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Review Article

Impact of AI Adoption Intention in Performance Appraisal Process on Actual Usage and Its Effect on Perceived Accuracy and Satisfaction: An Empirical Study

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Abstract

The present study aims to investigate the impact of the willingness of HR Managers to adopt AI, and how this willingness creates greater levels of actual usage of AI in performance appraisals. The study also explores how using AI affects how one perceives the accuracy of the results, and overall satisfaction with appraisal results. A cross-sectional, quantitative survey of HR managers in the Indian IT services sector was the research design adopted in this study. Using a non-probability snowball sampling procedure, an experienced HR manager recruited further participants who provided a broad and adequately representative sample of HR managers. The analysis of the data collected from the questionnaires was done using Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the direct relationships between the key variables of interest in this study. Results show there is a strong correlation between the adoption intention and actual use by HR Managers of AI Technology. As more HR managers began to actively use AI Technology, their perceived accuracy and satisfaction level with their performance appraisals also increased. Additionally, the results of the study show that the Human Agency factor moderated the relationship between Intention and Actual Use of AI Technology, thereby strengthening the movement from Intention to Action. Organizations looking to leverage the benefits associated with an effective, transparent and satisfying use of HR Technology that utilizes AI will find the findings of this study valuable.

Keywords: Artificial Intelligence, Technology Adoption, AI Adoption Intention, Perceived Accuracy, Perceived Satisfaction.

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Introduction

Nowadays, artificial intelligence (AI) is leading the way in technological innovation, and its use is growing. The most recent research report from McKinsey (2025) and Netguru (2025) states that by 2025, almost 78% of multinational corporations will use AI in at least one aspect of their operations. This is regarded as one of the technologies that has been embraced the quickest during the past few decades. The impact of technology disruption in a variety of industries and business models is reflected in the expected growth of the global AI industry from roughly $391 billion in 2025 to almost $1.8 trillion by the end of 2030. Stanford HAI (2025). Its promise to improve decision-making and productivity is the reason for its growing popularity. AI is regarded as one of the most important tools for gaining a competitive edge in a variety of industries, including manufacturing, healthcare, finance, customer service, human resources, and even internal personnel management. Increasing performance, automating tedious operations, and offering data-driven insights are ways to accomplish this. The use of AI is growing in both personal and professional contexts, with millions of people use technologies like generative AI on a daily basis (Exploding Topics, 2025). Although the adoption of AI has significant importance and benefits, there are still numerous issues related to transparency, ethical use, potential bias and impacts on individual job opportunity thereby remaining difficult to implementation it in general (PwC, 2024; McKinsey, 2025). Even though AI has grown crucial, people and businesses may object to its imprecise algorithms and ambiguous decision-making (Anthropic, 2025). The digital divide and differences in infrastructures also inhibit AI globally (OECD, 2025). In a recent study by Stanford HAI, (2025) highlighted the scientific capabilities that AI brings with the social, organizational, and human factors significantly affect adoption and overall use. In order to fully realize the benefits of AI and minimize the negative effects, it is necessary to educate ourselves on these factors and ensure that the technology continues to be diffused in our workplace. Fear of losing one's job or fear of the AI may inhibit the individual from using it, and on the other hand, having confidence in interaction with AI would help to create acceptance. The social impact is another important influencer in determining adoption, as the attitudes and behaviors of peers or other individuals in social and organizational networks may drive the decisions in adoption (Grover et al., 2022; Horani et al., 2025). It is key that organizational elements like leadership endorsement, necessary infrastructure, and readiness for training would enable AI adoption greatly. Kar et al. (2021) discovered that individuals working in an organization with stronger innovation management processes and adequate technical resources are more likely to use AI productively because employees have better access to support and resources for integrating AI into their work. Alternatively, leadership not committed to utilizing AI in the organization or regulatory requirements not being clear would clearly influence its use.

Artificial intelligence is rapidly transforming enterprises by improving and automating a wide range of jobs across multiple departments. For instance, in order to expedite hiring and boost talent acquisition effectiveness, HR departments are increasingly using AI-powered tools like HireVue and Pymetrics to screen applicants, evaluate video interviews, and integrate new hires. Chatbots and virtual assistants, such as IBM

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Watson Assistant and Zendesk Answer Bot, are increasingly being utilized in customer service to answer simple questions and offer prompt assistance, freeing up human agents to concentrate on more complex problems. Accelerating the adoption of these tools will not only replace repetitive, data-heavy work but also support better strategic decision-making. Regardless of the function, these intelligent tools will change the organizational landscape. The increased usage of AI tools and technologies in organizational processes has created significant changes in how work is done and evaluated. More specifically, the relationships between employees' intention to adopt AI and their actual use of AI systems have become a topic of increased academic interest. Intention to adopt AI implies the capability or willingness of managers and employees to utilize AI tools at work, which is shaped by perceived usefulness, ease of use, organizational support, and trust in the technology. However, even if individuals have a positive intention, it does not necessarily imply that AI systems will be used in practice. The conversion of intention to actual use, i.e., usage behaviour, is determined by a better understanding of the interaction between individual motivation, organizational context, and the availability and use of AI tools accessible at work.

