enabled the evaluation of each construct and was included in the overall mean scores for trust, fairness, and transparency ($m = 3.51$). A Systematic Review and a causal Configurational explanation were used to conduct the research, which involved 41 employees from the service, banking, IT, and telecommunications industries in Nepal. The evidence shows a moderate level of AI-HR adoption (mean=3.69) and a moderate level of trust, fairness, and transparency (mean=3.51) within participants. The results also indicate that employees held favorable views regarding the impact of AI on their individual performance ($M=3.98$) and on organizational outcomes ($M=3.96$). Despite a high level of digital readiness (mean = 3.98), a number of concerns, including decline of human decision making (56.1%), job loss (51.2%), and privacy (46.3%), were expressed. Results have demonstrated that good practice in teaching and learning of AI requires responsible governance. Employee achievement is also positively associated with the company's success ($r = 0.73$, $p < 0.01$). Employee job ($\beta=0.42$, $p<0.001$) and AI utilization ($\beta=0.34$, $p=0.014$) were significant predictors of organizational performance in the regression analysis. Staff engagement, ethical practice, and access to continual AI-related information are needed to build confidence and attain institutional good practice.

Keywords: AI adoption, artificial intelligence, employee confidence, human resource management, job performance, organizational performance

INTRODUCTION

Artificial intelligence (AI) is a prominent term in information technology (IT) today, and it can deeply influence how organizations manage human resources. AI is a computer program that can learn, solve problems, interpret data, and understand natural languages (Caluori, 2023). The use of AI in HRM for recruiting, performance management, training, and employee retention is augmented by Analytics and algorithmic models (Purohit & Banerjee, 2025).

The use of AI in HRM may provide the organization with numerous advantages, including increased efficiency, reduced workload, enhanced decision-making accuracy, and greater strategic congruence. A number of researchers have shown that AI-based HRM processes result in reduced recruitment time, greater objectivity in performance appraisals, and heightened employee engagement. Yet the adoption of technology such as AI also comes with its portion of challenges, including machine bias, opacity, violations of worker privacy, and unemployment.

Although there is a substantial corpus of literature on AI-HRM in developed countries, few empirical studies have examined it in developing countries. The gap in the literature is more apparent when examining a South Asian country, Nepal, which is currently experiencing rapid digitalization, yet studies on employees' perceptions of AI remain in their infancy. Perception too matters, since employee acceptance is vital to the success of any AI program (Pandey et al., 2023).

This study applies a combined model of TAM, organizational trust theory, and STS theory. The models in the TAM family consider two factors as determinants of technology adoption (Dwivedi et al., 2023). TAM informed the choice and operationalization of the technology-related perception constructs; Trust Theory informed the focus on trust, equity, and transparency, as well as their measurement, while Socio-technical Systems Theory provided the lens to understand the relationship between technology-related perception and organizational context. This integrated model enabled a diverse exploration of the combined effects of the technological perceptions of AI adoption, trust-related constructs, and sociolect-organizational constructs.

The major research problems are the limited evidence from Nepal and employee perceptions understanding the use of AI. Few studies have addressed the Issue in the context of developing countries. The existing literature has emphasized developed countries, with very little focus on specific contexts within the South Asian region, such as Nepal. This lacuna is important because cultural, organizational, and technological environments are diverse. This paper fills this gap in the literature by studying perceptions of and outcomes from AI in Nepal.

The major research objectives of this study were to examine employée perceptions, to assess relationships among AI, trust, and performance.and to identify predictors of organizational performance.

This study is important in theoretical, practical, and policy terms. It advances the literature on Artificial Intelligence (AI) in Human Resource Management (HRM) by supplying evidence from Nepal, a developing country where studies on AI adoption in HR practices are scarce. Most previous research has concentrated on developed countries, leaving a gap in how people working in the digitally emerging world view and respond to AI-enabled HR systems. Secondly, the study broadens conceptual understanding through integrating the Technology Acceptance Model (TAM), the Organizational Trust Theory, and the Socio-Technical Systems Theory. This combined approach develops a novel conceptual model to investigate the impact of perceptions of AI use, trust, fairness, and transparency/digital readiness on employee and organizational outcomes.

