

# Employee Acceptance of Generative AI in HR Decision-Making: An Extended Technology Acceptance Model Approach

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## Abstract

Generative Artificial Intelligence (GenAI) has reshaped current Human Resource Management (HRM) practices, presenting organizations with unparalleled opportunities and challenges in talent acquisition, performance insights, workforce planning, and engagement. While efficiency has been witnessed, a successful institutionalization of GenAI enabled HR systems still relies on employees' willingness to use GenAI technologies. This study proposes and empirically tests an Extended Technology Acceptance Model (TAM) focusing on the GenAI-HRM context, which includes six theoretically grounded antecedents: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in AI (TAI), Perceived Risk (PR), AI Literacy (AIL), and Organizational Support (OS). A quantitative, cross sectional design was used and primary data collected from a large sample of employees and HR professionals from various organizational contexts through a structured, Likert scale data collection instrument. The measurement model was validated using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS, and the structural path analysis technique was employed to analyze the results. The measurement model had good psychometric properties, having Composite Reliability and Average Variance Extracted values above the recommended cut-off point, indicating good convergent and discriminant validity. Trust in AI was found to be the most significant predictor of Employee Acceptance in the structural analysis of the results, while the next best predictors included Perceived Usefulness, Organizational Support, AI Literacy, and Perceived Ease of Use. Perceived Risk had a statistically significant adverse effect on acceptance intentions. The model identified a significant proportion of variance in Employee Acceptance and exhibited a high level of predictive relevance; therefore, the model established explanatory relevance. The findings enhance the theoretical foundation of AI adoption in HRM environments, while also offering valuable managerial guidance on organization considerations when they implement responsible AI adoption processes.

**Keywords:** *Generative AI; Human Resource Management; Technology Acceptance Model; Employee Acceptance; Trust in AI; AI Literacy; PLS-SEM*

## **Introduction**

AI is changing how we do business around the globe. HR has experienced incredible change as well. Generative AI represents a new category of deep learning frameworks that generate coherent output given a set of input data, develop analytical insights regarding the data, and assist with multi-layered decision making process. Generative AI represents a new frontier in technology for organisations, perhaps the most impactful technology currently being explored to improve how organisations operate and make decisions. Generative AI-based systems are capable of executing many HR functions (e.g. candidate screening, developing competency based interview questions, providing real-time performance feedback, creating personalized learning pathways, and model predicting attrition), which traditional rule-based technologies simply cannot do (Khan et al., 2024; Kim, 2025). AI's involvement in HRM is not new. This has been followed by studies that provide foundational frameworks to understand how AI is a systemic force that disrupts labour intensive processes, shifting the focus to the mechanisms by which large language model and natural language processing influence talent acquisition and workforce analytics (Rana & Kumar, 2025; Bandara, 2025). The advent of GenAI brings in new and qualitatively different factors: its results are generative instead of classificatory, key decision logic is opaque, and its use is broadly applicable, covering almost every step of the HR value chain. In spite of the clear technological potential, organisations often face obstacles to adoption beyond infrastructure or budget. In the context of leveraging AI in operational systems, employee perceptions, attitudes, and behavioral intentions are key factors in determining the success of achieving meaningful operational penetration (Bankins et al., 2024; Kim, 2025). Psychological connection between users and technology, formed by the beliefs of usefulness, reliability, risk and ease of involvement, has been found to significantly influence technology adoption outcomes in the literature on technology acceptance (Davis, 1989; Venkatesh et al., 2003). In the HR field, it is even more complex because of the evaluative stakes involved in decisions made with AI: Once an employee realizes that an AI tool is involved in their recruitment, appraisal or promotion decisions, their trust dispositions and risk perceptions become much more salient. The existing literature explores the adoption of AI from various perspectives such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT) and Diffusion of Innovation theory. But there is still early scholarship on the topic of GenAI acceptance in HRM contexts (Gillespie et al., 2025; Bandara, 2025). Furthermore, the previous research rarely included these four constructs (trust, literacy, organisational support, and risk) in a single model that was specifically developed for the HR context. This is a significant deficit in theory and practice. The aim of the current study is to fill this gap by developing and testing an Extended TAM (ETAM) comprising constructs from the literature of AI ethics (Trust in AI, Perceived Risk), of new digital competence frameworks (AI Literacy), and from the field of organisational behaviour (Organisational Support). The empirical analysis is based on the responses of 350 employees and HR professionals, and was analyzed using PLS-SEM, which is commonly recommended for theory development settings where accuracy of construct measurement and the power of the models to predict is of primary concern (Hair et al., 2022). The study contributes three main ways: (i) it extends TAM to the GenAI-HRM context, by integrating constructs which were not previously combined in a single study; (ii) it provides strong empirical evidence on the relative magnitude and direction of adoption antecedents; and (iii) it gives theoretically grounded prescriptions for organisations when implementing GenAI responsibly, equitably and effectively.