This understanding is key because it is the actual use of AI that will, in part, dictate the extent to which AI can provide benefits as promised, e.g., more objectivity, data-driven feedback, personalized recommendations, etc. When managers and employees transition from just creating an intention to use an appraisal system that enables AI use, those systems can provide more thoughtful and refined evaluations that are better represented. This does not just inform employees' beliefs that their performance appraisal was accurate, but also if individuals experience feedback that is timely, relevant, and derived from information and analysis, they are also more likely to believe their review was fair, linked to individual experiences and contributions. The present study attempts to study the same.

Rationale behind the study:

Examining how employees' confidence in using technology affects their intention to implement AI in the workplace is one of the study's main goals. Employees are more inclined to think about the benefits of utilizing the AI system and are more receptive to implementing the new system, even in the face of difficulties, when they feel proficient with technology (Chang et al., 2024). On the other hand, workers may quit utilizing AI entirely if they are overwhelmed by the complexity of a new system or do not comprehend it. Additionally, AI has made workers more adaptable, self-assured, and independent, which boosts their well-being and engagement at work (Soulami, 2024). Although the role of AI is to enhance processes within organizations is well recognized, a fundamental question remains unaddressed about how a manager's intention to use AI will ultimately lead to the actual adoption of AI-based tools for evaluating their employees' performance. The transition from positive intention to actual usage may not be straightforward. Instead, it gets impacted by a multifaceted interaction of individual, organizational, and technological variables. This represents a significant challenge for developers and designers of AI-based performance evaluation systems, more than simply ensuring their technology works. If the end-users of the systems do not perceive the systems as matching their

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expectations, characteristics of work habits, or evaluation goals, then their actual usage will lag behind their positive intentions for AI-based appraisals. This risk contributes to diminished potential for AI to improve the fairness, accuracy, and quality of evaluations of employees' performance. Therefore, it is vital to identify and analyze the determinants that motivate managers to move from intention to using these tools within the performance evaluations process.

Theoretical Background:

A robust theoretical framework is crucial for academic inquiry, providing a structured lens for comprehending and scrutinizing phenomena. Integrating theory into research is crucial, since it guides the formulation of research questions and hypotheses, and also affects the design, methodologies, and interpretation of findings (Kerlinger, 1966). Theoretical frameworks link novel studies to existing data, fostering cumulative knowledge advancement and facilitating substantial comparisons among investigations (Eisenhardt, 1989). Established theories in technology innovation and adoption are essential for understanding user behaviors, intentions and outcomes ensuring that research is grounded in existing knowledge while promoting the development of new insights.

The Unified Theory of Acceptance and Use of Technology (UTAUT):

This represents a significant advancement in the study of individual technology use. It synthesizes components from eight prominent models, including the TAM, the Theory of Reasoned Action, and the TPB, into a single, integrated framework. In their research work, Venkatesh et al. (2003) developed the UTAUT model as a means to synthesize the best aspects from previous acceptance models into one single model. The UTAUT model suggests that four key variables, performance expectancy, effort expectancy, social influences, and facilitating conditions, can directly influence users' behavioral intention to use technology. Performance expectancy is defined as the degree of benefits an individual would expect from using the technology, while effort expectancy is defined as the degree of ease associated with the use of technology. Social influences are defined as the degree to which individuals perceive that their friends or family members, or significant others, will use or accept the new system. Facilitating conditions are defined as the degree of support an individual perceives as available to complete the behavior. The authors also identified four key moderators that can affect technology acceptance, which include gender, age, experience, and the individual's willingness to use technology. Empirical validation of UTAUT was conducted on data from four firms and over 1,600 customers, indicating significantly improved explanatory power over earlier models by explaining up to 70% of the variance in behavioral intention, indicating a significant improvement over prior models (Venkatesh et al., 2003). This result defined building UTAUT as the leading model for technology adoption research, particularly in organizational and workplace settings. The strength of the model and predictive reliability has been continuously validated in a variety of domains, including health care (Kijsanayotin et al., 2009), education (Šumak et al., 2011), mobile banking (Zhou et al., 2010), and e-Government (AlAwadhi & Morris, 2008), along with technology initiatives in government. Since its inception, UTAUT has initiated a number of