This study offers some practical consequences for organizations that want to implement AI-enabled HR. By identifying the factors that create trust in and acceptance of AI-based solutions, the study adds to the design of HR IS that improve employee performance, promote corporate success, and tackle privacy and employment-related concerns, as well as human monitoring. Fourth, the study has policy consequences for the rest of the world, especially for underdeveloped countries like Nepal, in the new era of digitalization. The studies show the requirement for ethical AI governance, employee participation in AI, transparency in AI, and AI literacy training to guarantee the responsible and sustainable development and use of AI tools in organizations. Finally, this research creates a channel for upcoming studies on the adoption of AI in HRM via addressing other relevant issues that deserve further investigation, such as organizational trust, worker well-being, digital readiness, and the long-term impact of AI on workforce management.

LITERATURE REVIEW

AI in human resource management

AI applications in HRM cover the entire employee life cycle, including recruiting, training, managing, and retaining employees (Thulasidoss et al., 2023). Algorithms scan resumes, predict candidate success, and reduce recruiting bias, all with the help of machine learning. Sentiment analysis of employee surveys and automated replies are also possible thanks to natural language processing. High performers are identified using a predictive analytic turnover model. These capabilities enable HR to make decisions more quickly and accurately, thereby permitting them to focus more on tactical work (Vrontis et al., 2022).

Nevertheless, there are major challenges to applying AI to HMR. Algorithmic management delegates decision-making to intelligent systems, eliciting concerns about transparency, accountability, and the role of humans (Chowdhury, S. et al., 2021). The “black box” character of many AI tools diminishes the trust and confidence of the employees, especially when decisions related to hiring, performance and career progression are still being made via algorithms (Newman et al., 2020).

Trust, fairness, and transparency in AI-HRM

Trust is a key predictor of employees' acceptance of AI-based HR practices (Glikson & Woolley, 2020). They will be more likely to trust such systems if they perceive them to be fair, transparent, and explainable (Langer et al., 2021). There are indications of a ‘trust deficit’ in the literature on automated decision support, and the opacity of AI systems is deemed even larger in consequential contexts (Newman et al., 2020). Although AI makes better predictions than humans, many still have a preference for human decisions based on context sensitivity (Lee, 2018). Fairness beliefs are comprised of two types of justice: procedural justice, the way a decision is made, and interactional justice, the way decisions are communicated (Tyler, 2023). In the absence of meaningful human participation, employees will perceive AI-driven HR decisions as less procedurally fair. Likewise, disclosure, explainability, and similar products considerably affect employees’ attitudes. A poor awareness of the underlying algorithms and their results or recommendations may weaken trust, while too much information may confuse consumers (i.e., the "transparency paradox").

Employee concerns regarding AI adoption

Employee Views on the Benefits and Risks of AI Adoption. The good news is that AI leads to higher productivity, lowered administrative burden, and more data-informed decisions. (Pandey et al., 2023) On the warm side of the fence-breaching dotted line, views on AI are relatively evenly split: the technology should make life easier, but the most common concerns are threats to job security, expanded surveillance, dehumanization, and data breaches. Such concerns, in particular the potential loss of jobs and the mechanization of work, are deterrents to business adoption of Artificial intelligence.

AI and organizational performance

The existing literature predominantly shows positive relationships between the application of AI in HRM and business performance (Mikalef & Gupta, 2021), though with some limitations. By their nature, AI-driven HR practices boost effectiveness, innovation, and the quality of decision-making (Pandey et al., 2023). But these are predictions based on the “if” the right Socio-technical system design, employee participation, and moral governance were in place. AI will not fulfill its promise without the right structures and employee involvement (Basu et al., 2023).

CONCEPTUAL FRAMEWORK

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a theory that posits two constructs, perceived usefulness and perceived ease of use, as the main predictors of technology acceptance and use (Davis, 1989).

Organizational Trust Theory

Organizational Trust Theory holds that there are three dimensions: ability, benevolence, and integrity that influence trust, and that these dimensions’ influence whether individuals are willing to trust the system or its outputs in an organizational context (Mayer et al., 1995).

Socio-Technical Systems Theory

Socio-Technical Systems Theory is a theory of organizational form that claims that the social and technical elements of an organization should be considered and jointly optimized to achieve organizational efficacy (Trist & Bamforth, 1951).

HR Analytics and AI-HRM

The increasing use of HR analytics and AI enables HR management to move from an administrative role to a strategic management role within the organization (Marler & Boudreau, 2017).