## **2. Literature Review and Theoretical Framework**

### ***2.1 Generative AI in Human Resource Management***

As generative AI has continued to integrate and evolve into HRM, it has become increasingly represented in various tools, applications, and models that harness the power of LLM and MMMs to comprehend context, produce coherent responses, and respond to prompts tailored to the specific organisation. For recruitment, GenAI tools are currently used to generate job descriptions, parse resumes, create structured interview questions, and summarise candidate assessments, all while increasing the efficiency of the learning process and employee development. (Khan et al., 2024; Rana & Kumar, 2025). In the field of learning and development, GenAI platforms are leveraging their capabilities to build adaptive curricula that cater to each individual's competency profile, boosting training effectiveness and employee growth. (Bankins et al., 2024).

Algorithmic bias, where AI algorithms may perpetuate and even exacerbate historical inequities found in the algorithms used for training, poses a major risk to equitable HR practices. Additionally, privacy concerns linked to the handling of sensitive employee data and the 'black box' nature of generative models pose further challenges to ethical usage. Moreover, the opacity of generative models ('black box' effect) and privacy concerns related to the processing of sensitive employee data further complicate ethical deployment. These worries are a crucial underpinning factor when it

comes to employee attitudes towards GenAI-powered HR systems. These concerns are a major consideration when thinking about employee sentiments on GenAI-powered HR systems. 2025 (Bandara, 2025; Sony et al., 2025)

## **2.2 Technology Acceptance Model: Theoretical Foundations and Extensions**

The theoretical foundations of TAM are discussed and extensions to TAM are examined. (Davis 1989) adapted the Theory of Reasoned Action to apply to the field of information systems adoption to create the Technology Acceptance Model. TAM assumes that there are two major cognitive beliefs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), that jointly affect a technologies' attitude toward it and thus user's behavioural intention to use it. The simplicity and predictive ability of TAM has made it a popular framework in a variety of technological environments such as ecommerce, healthcare information systems, mobile banking and enterprise software. TAM2 and TAM3 built on the original model by introducing an extra variable—social influence to the model of PU, and cognitive instrumental process to the model of PEOU. The Unified Theory of Acceptance and Use of Technology (UTAUT), combined several existing theories on technology acceptance into a streamlined model and further included moderators (facilitating conditions, social influence, and experience).

In the context of adoption in AI specifically, researchers have added constructs that capture the unique features of AI systems, such as trust, perceived intelligence, and explainability to TAM. The present study builds on the core model of TAM and includes four theoretically-informed additional constructs: Trust in AI, Perceived Risk, AI Literacy and Organisational Support. This integration is supported both by previous empirical evidence and by the unique contextual characteristics of the use of GenAI in HR decision-making.

## **2.3 Construct Development and Hypotheses**

### **2.3.1 Perceived Usefulness and Employee Acceptance**

Perceived Usefulness is a key construct in the TAM, which is the extent to which employees think that using the GenAI-based system will improve the performance of their jobs, and it has received strong support in empirical studies of AI adoption. Adoption intentions are much higher if employees see how AI tools can help them make better decisions, cut down on administrative tasks, or make HR services more effective. In HRM, PU is also influenced by firsthand experiences with AI-generated work products and communication about AI capabilities within the organization.

H1: Perceived Usefulness exerts a significant positive influence on Employee Acceptance of Generative AI in HR decision-making.

### **2.3.2 Perceived Ease of Use and Employee Acceptance**

Perceived usefulness positively affects Employee Acceptance of Generative AI in HR decision making tasks significantly. The perceived ease of use and employee acceptance are the two factors that should be evaluated. PEOU is a measure of user's beliefs about how much cognition is needed to use a technology. (Davis, 1989). For GenAI-HRM, ease of use includes the intuitiveness of AI interfaces, the naturalness of human-AI interaction modalities, and contextual guidance. Empirical studies have confirmed that PEOU is directly associated with acceptance and indirectly with PU via reduction in perceived adoption costs. (Venkatesh & Bala, 2008). If the use of AI interfaces requires high cognitive effort or technical expertise, it will also stymie the adoption by employees.