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substantial model developments and applications. Venkatesh et al. (2012) introduced UTAUT2 to account for consumption settings and included items like hedonic motivation, price value, and habit. This expanded the model's utility for understanding how individuals adopt new technologies. UTAUT2 has emerged as a frequently cited framework for studies related to mobile applications, e-commerce, and other newly adopted digital services. UTAUT was first introduced by Venkatesh et al. (2003), and research was subsequently conducted on its use across multiple settings and cultural backgrounds.

The studies validated the robustness of UTAUT in quantitative methods, providing opportunities for context-specific modifications. As is a common theme with all the early studies, context-specific considerations of constructs for specific technologies, contexts, and user communities were urged. The ongoing significance of UTAUT lies in its highly accessible, empirically grounded, coherent, flexible framework accounting for technology adoption and use among individuals, whether social or commercial. The work done with UTAUT has been pivotal for academic study and practical approach for technology adoption or implementation, thus reaffirming its prominence as a primary framework of study for information systems.

Figure 1 below shows the UTAUT model.

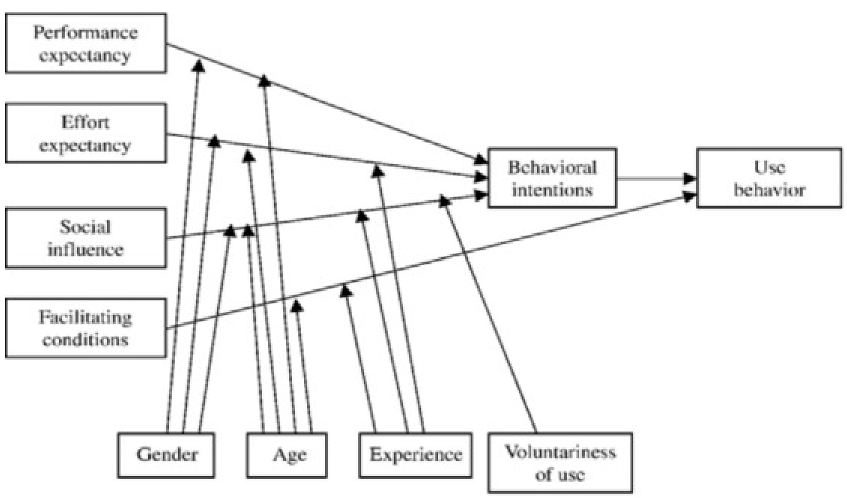

Figure 1: Unified theory of acceptance and use of technology

Source: Venkatesh et al. (2003)

Literature Review

AI Adoption Intention and AI Usage Behaviour during Performance Evaluation Process:

The significance of behavioral intention as a direct and powerful predictor of actual usage behavior in businesses is shown by larger studies on technology adoption. The most direct precursor to real system use is an individual's intention to utilize new technology, which is based on an individual's judgments of the technology's value and simplicity of use, according to early theories like TAM (Davis, 1989). The UTAUT paradigm reiterates and reinforces the fundamental concept of behavioral intention. Behavioral intention is demonstrated to be a substantial and direct predictor of technology utilization across a broad range of information systems and organizational settings in this synthesis of many theoretical streams (Venkatesh et al., 2003). According to Jarrahi (2018), managers' readiness and willingness to adopt AI-informed technologies affect not only their own preferences but also the depth, willingness, and extent of AI use across the firm. This link is highlighted in the context of performance appraisals when AI is incorporated into the review process since it will impact the form of appraisal through improved objectivity, data-driven insights, and process efficiency.

In recent research situated in human resources and in the specific appraisals context, similar and additional evidence continues to support the intention to use. For example, in a study of AI for appraisals in organizations, Shahid et al. (2024) determined that managers who reported an intent to adopt an AI tool for appraisals also reported actual high use of the AI tool to evaluate an employee during the appraisal period. This research lends credibility to the hypothesized relationship of behaviour intention as a precursor of observed changes in actual usage behaviour for AI-mediated appraisals. The literature recognizes a number of intervening variables which may either inhibit or facilitate this transition, including promoting workplace policies, access and usability of AI systems, and consideration for AI functionality which relates to the manager's actual job processes (Frankiewicz & Chamorro-Premuzic, 2020). It makes sense that managers' intentions to use AI are directly and significantly correlated with their use of AI technologies in performance reviews. In this particular instance, the manager can be anticipated to see this as a task-oriented work function with organized application of the AI tools used to apply AI to the performance time if they are able to express their purpose to adopt AI (Al- Mamary, 2025; Emon et al.,2023). The following positive alternative hypothesis is proposed based on extensive documentation of evidence in the literature:

H1: AI adoption intention of managers has a significant positive impact on actual AI usage.