Digital HRM

Digital HRM is the use of digital technology to transform HR processes and to increase organizational performance (Strohmeier, 2020). The results are consistent and enhance the conceptual models underlying this study. In line with TAM (Davis, 1989), the high scores for perceived usefulness (employee performance, m=3.98) and perceived ease of use (m=3.85) indicate that these variables are the most important determinants of AI acceptance. The significant positive relationship between AI Usage and Employee Performance ($r=0.58$, $p<0.01$) is consistent with the prior assertion in TAM that Technology adoption is mainly influenced by Perceived Usefulness.

Organizational Trust Theory is upheld by the finding that trust, fairness, and transparency (mean=3.51) are moderately but significantly correlated with both employee performance ($r=0.54$, $p<0.01$) and organizational performance ($r=0.61$, $p<0.01$). The "trust deficit" documented in developed countries (Duggan et al., 2020) appears to be present in Nepal, as well, with trust levels remaining only moderate despite AI's perceived usefulness.

Type of Socio-Technical Systems Theory: Technological efficiency is not the only thing that matters; organizations also need trust, transparency, and human participation to achieve good results. Considerable employees' concerns that (1) human decision processes diminished (56.1%) and (2) job loss (1.2%) point out the need for technical balance.

Research Hypotheses

H1:The use of AI has a positive impact on organizational performance.
H2: Trust, Equity, and Transparency are positively related to Corporate Performance.
H3:The use of AI has a positive impact on employee job performance.
H4: Employee Job Performance is positively related to Organizational Performance.
H5: Digital Readiness positively impacts AI Adoption.

METHODS

Research design

A descriptive design was used to objectively describe employees' attitudes towards the use of AI. There were also differences in individuals' perceptions of AI between these two outcomes, as determined by the causal-comparative design. However, causal-comparative designs do not establish cause and effect but identify possible cause-and-effect associations that can be investigated further (Creswell & Creswell, 2018).

Population and sample

For the purpose of this research, the population consisted of employees in the service, banking, IT, and telecom industries in Nepal who are considered more ready for AI implementation owing to their high degree of digitization. The sampling process was limited due to the lack of a complete list and was confined to employees reached through professional associations, e-mail, and social networks. Of the 90 questionnaires distributed via an online survey, 41 (45.6%) responses were valid and thus included in the analysis.

Post hoc G*Power analysis (medium effect size, $\alpha = 0.05$, predictors = 5) was conducted for regression, and power = 0.52 was observed, indicating that statistical power was insufficient for the analyses. Such a small power makes certain Type II errors more likely; it is possible that some true effects were not detected as significant. Thus, the findings, particularly those that came close to but did not exceed conventional significance cut-points, should be viewed with caution because the chances of false negatives and effect-size imprecision are both greater. Under-powered statistical analyses represent a considerable limitation of the present work, and the reader should keep this in mind when considering the reliability of the results.

Pilot test

During adaptation, some terms and expressions were modified for clarity plus cultural fit. For instance, AI-HR and HR process-related vocabulary were replaced with terms. We collected original data through a web-based 35-item Likert-scale (1=strongly disagree to 5=strongly agree) questionnaire that was originally designed and validated. For this study, the questionnaire was carefully translated into Nepali and then back-translated into English to maintain conceptual equivalence. It was made familiar to local users, and references to organizational structures were adapted to the Nepalese work environment. A pilot study involving 5 employees was carried out to assess readability and understanding. Moreover, a few items were reworded for clarity following the pilot study, for example, by reducing sector-specific terminology or adapting examples to better represent the scenarios encountered by workers in Nepal. All the modifications were carried out to retain the items' original meaning and tailor them to the context of respondents in Nepal. Two HR academic experts review the established content validity. Content Validity Index (CVI) of 0.86 (the acceptable threshold for CVI is >0.78 (Polit & Beck, 2006).

Table 1
Cronbach's Alpha

AI Usage & Integration	5	0.78	Acceptable
Trust, Fairness & Transparency	6	0.82	Good
Employee Job Performance	5	0.84	Good
Organizational Performance	6	0.86	Good
Digital Readiness	3	0.72	Acceptable
Employee Concerns	3	0.65	Questionable
Overall Instrument	28	0.89	Good

The instrument as a whole demonstrated good internal consistency (α = 0.89). Most sub-scales are adequate—Employee Job Performance (0.84), Organizational Performance (0.86), and Trust, Equity and Transparency (0.82) are all within the acceptable range. AI Usage & Integration (0.78) and Digital Readiness (0.72) are both acceptable, though the latter is borderline low for a three-item scale. The strongest limitation is Employee Concerns (α = 0.65), which is questionable – its three items do not appear to measure the same underlying concern in a reliable manner. In short, the survey is reliable overall, but any results specific to the Employee Concerns construct should be treated with caution.