H2: Perceived Ease of Use exerts a significant positive influence on Employee Acceptance of Generative AI in HR decision-making.

### **2.3.3 Trust in AI and Employee Acceptance**

Trust in Artificial Intelligence is multi-faceted and encompasses evaluations of a given AI system's competence (how accurately the AI performs tasks) as well as its benevolence (how well the AI's objectives align with user goals) and integrity (how well the AI's actions align with ethical principles) (Bandara, 2025). In Human Resource settings, trust dispositions have strong implications for how individual's career paths will thereby influence AI-augmented AR decision-making, therefore, many studies have concluded that trust is one of the most important determinants of acceptance of AI-related technologies when the likelihood of successful results is very low from probabilistic standpoint.

The key antecedents of AI trust formation include transparency, explainability, and demonstrated accuracy. (Gillespie et al., 2025; Kim et al., 2026)

H3: Trust in AI exerts a significant positive influence on Employee Acceptance of Generative AI in HR decision-making.

### 2.3.4 Perceived Risk and Employee Acceptance

Perceived risk in the context of AI adoption is the extent to which employees believe there are negative consequences that could arise from the use of GenAI, such as privacy concerns, algorithmic discrimination, data misuse and accountability diffusion for organisations. (Sony et al., 2025). These issues are especially critical in HRM, where HR systems handle confidential employee data and could affect critical hiring and firing choices. Empirical literature finds that an increase in risk perceptions always reduces adoption intentions. The perceived risk has a significant negative effect on the Employee Acceptance of Generative AI for HR decision-making (Kim et al., 2026; Gillespie et al., 2025).

H4: Perceived Risk exerts a significant negative influence on Employee Acceptance of Generative AI in HR decision-making.

### 2.3.5 AI Literacy and Employee Acceptance

AI Literacy and Employee Acceptance Empirical studies have identified AI Literacy as a critical factor in many scenarios (Long & Magerko, 2020) examining the adoption of AI systems, defined as the ability to comprehend, critically analyze, and adeptly use AI systems. Staff that are more AI literate express confidence in their capacity to comprehend AI suggestions, understand possible inaccuracies, and provide careful oversight, which helps eliminate adoption anxiety and boosts adoption acceptance. (Gillespie et al., 2025). Targeted training initiatives have therefore emerged as a key call to action in AI governance policies aimed at fostering the strategic development of AI literacy.

H5: AI Literacy exerts a significant positive influence on Employee Acceptance of Generative AI in HR decision-making.

### 2.3.6 Organisational Support and Employee Acceptance

Organisational Support for Technology Adoption includes management support, training and development opportunities, technical facilities and supportive cultural norms. (Venkatesh et al., 2003; Bankins et al., 2024). The theory of Perceived Organisational Support suggests that workers who feel a sense of value and care from the organization, demonstrate greater reciprocity commitment, which includes openness to technological changes endorsed by the organization. In the context of AI, organisational support is defined by the presence of AI policies, AI champions, AI change management and learning materials.

H6: Organisational Support exerts a significant positive influence on Employee Acceptance of Generative AI in HR decision-making.

Figure 1: Conceptual Research Model — Extended TAM for GenAI Acceptance in HR Decision-Making

[PU, PEOU, TAI, AIL, OS → (+) Employee Acceptance ← (-) PR]

## 3. Research Methodology

### 3.1 Research Design

The study is positivist in nature with a quantitative approach and a cross sectional survey design. This methodological approach is in line with the study's goal of testing a priori theoretically derived hypotheses and estimating the relationships of direction and magnitude among the latent constructs (Creswell & Creswell, 2018). Cross-sectional designs are used extensively in TAM-based studies on adoption and also are suitable for obtaining a snapshot of attitudes at a given time.