Actual AI Usage Behaviour on Perceived Accuracy of Work and Perceived Satisfaction over Performance Appraisal:

The way employees approach and assess their work has drastically changed as a result of the integration of AI technologies into organizational operations. Constructs that have emerged as part of this technological transformation include the link between real AI usage behavior—that is, the experience and intensity with which employees engage with AI technologies—and perceptions of output correctness. Employees who utilize AI systems more frequently report doing their tasks more accurately, according to research. This is believed to be due to the superior analytical ability and data handling capacity of AI, which has been demonstrated to decrease human error and improve decisions around quality and accuracy (Jarrahi, 2018). Employees performing tasks like data analysis, forecasting, and quality assurance who depend on AI benefit from consistency and precision of computation, which enables them to feel greater confidence in the correctness of their output (Brougham & Haar, 2018). Employees who regularly employ AI for routinized tasks are likely to view their work as more accurate and less prone to oversight simply because AI can alert them to anomalies,

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can verify computations, or can provide recommendations based on evidence (Shrestha et al., 2019). A positive correlation between actual AI use and perceived accuracy has also been shown to occur in knowledge-intensive domains. For instance, in healthcare, research has indicated that clinicians using diagnostic AI applications perceive their diagnostics to be more accurate and evidence-based thanks to the decision support capabilities of AI technology. Within finance and audit sectors, employees who more regularly employ AI-fuelled analytics indicate enhanced levels of accuracy and objectivity in their assessments (Lee & Tajudeen, 2020). AI systems' built-in feedback mechanisms are also crucial. According to Jarrahi et al. (2021), AI solutions that offer clear feedback with an actionable reaction can help users see the precise benefits of AI advice on the accuracy of their work.

Additionally, employees expressed greater levels of satisfaction when there is transparency, explainability, and clarity on how assessments are made in AI systems and how managers defend their choices that incorporate AI in the evaluation process (Binns et al., 2018). When a manager or boss is ethically using AI tools and is digitally educated, employees generally express higher levels of satisfaction (Siau & Wang, 2018; Wang et al., 2025; Meijerink et al., 2021). Based on the above claims, the following hypotheses are proposed:

H2: Managers' AI usage has a significant positive impact on managers' perception of the accuracy of the evaluation process

H3: AI usage has a significant positive impact on managers' perception of employees' satisfaction with the evaluation process

Research Methodology

Research Design:

The study uses a quantitative, cross-sectional research methodology within a post-positivist framework to methodically investigate the connections between HR managers' intentions to adopt AI and their actual use of it during employee performance reviews, which ultimately results in employees' perceptions of the accuracy of their work and their level of satisfaction. Because it addresses potentially complicated interactions between variables while being largely faithful to the normative working situation, the correlational design is suitable for the study (Creswell & Creswell, 2017). Further, using Structural Equation Modeling (SEM) allows the researchers to simultaneously investigate direct and moderated relationships as structural relationships suggested in the proposed conceptual model (Kline, 2023).

Instrument design:

The data for this research were collected using a structured questionnaire that incorporated scales adopted from established and validated instruments used in previous research studies **(Table 1).** The questionnaire evaluated key constructs relating to AI adoption and use in performance appraisal within the Indian IT services

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sector. Each of the scales was measured using a seven-point Likert scale of agreement (1=Strongly Disagree, 5=Strongly Agree).

Table 1 Construct and their literature source:

Construct	Literature Source
AI adoption intention	Venkatesh et al. (2003), Baumsteiger & Siegel, 2018
AI usage in performance appraisal	Carlsson et al. (2006), Attuquayefio & Addo, 2014, Oh & Yoon, 2013
Performance appraisal accuracy	Sharma et al. (2015)
Performance appraisal satisfaction	Jawahar,2007

Sampling Design

Population and Sample:

Senior and mid-level HR managers with at least a year of experience managing and/or implementing performance appraisal systems who are currently working as HRM professionals within the Indian IT services sector companies like Tata Consultancy Services (TCS), Infosys, Wipro, HCL Technologies, and Tech Mahindra will make up the study's sample. In order to guarantee that every member of the sample has current and pertinent experience with the recent and ongoing usage of AI technologies in HRM, particularly in the area of performance management systems, which has been implementing new models over the past year, one year was chosen. HRM professionals who are not currently employed as HRM professionals or who lack direct appraisal experience will not be included in the sample.