Ethical issues

The ethical approval stated that participation was voluntary, that participants had the right to withdraw at any time, and that the confidentiality of data and contact information would be maintained. The data were collected anonymously; potential email addresses (optional) were stored separately and password-protected. The responses were aggregated; it was not possible to identify any individual. The data will be stored for five years and then erased. There was no coercion, and the participants had the option to receive a summary of the study's results.

The data were analyzed in SPSS Version 26.0 and Microsoft Excel. Data preparation and analysis were conducted, with data cleaned, negative items reverse-coded, and composite scores computed (Manago, 2023). Descriptive analysis, including frequency, percentage, mean, and standard deviation, was also conducted. The inferential analyses consisted of Pearson correlations, independent-samples t tests, one-way between-subject's analysis of variance (ANOVA), and multiple regression (Kharel & Niraula, 2026) The level of significance was set at α = 0.05, two-tailed (Rao et al., 2024).

DATA ANALYSIS

Table 2
Demographic Profile

Gender	Male	33	80.5%
	Female	8	19.5%
Age	Below 25	2	4.9%
	25-34	12	29.3%
	35-44	9	21.9%
	45+	18	43.9%
Education	Bachelor's	9	22.0%
	Master's	28	68.3%
	MPhil/PhD	2	4.9%
	Other	2	4.9%
Sector	Service	19	46.3%
	Banking	13	31.7%
	IT/Telecom	3	7.3%
	Other	6	14.6%
Experience	<2 years	5	12.2%
	2-5 years	6	14.6%
	6-10 years	7	17.1%
	>10 years	22	53.7%

Position	Entry	6	14.6%
	Mid-level	15	36.6%
	Managerial	12	29.3%
	Senior	5	12.2%

Descriptive information for the 41 respondents is shown in Table 2. Most were males, 80.5%, and females were 19.5%. Most of the respondents were 45 years and above (43.9%), followed by those in the age groups 25–34 years (29.3%) and 35–44 years (21.9%). In terms of education, most respondents held a Master's degree (68.3%), and the rest held a Bachelor's, M Phil/PhD, or other qualifications. Sector-wise distribution: Almost half of the respondents belong to the service sector (46.3%), followed by banking (31.7%), and IT/Telecom (7.3%. Over half of the respondents (53.7%) had more than 10 years of work experience, denoting an experienced sample. Mid-level employees (141; 36.6%) constituted the largest group, followed by managerial-level employees (113; 29.3%). In general, the sample was dominated by males who were highly educated, experienced, and mainly employed in service and banking.

Table 3
The Use and Integration of AI (M=3.69)

AI improves HR efficiency	4.02
AI supports HR decision-making	3.90
AI technologies are easy to use	3.85
AI integrated into HR practices	3.54
AI used in recruitment	3.51
AI evaluates employee performance	3.32

From Table 3, overall, the respondents somewhat agree that AI is applied and embedded in human resources (M=3.69 out of 5). Improving efficiency (4.02) and informing decision-making (3.90) received the highest ratings, reflecting that AI is regarded as an operational support tool. The lower ratings in recruitment (3.51), inclusion in practices (3.54), and, above all, performance appraisal (3.32) indicate that these aspects reflect lower-level or less mature AI implementation. In short, AI is considered helpful with mundane labor, but it is not yet ubiquitous across all areas of HR.

Table 4
Trust, Fairness, and Transparency (Weighted Mean=3.51)

Organization uses AI responsibly/ethically	3.63
Trust AI systems in HR processes	3.54
AI treats employees without bias	3.54
Confident relying on AI-driven HR decisions	3.51
AI systems are transparent	3.46
AI-based HR decisions are fair	3.39

Table 4 shows respondents are moderately positive about trust and equity (mean = 3.51), but doubt persists. The highest score for responsible/ethical use (3.63) shows confidence in the organization's intent. However, lower scores for transparency (3.46) and justness of AI decisions (3.39) reveal perceived gaps between good intentions and actual outcomes. Trust in systems (3.54) and reliance on AI decisions (3.51) are only middling. In short, while people believe the organization means well, they are less convinced that AI systems are open, unbiased, or consistently fair in practice.