### 3.2 Population, Sampling, and Data Collection

The participating audience included employees and HR professionals in organisations that had either already embraced or were planning to use GenAI in HR. Since no sampling frame was available that listed all such organisations, purposive sampling was used to ensure that the respondents had a substantive awareness of the applications of AI in contexts other than personal ones, which is recommended in exploratory-confirmatory research on AI adoption (Bhattacharjee, 2012). The structured questionnaire was sent out via professional networks (LinkedIn), HR professional associations and direct contacts within the organisations in the technology, financial services, healthcare, education, and manufacturing industries. Data collection took place for eight weeks. A total of 371 questionnaires were received out of 412 questionnaires distributed, with 350 questionnaires being judged as valid based on the exclusion of incomplete questionnaires and straight-line responses. This results in an 84.95% response rate which is over the accepted level of 70% for organisational surveys.

### 3.3 Sample Size Justification

Multiple criteria were used to assess the representativeness of the 350 observations in the sample. The rule-of-ten guideline for PLS-SEM (ten observations per predictor path) is far surpassed with the six predictor structural model used here. The present sample size is greater than the minimum sample size on which Cohen (1992) reported that his power analysis for detecting medium effect sizes ( $f^2 = 0.15$ ) with six predictors yielded a power of greater than 0.99 at  $\alpha = 0.05$ . Moreover, for complex structural models, Hair et al. (2022) suggest at least 200 observations, which was also met.

### 3.4 Instrument Development

All the measurement items were borrowed from the validated measurement scales in the existing literature on TAM and AI adoption. The items for perceived usefulness and perceived ease of use were adapted from Davis (1989) and Venkatesh and Bala (2008). The AI items were derived from McKnight et al. (2011) and Hancock et al. Items for Perceived Risk were adapted from Featherman and Pavlou (2003). Items for AI Literacy were created based on Long and Magerko (2020) and Carolus et al. (2023). Eisenberger et al. (1986) and Venkatesh et al. (2003). – Organisational Support item were adapted. The analysis of the Employee Acceptance items showed a consistency with the TAM convention, as they captured employees' behavioral intentions to utilize GenAI for HR-related tasks. Three HRM academics and two HR practitioners reviewed all items for content and contextual validity. Ambiguous or redundant items were edited or deleted. The final instrument was made up of 28 items spanning seven constructs measured with a 5-point likert scale (where 1 = Strongly Disagree and 5 = Strongly Agree). The instrument was then pre-tested with 32 respondents from the target population to ensure the instrument was comprehensible and the item performance.

### 3.5 Analytical Strategy

Data analysis was conducted in two stages as follows: SmartPLS 4.0 (Ringle et al., 2022), was applied in two stages. The measurement model was assessed in Stage 1 for indicator reliability (outer loadings  $\geq 0.70$ ), internal consistency (Cronbach's Alpha  $\geq 0.70$  and Composite Reliability  $\geq 0.70$ ), the Fornell-Larcker criterion for convergent validity (AVE  $\geq 0.50$ ), and the HTMT ratio for discriminant validity (threshold  $< 0.90$ ). In the Stage 2, the structural model was evaluated by using path coefficient estimation, bootstrapping with 5,000 subsampling for significance testing, coefficient of determination ( $R^2$ ), effect size ( $f^2$ ) and predictive relevance ( $Q^2$ ) through blindfolding. The single factor test (Harman's test) and common latent factor were performed to assess common method variance, and the results showed that there was no dominant single factor; therefore, common method variance was not a concern.

## 4. Results

### 4.1 Respondent Profile

Table 1 presents the demographic characteristics of the 350 respondents. The sample was predominantly male (56.0%), with a substantial female representation (44.0%). Most of the working population were 21 to 30 years old (48.0%). 36.9% aged 21 to 40, typical of the digital-native workforces common among many organisations that have adopted technology. The majority of participants have 5 to 10 years experience in a professional capacity (43.7%). Most of the sample (62.0%) indicates frequent or very frequent use of AI in their work, demonstrating familiarity with AI rather than simply an explanation.

Table 1: Demographic Profile of Respondents (N = 350)

| Category           | Group              | Frequency (n) | Percentage (%) |
|--------------------|--------------------|---------------|----------------|
| Gender             | Male               | 196           | 56.0           |
|                    | Female             | 154           | 44.0           |
| Age Group          | 21–30 Years        | 168           | 48.0           |
|                    | 31–40 Years        | 129           | 36.9           |
|                    | 41–50 Years        | 42            | 12.0           |
|                    | Above 50 Years     | 11            | 3.1            |
|                    |                    |               |                |
| Work Experience    | Less than 5 Years  | 98            | 28.0           |
|                    | 5–10 Years         | 153           | 43.7           |
|                    | More than 10 Years | 99            | 28.3           |
| AI Usage Frequency | Never / Rarely     | 31            | 8.9            |
|                    | Sometimes          | 102           | 29.1           |
|                    | Frequently         | 139           | 39.7           |
|                    | Very Frequently    | 78            | 22.3           |

#### 4.2 Measurement Model Assessment

The measurement model was analyzed through four psychometric criteria through structural analysis. Results are summarized in Table 2.