Sampling Technique:

To gather relevant and accurate data and information from an expansive and highly relevant population, this study adopts the non-probability-snowball sampling design that is recognized for its effectiveness in identifying specialized and networked professional communities (Noy 2008). Using a snowball sample was particularly suitable for this study, which focused on a specialized occupational manager group whose participants may not be easily reached via standard probability sampling methods (Sadler et al., 2010).

Sample Size:

With respect to the sample size determination, this study relied on established statistical formulas and methodological guidelines. For populations where the exact size is unknown, the minimum required sample size (n) can be calculated using the following formula:

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The sample size calculation formula is

$S= Z^2 NP (1-P) / d2 (M-1) + Z^2 P (1-P)$

By considering variables such as the population size, confidence level, and expected margin of error, around 385 is the right sample size required for their study (Cochran, 1977). Based on the above criteria and data collection procedure resulted in the final usable sample of 573 responses for the final analysis.

Data Collection Procedure:

Snowball sampling was the first method used in this study's data gathering process since it is an effective way to reach a certain group of people, such as HR managers. In order to participate in the study based on purposive sampling, which requires that they have been utilizing AI for performance evaluation for at least a year, the HR managers within the known contact were first provided a link to the online questionnaire. The survey was conducted using Google Forms, a secure online data collection technology that was selected due to its accessibility for participants in various organizational contexts, geographical locations, and personal and professional devices. In addition to known contacts, the HR managers were also encouraged to forward the questionnaire link to their professional networks using a variety of communication platforms such as LinkedIn groups and other social media platforms. This process also encouraged receiving more responses. The snowball sampling strategy allowed the sample to grow and develop over a period of time.

Pilot Study:

A pilot study was started by qualitative validation of the questionnaire items by academicians and industry experts. A few changes were suggested by the experts, and accordingly, some items were modified, and others were added. This was followed by a reliability analysis to confirm the consistency of the instrument. **Table 2** below shows the results of the reliability analysis.

Table 2 Reliability

Construct	Initial No of Items	Final Items Retained	Cronbach's Alpha (α)
AI Adoption Intention	3 (1 modified)	3	0.910
AI Usage in Performance Appraisal	6	6	0.879

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Perceived Accuracy	3 (1 added)	4	0.885
Perceived Satisfaction	3 (1 added and 1 modified)	4	0.888
Total	**15**	**17**	

Analysis

Estimated Model for Reliability and Validity:

Table 3 Reliability and Validity

Construct	**Composite Reliability**	**AVE**	**Lowest Outer Loading**	**All Values Meet Threshold?**
AI Adoption Intention	0.854	0.661	0.723	Yes
AI Usage in Performance Appraisal	0.890	0.575	0.723	Yes
Perceived Accuracy	0.862	0.610	0.739	Yes
Perceived Satisfaction	0.868	0.622	0.741	Yes

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Composite reliability is a way to remedy this problem by using the individual indicator loadings to calculate the reliability of each scale. Composite reliability provides a more precise and comprehensive view of a scale's reliability than Cronbach's alpha, especially when used in SEM. Values greater than or equal to 0.7 are considered reliable, with values over 0.8 or 0.9 representing a high degree of reliability. The construct validity measures the extent to which a measurement tool accurately measures the theoretical construct it claims to measure and not some other variable. Construct validity is usually determined through empirical testing, including convergent validity, i.e., how strongly items measured by a particular construct correlate with each other, and discriminant validity, i.e., how well measures of different constructs remain distinct. The primary analyses conducted to establish construct validity include confirmatory factor analysis (CFA), which involves an evaluation of the factor loading, average variance extracted (AVE), and fit indices (Hair et al., 2019). From Table 3, it could be understood that the psychometric properties were found to be strong for all ten constructs, demonstrating the reliability and validity of the measurement model. The lowest outer loading (0.723) was above the recommended minimum of 0.7, and the composite reliability of all constructs is also above the acceptable threshold. Similarly Average Variance Extracted (AVE) of all constructs is above the threshold limit of 0.5. All the outer loadings that depict the relationship between the indicators and their latent constructs are above 0.7, thus establishing convergent validity. This was followed by establishing discriminant validity through the Fornell-Larcker criterion.