Table 5
Digital Readiness

Comfortable using advanced digital technologies	4.15
Can easily learn new AI-based systems	4.07
Understand how AI systems function	3.71

Respondents report strong confidence in their digital adaptability—scoring highest for comfort with digital tech (4.15) and ease of learning new AI systems

(4.07). However, their understanding of how AI functions drops noticeably to 3.71. This reveals a clear gap: people feel capable of using AI tools and picking them up quickly, but they lack deep technical literacy about how the systems actually work underneath the surface. In short, high user proficiency, but low algorithmic comprehension.

Correlation Analysis

Table 6

Correlations Analysis

AI Usage & Integration	.00					
Trust, Fairness & Transparency	.62**	.00				
Employee Job Performance	.58**	.54**	.00			
Organizational Performance	.71**	.61**	.73**	.00		
Digital Readiness	.45**	.38*	.52**	.49**	.00	
Employee Concerns	0.29	0.34*	0.23	0.19	0.08	.00

Table 6 correlations show that most of the studied variables were positively significant. A strong and positive association was found between AI Usage & Integration and Organizational Performance (r = 0.71, p < 0.01), indicating that higher levels of AI utilization would lead to better organizational performance.

The users of AI systems- AI Usage & Integration are also statistically significantly positively correlated with Trust, Fairness & Transparency (r = 0.62, p < 0.01) and Employee Job Performance (r = 0.58, p < 0.01), meaning that successful application of AI techniques can increase both trust and employee performance. Trust, fairness & transparency are also positively related to employee job performance (r = 0.54, p < 0.01) and OP (r = 0.61, p < 0.01), which stresses the importance of trustworthy, fair, and transparent AI systems. The present finding is that employee job performance correlates most strongly with corporate performance (r = 0.73, p < 0.01), again suggesting that better employee performance is a major contributor to company success.

DR is positively related to all the focal constructs, with the strongest association in Employee Job Performance (r = 0.52, p < 0.01), indicating that the more digitally ready employees are, the more they would potentially benefit from AI. Employees' concerns are negatively correlated with the other variables. Significant negative association with Trust, Fairness & Transparency (r = -0.34, p < 0. Based on this data, it seems that digital readiness, AI adoption, and trust in AI improve employee and organizational performance, while employee concerns impede these advantages.

Table 7

Independent Samples t-Test by Gender

AI Usage & Integration	3.72 (0.68)	3.58 (0.82)	0.48	0.632
Trust, Fairness & Transparency	3.54 (0.71)	3.41 (0.65)	0.49	0.627
Employee Job Performance	3.96 (0.59)	4.08 (0.63)	-0.51	0.612
Organizational Performance	3.98 (0.62)	3.91 (0.71)	0.27	0.791
Digital Readiness	3.95 (0.55)	4.08 (0.61)	-0.58	0.565
Employee Concerns	3. 48 (0.83)	3. 29 (0.79)	.59	.557

Table 7 shows the results from the independent-samples t-test show that differences between male and female respondents across all study variables are not significant (all p-values > 0.05). Though small differences in average scores were found, none were significant. This indicates that, in general, male and female employees share the same views on AI Usage & Integration, Trust, Fairness & Transparency, Employee Job Performance, Organizational Performance, Digital Readiness, and Employee Concerns. Hence, in the context of the study, gender does not appear to have a bearing on respondents' opinions regarding AI adoption and its effects on organizations.

Table 8
Multiple Regression Analysis Predicting Organizational Performance

(Constant)	.68	.45		.51	0.139	
AI Usage & Integration	.31	.12	.34	.58	0.014*	.82
Trust, Fairness & Transparency	.18	.10	.21	.80	0.080	.56
Employee Job Performance	.38	.09	.42	.22	<0.001**	.38
Digital Readiness	.12	.11	.12	.09	.282	.44
Employee Concerns	0.06	.08	0.08	0.75	.458	.27

R^2=0.61, Adjusted R^2=0.56, $F(5,35)$=11.04, $p<0.001$

The model explains the variation in organizational performance. Employee Job Performance (β=0.42, $p<0.001$) and AI Usage & Integration (β=0.34, p=0.014) predicted significantly. Trust, Fairness & Transparency were near significance (β = 0.21, p = 0.080). Digital Readiness and Employee Concerns were not significant.