Table 2: Measurement Model Results: Reliability and Convergent Validity

| Construct                    | Items | Cronbach's $\alpha$ | CR          | AVE         |
|------------------------------|-------|---------------------|-------------|-------------|
| —                            | —     | $\geq 0.70$         | $\geq 0.70$ | $\geq 0.50$ |
| Perceived Usefulness (PU)    | 4     | 0.891               | 0.924       | 0.753       |
| Perceived Ease of Use (PEOU) | 4     | 0.863               | 0.905       | 0.704       |
| Trust in AI (TAI)            | 4     | 0.915               | 0.940       | 0.798       |
| Perceived Risk (PR)          | 4     | 0.846               | 0.896       | 0.684       |
| AI Literacy (AIL)            | 4     | 0.878               | 0.916       | 0.732       |
| Organizational Support (OS)  | 4     | 0.902               | 0.931       | 0.770       |
| Employee Acceptance (EA)     | 4     | 0.907               | 0.936       | 0.785       |

#### Indicator Reliability

All 28 indicator outer loadings exceeded the 0.70 threshold (range: 0.782 to 0.916), with no items requiring exclusion. This confirms that each indicator reliably reflects its associated latent construct.

### Internal Consistency Reliability

The values of Cronbach's Alpha measure ranged from .846 which was obtained from the Perceived Risk to .915 from Trust in Artificial Intelligence, while Composite Reliability ranges from .896 to .940, both being greater than the minimum threshold value of .70. Therefore, these results demonstrate satisfactory internal consistency among the construct measured.

### Convergent Validity

The AVE for the eight construct ranged between 0.684 for perceived risk and 0.798 for Trust in AI, all of which exceeded the 0.50 threshold established by Fornell and Larcker (1981). Therefore, each of the construct was found to have captured more than half of the variance in its indicators (indicating satisfactory levels of convergent validity).

### Discriminant Validity

As demonstrated in Table 3, the Heterotrait-Monotrait (HTMT) ratio was used to evaluate discriminant validity, with all pairwise relationships measuring under 0.85 (minimum=0.362, maximum= 0.721). Additionally, the Fornell-Larcker criterion was also confirmed, as the square root of each construct's average variance extracted (AVE) was greater than the correlation with all other constructs. Thus, these findings suggest evidence of empirical separation among the seven constructs.

Table 3: *Discriminant Validity: HTMT Ratios*

| Construct | PU    | PEOU  | TAI   | PR    | AIL   | OS    | EA |
|-----------|-------|-------|-------|-------|-------|-------|----|
| PU        | —     |       |       |       |       |       |    |
| PEOU      | 0.612 | —     |       |       |       |       |    |
| TAI       | 0.584 | 0.541 | —     |       |       |       |    |
| PR        | 0.423 | 0.398 | 0.447 | —     |       |       |    |
| AIL       | 0.593 | 0.627 | 0.512 | 0.381 | —     |       |    |
| OS        | 0.561 | 0.509 | 0.573 | 0.362 | 0.548 | —     |    |
| EA        | 0.674 | 0.598 | 0.721 | 0.489 | 0.639 | 0.618 | —  |

### **4.3 Structural Model Assessment**

Structural model assessment was conducted following confirmation of adequate measurement model properties, using 5,000 bootstrap subsamples for path coefficient significance testing. Results are presented in Tables 4 and 5.

Results reflect (Table 4 and 5), Structural model assessment was applied showing adequate model properties, which utilized 5,000 (bootstrap samples) to be significantly tested.