Table 4 Discriminant Validity

Constructs	**AI Usage during Performance Appraisal**	**AI adoption Intention**	**Perceived Accuracy**	**Perceived Satisfaction**
AI Usage during Performance Appraisal	***0.759***			
AI adoption Intention	0.197	***0.813***		
Perceived Accuracy	0.176	0.195	***0.781***	

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Perceived Satisfaction	0.138	0.138	0.188	***0.789***

For constructs to meet the Fornell-Larcker criterion, each diagonal element must be greater than the highest off-diagonal correlation coefficient for any of the other constructs. This shows that for each construct, its indicators account for more variance than that shared with the indicators of any other construct, and therefore, each construct measures independently from the other constructs. Examining **Table 4** above establishes discriminant validity.

Path Analysis:

Smart PLS 4 was used to evaluate the path model of the study based on PLS-SEM methodology. SmartPLS 4 is particularly advantageous for complex models that are examined with smaller sample sizes or non-normal distributions. Exploratory, as well as predictive research, works the best with PLS-SEM as it was developed to maximise the variance explained on dependent variables. Prior to investigating the structural model, a measurement model had to be examined, which resulted in valid and reliable measures for the latent constructs under consideration and any relationships between them. Statistical significance was determined by researchers estimating p-value, and path coefficients (β) using bootstrapping techniques with 5000 resamples.

In the context of PLS-SEM, R-square (R^2) indicates what proportion of variance in the dependent variable can be explained by the independent variable(s) within the structural model. Thus, R^2 ranges from 0-1 for the predictive capability of a given model, with a greater R^2 indicating greater predictive capability. In behavioural research, however, there is no standard for defining R^2. In addition to indicating the model's predictive power, R^2 also indicates how Q^2 Predictive Relevance was used to further validate the model and R^2 Adjusted as applied to the researchers' complex models (Hair et al., 2022). The bootstrapping function included with SmartPLS 4 has provided evidence of the presence of probable mediation and/or moderation relationships in the data analysed because statistical analysis can produce reliable results for investigating these aspects of mediation and moderation. Furthermore, when used in combination with other methodologies, PLS-SEM provides statistical evidence of the methods that can be applied in technology adoption, organisation behaviour and human resource management studies.

Table 5 Quality Criteria: Total Variation Explained

Model	R-square	Adjusted R-square
Adoption Intention	0.45	0.44

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Actual Usage of AI	0.32	0.30
Perceived Accuracy	0.33	0.31
Perceived Satisfaction	0.29	0.28

Table 5 above shows that when HR managers intend to adopt AI, they are likely to utilize AI to a greater degree in their performance evaluation of employees (adjusted R^2= 0.30). Additionally, the high R^2 value indicates that AI Adoption Intention is an excellent indicator of how much AI will be used by an individual during the performance appraisal process.

Direct Effects:

Table 6 Estimated Path Coefficient and Statistical Significance of Direct Effect

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AI Adoption Intention → AI Usage in Performance Appraisal	0.210	0.211	0.040	5.250	0.000

Table 7 Estimated Path Coefficient and Statistical Significance of Direct Effect

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values

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AI Usage in Performance Appraisal → Perceived Accuracy	0.185	0.187	0.038	4.868	0.000
AI Usage in Performance Appraisal → Perceived Satisfaction	0.145	0.147	0.041	3.537	0.001

Results in **Tables 6 and 7** support the hypotheses H2 & H3 of the study. The results for AI intention as a predictor of AI actual usage during the performance appraisal process by HR managers are also highly significant ($\beta = 0.21$, $t = 5.25$, $p < 0.001$). Further, it is clearly brought out that AI usage during the performance appraisals process has a substantial positive influence on perceived accuracy ($\beta = 0.19$, $t = 4.87$, $p < .001$). The above analysis result supports H2, as it indicates that the usage of AI technology will indeed enhance the accuracy of the performance evaluation outcomes. Finally, the use of AI tools within the appraisal process appears to help managers assess how satisfied employees are with their evaluations higher than if they were not using AI technology ($\beta = 0.15$, $t = 3.54$, $p < .001$, $r = 0.15$), thus supporting H3. Figure 2 below depicts the conceptual model.