DISCUSSION

This study aimed to examine employees' perceptions of the adoption of artificial intelligence in HRM practices in Nepal and to investigate the impact of AI use on trust, fairness, transparency, digital readiness, employee job performance, and organizational performance. The results present multiple key findings that both reinforce and expand on recognized conceptual models, particularly the Technology Acceptance Model (TAM), Organizational Trust Theory, and Socio-technical Systems Theory, and reveal the specific situational subtleties of the developing South Asian nation.

AI Adoption and digital readiness: The Illusion of Knowing. Aligned with the Technology Acceptance Model (TAM) (Davis, 1989), the positive attitude toward AI usage and integration (M = 3.69) could be attributed as perceived usefulness (improving efficiency, 4.02; supporting decision-making, 3.90). Employees have come to expect that, on the operational side of AI, it will relieve them of administrative duties. Yet lower ratings for performance evaluation (3.32) and recruitment (3.51) indicate that, while employees see AI as useful for everyday assistance, they are not completely convinced of its value when making high-stakes, subjective, and human-centered decisions. This reluctance mirrors findings from Newman et al. (2020), who observed that consequential areas such as hiring and firing tend to elicit greater distrust of algorithmic decision-making. Move all present theoretical interpretations here.

A key paradox of digital readiness was highlighted. Participants expressed strong beliefs about their ability to use digital technologies (mean = 4.15) and to apply new AI systems (mean = 4.07), but their understanding of AI systems from a functional perspective declined dramatically (mean = 3.71). This difference shows high user skill and low algorithmic literacy. The employees, meanwhile, are digitally nimble, able to tap and swipe through interfaces, but they don't really know how those systems crunch data and make decisions. Such superficial acquaintance may generate unwarranted overconfidence or, conversely, heighten anxiety about system failures, stressing the importance of focused, rather than generic, AI literacy interventions.

Trust, fairness, and transparency

The moderate degree of trust, equity, and openness (M=3.51) is consistent with the Organizational Trust Theory (Mayer et al., 1995), which argues that trust is multifarious and fragile in automated environments. Trust in the organizational use of AI is higher than trust in the fairness of AI-based decisions (3.39) and in the perceived transparency of AI systems (3.46), although employees perceived their organizations as accountable and ethical in the use of AI (3.63). This difference illustrates a salient 'trust gap'between perceived (organizational) intent and perceived (systemic) outcomes.

This result resembles the "trust deficit" observed in the global North (Duggan et al., 2020) and demonstrates that Nepali workers, operating within a specific cultural and economic milieu, have comparable concerns about the "black box" characteristic of AI. That TFT correlates moderately with both employee ($r=0.54$, $p<0.01$) and organizational ($r=0.61$, $p<0.01$) performance implies that trust is not only a soft aspect but also a salient antecedent to positive AI adoption. When workers don't know how or why decisions are made, confidence in those systems (3.51) is stale when it comes to purchasing.

Predictors of organizational and employee performance

The evidence in Table5 regarding the running and control variables suggests a strong model, as 61 percent of the variance in organizational performance was accounted for ($R^2=0.61$, $p<0.001$). The significant predictors were EJP ($\beta=0.42$, $p<0.001$) and AI Usage & Integration ($\beta=0.34$, $p=0.014$). This lends robust empirical support to H1 (The Impact of AI on Organizational performance is positive) as well as to H4 (Organizational performance is positively influenced by Employee performance). The data show that AI contributes to organizational performance predominantly through its effect on individual employee productivity – a result consistent. (Mikalef &Gupta, 2021).

Nevertheless, H2—that trust, fairness, and transparency have a positive effect on organizational performance—was only marginally supported ($\beta=0.21$, $p=0.080$). Although TFT was highly correlated with corporate performance ($r=0.61$), its unique variance was eclipsed by AI Usage and Employee Performance in the regression. This would mean that trust matters, but that its influence on the organizational-level outcomes might be fully mediated through individual job performance and the extant use of AI. Put differently, organizations can only experience the performance payoff of trust when that trust leads to better day-to-day work outputs.

H5 in relation to Digital Readiness as a driver of AI adoption was supported by the correlation ($r=0.45$, $p<0.01$), although it did not significantly predict the regression model ($\beta=0.12$, $p=0.282$). This indicates that digital readiness serves as a precondition, not as an actual determinant of outcomes, when AI technology has been adopted. Similarly, Employee Concerns did not predict significance in the regression, although it was negatively correlated with TFT (-0.34). This may suggest that, while worries about job loss and dehumanization are widespread (which are abstracted even further below), they may be more "background" anxieties that do not immediately interfere with performance expectations, or that they are overridden by the very strong perceived utility of AI mechanisms.