### *Hypothesis Testing*

Table 4: *Structural Model Results: Path Coefficients and Hypothesis Testing*

| Hypothesis                | Path                  | $\beta$ | t-Value | p-Value | f <sup>2</sup> | Decision  |
|---------------------------|-----------------------|---------|---------|---------|----------------|-----------|
| H1: PU $\rightarrow$ EA   | PU $\rightarrow$ EA   | 0.286   | 5.712   | 0.000   | 0.108          | Supported |
| H2: PEOU $\rightarrow$ EA | PEOU $\rightarrow$ EA | 0.184   | 3.642   | 0.000   | 0.047          | Supported |
| H3: TAI $\rightarrow$ EA  | TAI $\rightarrow$ EA  | 0.311   | 6.104   | 0.000   | 0.142          | Supported |
| H4: PR $\rightarrow$ EA   | PR $\rightarrow$ EA   | -0.147  | 2.987   | 0.003   | 0.031          | Supported |
| H5: AIL $\rightarrow$ EA  | AIL $\rightarrow$ EA  | 0.228   | 4.421   | 0.000   | 0.074          | Supported |

|             |         |       |       |       |       |           |
|-------------|---------|-------|-------|-------|-------|-----------|
| H6: OS → EA | OS → EA | 0.261 | 5.018 | 0.000 | 0.096 | Supported |
|-------------|---------|-------|-------|-------|-------|-----------|

Relationship predicted have been supported by the current tables. Trust in AI ( $\beta = 0.311$ ,  $t = 6.104$ ,  $p < 0.001$ ). H3 highlights as a positive predictor of Employee Acceptance.

Perceived Usefulness ( $\beta = 0.286$ ,  $t = 5.712$ ,  $p < 0.001$ ) and Organizational Support ( $\beta = 0.261$ ,  $t = 5.018$ ,  $p < 0.001$ ) constituted the second and third strongest positive antecedents, supporting H1 and H6 respectively. AI Literacy ( $\beta = 0.228$ ,  $t = 4.421$ ,  $p < 0.001$ ) and Perceived Ease of Use ( $\beta = 0.184$ ,  $t = 3.642$ ,  $p < 0.001$ ) exerted moderate positive effects, confirming H5 and H2. Perceived Risk ( $\beta = -0.147$ ,  $t = 2.987$ ,  $p = 0.003$ ) exerted a significant negative effect, supporting H4.

#### Model Fit and Predictive Power

Table 5: Model Fit and Predictive Relevance Statistics

| Criterion                             | Value Obtained | Threshold            | Assessment  |
|---------------------------------------|----------------|----------------------|-------------|
| R <sup>2</sup> (Employee Acceptance)  | 0.684          | ≥ 0.26 (substantial) | Substantial |
| Adjusted R <sup>2</sup>               | 0.679          | ≥ 0.26               | Substantial |
| Q <sup>2</sup> (Predictive Relevance) | 0.472          | ≥ 0.35 (large)       | Large       |
| SRMR                                  | 0.061          | < 0.08               | Acceptable  |
| NFI                                   | 0.923          | ≥ 0.90               | Acceptable  |

0.684% (R<sup>2</sup>) indicates all the predictors together account for variance in employee acceptance (Cohen (1992) and Hair et al. (2022)). Q<sup>2</sup> = 0.472 confirms large predictive relevance. SRMR = 0.061 and NFI = 0.923 indicate acceptable model fit.

## 5. Discussion

### 5.1 Interpretation of Findings

Findings support largely concepts developed and presented, confirming generative AI adoption in decision making. This finding of the primacy of Trust in AI ( $\beta = 0.311$ ) aligns with previous studies that have reported on the importance of Trust in the context of high-stakes human-AI interaction scenarios (Choung et al., 2023; Hancock et al., 2011). Employees adopt high levels of disposition-based and institution-based trust evaluation in the HRM context where their level of trust is expected to affect recruitment selection, performance ratings and career advancement decisions made by the AI recommendation. This drives the conclusion that, for a system to be successful as an adoption enabler, it should be transparent, it should be interpretable, and it should be accurate.

Perceived Usefulness ( $\beta = 0.286$ ) was found to be the second strongest determinant that supported the overall findings in the literature on the TAM (Davis, 1989) and AI adoption studies in different domains(Sohn & Kwon, 2020). Those who report concrete productivity gains, such as fewer screens to view, more effective appraisal feedback, or better workforce planning information, show much higher intentions to adopt.

Organisational support ( $\beta = 0.261$ ) positively correlated with acceptance, in line with Perceived organisational support theory and the research results of Srivastava et al. (2022) in relation to technology adoption. The result implies that support for GenAI from the institutional perspective is not only an enabling condition but an active antecedent of acceptance of employees; that is, employees feel psychologically more comfortable with adopting the technology, if they are aware of institutional support for it. Positive correlation between acceptance and AI Literacy ( $\beta = 0.228$ ) is another result which complements the findings of Long and Magerko (2020) and Carolus et al. (2023) in the HR area. The fact that employees can question outputs generated by AI and reduce anxiety caused by uncertainty and excessive trust means that building AI literacy should be considered strategically.