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Figure 2 Proposed Conceptual Model

Source: Authors owns creation

Discussion and Conclusion:

The results of the study showed a strong, positive correlation between AI adoption intention and the application of AI tools when performing performance appraisals of an employee. In particular, the higher the degree of AI adoption intention by the HR manager(s), the greater the frequency at which they use AI tools to perform evaluations of employees' performance. This finding is consistent with existing models of technology acceptance, which state that the most immediate predictor of actual behaviour will ultimately be behavioural intention (Davis, 1989; Venkatesh et al., 2003). The UTAUT and its various related studies have identified that intention to use technology as one of the most powerful and reliable indicators of whether or not it will be adopted for use in an organisational environment (Venkatesh et al., 2012; Sun & Zhang, 2006). Similar other studies have also shown that this relationship is supported by the psychological theory of intention, which suggests that intention is indicative of both the willingness and preparedness of an individual to take action, given the influence of individual attitudes, perceived usefulness, perceived ease of use, support from organisations and social contacts (Ajzen, 1991; Oliveira et al., 2014).

A number of contextual elements present in the Indian IT services sector may be connected to the positive connection found in this study. There are fewer obstacles between purpose and action when there is a high rate of technology use, an innovative culture, and a highly digitally savvy workforce. This relatively smooth transition from intention to actual use is caused by a number of factors, including the sector's intense focus on competition, growing demands for HR functions to be effective and equitable, and ongoing investment in technology infrastructure (Khan et al., 2024; Noerman et al., 2025). Furthermore, the data shows that organizational policy and leadership support, which are generally strong in this industry, are crucial in converting intention to real implementation (Baabdullah, 2024; Rathnayake et al., 2025). As a result, the findings' generalizability is reinforced not only by comments in this industry but also by comparable outcomes in other technology-driven businesses and international contexts. For instance, studies in the finance industry have found that the degree to which AI is really used to evaluate credit and detect fraud is directly correlated with the goal to apply AI-based analytics (Baabdullah, 2024; Camilleri, 2024).

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The results of this study also demonstrate that employee satisfaction with the process's outcomes and the perceived accuracy of the assessment process both rise with the degree to which AI technologies are used in performance reviews. More precisely, the data shows that managers feel more trust in the objectivity, dependability, and correctness of their performance reviews when they use AI tools frequently and extensively. Additionally, these managers believe that because of perceived improvements in fairness, transparency, and the speed at which performance feedback was received, employees expressed higher levels of satisfaction with the appraisal process. This lends credence to the body of research showing that the application of AI and digital tools in HRM enhances performance evaluation satisfaction and perceived accuracy (Jarrahi, 2018; Köchling et al. 2021). Veliz et al. (2021) claim that AI solutions for HR managers boost people's confidence in the accuracy of assessments by lessening the impact of subjectivity and creating a more consistent, data-driven review process. Similarly, Sharma et al. (2020) and Bianchini et al. (2025) discovered that integrating AI into the HR process increases employee and appraiser satisfaction due to improved process transparency and fast and useful feedback.

The results presented in this study can be applied to most nations and areas that have embraced AI applications connected to human resource management (HRM) and, to a much lesser degree, to nations and areas that employ HRM technology less often. Regarding the use of an AI-based tool to enhance perceptions about the quality of appraisals and overall satisfaction with the appraisal results, the financial and healthcare services industries exhibit data trends that are comparable to those shown above by this study (Baabdullah, 2024; Camilleri, 2024). These results are consistent with international research and industry standards/guidelines. They also show that varying degrees of preparedness, industry standards, and geographic circumstances will affect how much each organization benefits (Jarrahi, 2018; Köchling et al., 2021; Bianchini et al., 2025). The fundamental factors identified in this study will probably help businesses develop more effective, reliable, transparent, and fulfilling performance management procedures as they continue to invest in digital HR systems across all sectors and regions of the globe.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

AlAwadhi, S., & Morris, A. (2008, January). The Use of the UTAUT Model in the Adoption of E-government Services in Kuwait. In *Proceedings of the 41st annual Hawaii international conference on system sciences (HICSS 2008)* (pp. 219-219). Ieee.

Al-Mamary, Y. H. (2025). A comprehensive model for AI adoption: Analysing key characteristics affecting user attitudes, intentions and use of ChatGPT in education. *Human Systems Management*, *44*(6), 978-999.

Attuquayefio, S., & Addo, H. (2014). Using the UTAUT model to analyze students' ICT adoption. *International Journal of Education and Development using ICT*, *10*(3).

Baabdullah, A. M. (2024). The precursors of AI adoption in business: Towards an efficient decision-making and functional performance. *International Journal of Information Management*, *75*, 102745.

Baumsteiger, R., & Siegel, J. T. (2019). Measuring prosociality: The development of a prosocial behavioral intentions scale. *Journal of personality assessment*, *101*(3), 305-314.