Demographic differences

The independent-samples t-test indicated no statistically meaningful gender differences in any of the study variables. Consistent with recent literature indicating professional technology acceptance is more a function of role, experience, and education than gender. The well-educated sample (68.3% with a Master's degree) and extensive work experience (53.7% with >10 years of work experience) formed a homogeneously competent population, which has weakened the demographic differences.

Theoretical contributions

This research has several conceptual implications. First, it builds on TAM based on high perceptions of ease of use and usefulness but low levels of actual knowledge – which implies that a construct of"Deep Comprehension" is needed in future AI adoption theories/models. Second, it confirms the validity of Organizational Trust Theory in a non-Western environment and thereby substantiates the claim that transparency is the blind spot (weakest dimension) of the trust wheel. Third, through integrating Socio-Technical Systems Theory, the study shows that concerns about employee dehumanization remain salient even when performance outcomes are favorable, illustrating the importance of combined optimization.

Practical and policy implications

The findings point to a number of actions that organizations in Nepal and other developing economies can take:
Support transparency: Amid the moral, hardware (environment, energy usage), and privacy challenges mentioned above, organizations need to be more transparent – by demonstrating that they are using AI ethically, how they are using it, and what they can do to protect users.

Prioritize Functional Literacy: Educational modules should evolve beyond "how to click" to include "how it works" to help close the comprehension gap.

Strengthen Human Monitoring: Because of widespread fears about the decline of human decision processes, companies will need to institutionalize 'human-in-the-loop' mechanisms in which AI recommends but humans decide, especially when it comes to hiring and evaluating employees.

Regulatory models: In the context of human rights in the workforce and to potentially increase faith in digital transformation, Nepal's government officials can learn from models that exemplify disclosure-based AI regulation and adopt AI disclosure and impact assessment requirements in HR to safeguard employee rights and improve national digital trust.

Limitations and suggestions for future research

Certain limitations should be borne in mind when interpreting the results. A major limitation is the small sample size (N=41), resulting in low statistical power (post hoc power = 0.52). This low power increases the risk of Type II errors (i.e., non-detection of relationships) and may also explain why TFT's marginal significance in performance becomes significant in larger samples. The representatives is further limited by the high male bias (80.5% of the sample were males) and the high educational level (Master's degree holders formed 68.3%), which may or may not reflect the rest of the Nepali working population.

Further studies should use larger, more heterogeneous samples and adopt long-term designs to track potential growth of trust in AI systems. Moreover, qualitative interviews might yield more detailed information about the emotions and psychological facets associated with the statistical trends presented in this study, notably about organizational-employee-related concerns.

CONCLUSION

This is the first study to report on employee perceptions of AI implementation in HR practices in Nepal, and it shows that positive perceptions of AI for process efficiency and decision support (M=3.69) co-exist with high levels of distrust, lack of transparency, and low levels of algorithmic literacy. The integrated theoretical model (TAM, Organizational Trust Theory, and Socio-Technical Systems Theory) was mostly supported, and AI Usage & Integration and Employee Job Performance were the strongest predictors of Organizational Performance ($R^2=0.61$, $p<0.001$). However, the only slight significance of Trust, Fairness & Transparency ($\beta=0.21$, $p=0.080$) in the regression model, whilst highly correlated with organizational outcomes ($r=0.61$, $p<0.01$), indicates that the effect of trust may be indirect, mediated by employee performance and the use of AI, rather than a direct effect. The cognitive bias of "illusion of knowing" (high perceived digital readiness, M=4.15, while restricted awareness of how AI works, M=3.71) calls for bespoke AI literacy programs, stronger transparency tools, and effective human-in-the-loop measures that are responsive to pervasive concerns about dehumanization (56.1%) and weakened human decision processes. Although the study offers implications to organizations and policy makers in emerging economies, implications should be drawn with caution due to the small sample size (N=41, power=0.52), male dominated sample (80.5 %), higher educations bias (68.3 % holding Master's degree), drawing attention to the need for further research with larger samples to confirm these relationships as well as long-term designs to observe trust development in AI-enabled HR systems over time.

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