As expected, there was positive correlation between acceptance and the parameter of perceived ease of use ( $\beta = 0.184$ ), but it had the smallest effect magnitude among other positive predictors. This is in line with research that usability improvements in the interface have diminishing returns, once a minimum level of accessibility is reached, as users become familiar and adept with the systems they use (Venkatesh & Bala, 2008). The results showed that Perceived Risk ( $\beta = -0.147$ ) had a significant negative relationship with acceptance, as theory predicted and privacy and bias concerns in AI-mediated HR settings are a salient factor (Raghavan et al., 2020; Featherman & Pavlou, 2003). This effect is moderate in magnitude compared to positive antecedents, indicating that risk concerns do not automatically and completely deter adoption, but do have a direct impact on willingness to engage with GenAI systems, with direct risk communication and mitigation implications.

### **5.2 Theoretical Contributions**

This study has three main theoretical contribution. First, it introduces the topic of GenAI adoption in HRM, which is an area that has received less attention and focus than other fields of IT adoption, but is nonetheless currently highly relevant. Second, the inclusion of the four, namely, Trust in AI, Perceived Risk, AI Literacy and Organisational Support in addition to the core TAM constructs leads to a theoretically comprehensive model that captures the unique social, cognitive, and institutional dynamics of AI-HR interaction. Third, the empirical design of the research, including the powerful method of measuring the model, and structural path analysis, sets a methodological standard for future research on the adoption of AI in HRM.

## **6. Practical Implications**

### **6.1 For HR and Technology Leaders**

Clear AI governance structures to be implemented proactively, Rationale, boundaries and responsibilities to be communicated clearly in order to foster trust among employees. Specific task related advantages should be explained specifically in order to improve the perceived usefulness. AI interfaces to be more focused and user-centric, this can be done by ease of accessibility. All those who have less or minimum experience with AI, this can boost up their perceived ease of use. An investment in AI literacy programs can help to boost up confidence, enhance conceptual knowledge, encourage critical thinking to increase hands on application and changed perception. Establish and promote strong data governance, data privacy, and bias auditing practices to mitigate concerns about Perceived Risk and ensure the institutional trustworthiness.

### **6.2 For Organisations Implementing GenAI**

Have visible, active backing of GenAI projects to show Organisational Support and ease employee uncertainty. Build change management plans to make GenAI a decision support augmentation tool, not a manager replacement tool, to lower existential anxiety for HR professionals. To be fair, accountable and transparent, create internal AI ethics committees with employee representation to develop participatory governance mechanisms.

## **7. Limitations and future research directions.**

Several boundary conditions for the present study are set, which will be helpful for the interpretation of the results and for further research directions. First, the cross-sectional design does not allow an analysis of the dynamics of adoption behaviour over time; longitudinal designs tracking the dynamics of attitudinal change during the different phases of the implementation of GenAI would yield richer causal insights. Second, the purposive sampling method used may limit the generalisability of the study to the specific industry, organisation size and culture. Stratified random sampling of diverse demographically and organisationally based populations is recommended for future studies. Third, common method variance, which was addressed and controlled by both procedural and statistical methods, is an inherent limitation of self-report survey methodology. To get more ecologically valid evidence, experimental designs could be implemented that integrate survey data with behavioural trace data that would be collected from the actual use of GenAI systems. Fourth, the constructs in this study reflect individual-level perceptions, while future studies could focus on team-level and organisational-level influences on GenAI adoption such as managerial leadership styles, change readiness and HR departmental culture. Fifth, the ability of GenAI is changing quickly, which could shift the importance and meaning of GenAI adoption predictors. For example, more explainable and auditable GenAI systems may lessen the perceived risk and increase the value of AI literacy. Longitudinal replication studies would be useful to follow these dynamic relationships. Gen AI acceptance may be increased through focused group discussions and monitoring.

## 8. Conclusion

Using Partial Least Squares Structural Equation Modelling, data on the Technology Acceptance Model (TAM) of 350 employees and HR specialists were used to develop an extended model of the TAM in the domain of generative artificial intelligence (AI) as applied in HR decision-making. The most salient finding of the study is that trust in AI is the most significant driver of employee acceptance of AI in HR systems. Other important positive antecedents of employee acceptance are perceived usefulness, organizational support, AI literacy, and perceived ease of use, while perceived risk is a significant barrier to employee acceptance. As evidenced by its 68.4% explanatory power, this integrated model of the TAM has strong explanatory capability and supports the theoretical coherence of extending the TAM into the GenAI-HRM context. Overall, the study provides valuable insights into AI adoption frameworks and offers suggestions for how organizations can achieve responsible AI adoption.

In order to achieve the transformative potential of technology through GenAI as a strategic HR capability, it will be necessary to build trust with employees and create literacy through investment, as well as establish a risk mitigation and require institutional endorsement in order to ensure both employee health and well-being and organizational equity. Additionally, future research must also continue examining these dynamics in different contexts over time using longitudinal designs. This will track how the nature of how humans and AI interact is evolving in the contemporary workplace.

## References

- Bhattacharjee, A. (2012). *Social science research: Principles, methods, and practices* (2nd ed.). University of South Florida.
- Budhwar, P., Malik, A., De Silva, M. T. T., & Thevisuthan, P. (2022). Artificial intelligence – challenges and opportunities for international HRM: A review and research agenda. *The International Journal of Human Resource Management*, 33(6), 1065–1097.
- Carolus, A., Koch, M. J., Straka, S., Latoschik, M. E., & Wienrich, C. (2023). *MAILS — Meta AI Literacy Scale: Development and testing of an AI literacy questionnaire based on a comprehensive AI competency model*. *Computers in Human Behavior: Artificial Humans*, 1(1), 100014.
- Cheng, Y., & Hackett, R. D. (2021). A critical review of algorithms in HRM: Definition, theory, and practice. *Human Resource Management Review*, 31(1), 100698.
- Cheng, X., Su, L., Luo, X., Benitez, J., & Cai, S. (2022). The good, the bad, and the ugly: Impact of analytics and artificial intelligence-enabled personal information collection on privacy and participation in ridesharing. *European Journal of Information Systems*, 31(3), 339–363.
- Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human–Computer Interaction*, 39(9), 1727–1739.
- Chou, S. W., Min, H. T., Chang, Y. C., & Lin, C. T. (2021). Understanding continuance intention of knowledge creation using extended expectation–confirmation theory: An empirical study of Taiwan and China online communities. *Behaviour & Information Technology*, 29(6), 557–570.
- Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112(1), 155–159.
- Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
- Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived organizational support. *Journal of Applied Psychology*, 71(3), 500–507.
- Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451–474.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50.
- Hair, J. F., Henseler, J., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

- Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y. C., de Visser, E. J., & Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. *Human Factors*, 53(5), 517–527.
- Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49(1), 30–50.
- Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1), 15–25.
- Lian, J. W., & Yen, D. C. (2014). Online shopping drivers and barriers for older adults: Age and gender differences. *Computers in Human Behavior*, 37, 133–143.
- Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). ACM.
- Malik, A., De Silva, M. T. T., Budhwar, P., & Srikanth, N. R. (2023). Elevating talents' experience and the role of digital HRM technologies: An investigation of SMEs in Australia during COVID-19. *Journal of Business Research*, 141, 545–556.
- McKnight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems*, 2(2), 1–25.
- Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management*, 32(10), 3199–3226.
- Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 469–481). ACM.
- Ringle, C. M., Wende, S., & Becker, J. M. (2022). SmartPLS 4. SmartPLS GmbH.
- Sohn, K., & Kwon, O. (2020). Technology acceptance theories and factors influencing artificial intelligence-based intelligent products. *Telematics and Informatics*, 47, 101324.
- Srivastava, S., Dey, B., & Bhatt, A. (2022). Technological transformation leadership and learning outcomes in the post-COVID-19 era. *Leadership & Organization Development Journal*, 43(3), 484–506.
- Starke, C., Baleis, J., Keller, B., & Marcinkowski, F. (2022). Fairness perceptions of algorithmic decision-making: A systematic review of the empirical literature. *Big Data & Society*, 9(2), 1–17.
- Strohmeier, S. (2022). Artificial intelligence and human resource management: A conceptual analysis. *Academy of Management Perspectives*, 36(2), 814–835.
- 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.
- Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: Implications for recruitment. *Strategic HR Review*, 17(5), 255–258.
- Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273–315.
- Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, 24(1), 115–139.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.