Bianchini, S., Müller, M., & Pelletier, P. (2025). Drivers and barriers of AI adoption and use in scientific research. *Technological Forecasting and Social Change*, *220*, 124303.

Binns, R. (2018). Fairness in machine learning: Lessons from political philosophy. In S. A. Friedler & C. Wilson (Eds.), Proceedings of the 1st Conference on Fairness, Accountability and Transparency (Vol. 81, pp. 149–159). Proceedings of Machine Learning Research. PMLR.

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239-257.

Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. *Technological Forecasting and Social Change*, *201*, 123247.

Carlsson, C., Carlsson, J., Hyvonen, K., Puhakainen, J., & Walden, P. (2006, January). Adoption of mobile devices/services-searching for answers with the UTAUT. In *Proceedings of the 39th annual Hawaii international conference on system sciences (HICSS'06)* (Vol. 6, pp. 132a-132a). IEEE.

Chang, P. C., Zhang, W., Cai, Q., & Guo, H. (2024). Does AI-driven technostress promote or hinder employees' artificial intelligence adoption intention? A moderated mediation model of affective reactions and technical self-efficacy. *Psychology Research and Behavior Management*, 413-427.

Cochran, W. G. (1977). Sampling Techniques (3rd ed.). New York: John Wiley & Sons, Inc.

Creswell, J. W., & Creswell, J. D. (2017). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of management review*, *14*(4), 532-550.

Emon, M. M. H., Hassan, F., Nahid, M. H., & Rattanawiboonsom, V. (2023). Predicting adoption intention of artificial intelligence-A study on ChatGPT. *AIUB Journal of Science and Engineering*, *22*(2), 189-196.

Exploding Topics. (2025). *50 new artificial intelligence statistics (July 2025)*. https://explodingtopics.com/blog/ai-statistics

Frankiewicz, B., & Chamorro-Premuzic, T. (2020). Digital transformation is about talent, not technology. *Harvard Business Review*, *6*(3), 1-6.

Grover, P., Kar, A. K., & Dwivedi, Y. K. (2022). Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions. *Annals of Operations Research*, *308*(1), 177-213.

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

Horani, O. M., Al-Adwan, A. S., Yaseen, H., Hmoud, H., Al-Rahmi, W. M., & Alkhalifah, A. (2025). The critical determinants impacting artificial intelligence adoption at the organizational level. *Information Development*, *41*(3), 1055-1079.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business horizons*, *61*(4), 577-586.

Jawahar, I. M. (2007). The influence of perceptions of fairness on performance appraisal reactions. *Journal of Labor research*, *28*(4), 735-754.

Kar, S., Kar, A. K., & Gupta, M. P. (2021). Modeling drivers and barriers of artificial intelligence adoption: Insights from a strategic management perspective. *Intelligent Systems in Accounting, Finance and Management*, *28*(4), 217-238.

Kerlinger, F. N. (1966). Foundations of behavioral research. https://psycnet.apa.org/record/1966-35003-000

Khan, A. N., Mehmood, K., & Soomro, M. A. (2024). Knowledge management-based artificial intelligence (AI) adoption in construction SMEs: the moderating role of knowledge integration. *IEEE transactions on engineering management*, *71*, 10874-10884.

Kijsanayotin, B., Pannarunothai, S., & Speedie, S. M. (2009). Factors influencing health information technology adoption in Thailand's community health centers: Applying the UTAUT model. *International journal of medical informatics*, *78*(6), 404-416.

Kline, R. B. (2023). Principles and practice of structural equation modeling (5th ed.). Guilford Press.

Köchling, A., Riazy, S., Wehner, M. C., & Simbeck, K. (2021). Highly accurate, but still discriminatory: A fairness evaluation of algorithmic video analysis in the recruitment context. *Business & Information Systems Engineering*, *63*(1), 39-54.

Lee, C. S., & Tajudeen, F. P. (2020). Usage and impact of artificial intelligence on accounting: Evidence from Malaysian organisations. *Asian Journal of Business and Accounting*, *13*(1).

McKinsey & Company. (2025). Superagency in the workplace: Empowering people to unlock AI's full potential. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/superagency-in-the-workplace-empowering-people-to-unlock-ais-full-potential-at-work

Meijerink, J., Boons, M., Keegan, A., & Marler, J. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *The InTernaTIonal Journal of human resource managemenT*, *32*(12), 2545-2562.

Netguru. (2025). *AI adoption statistics in 2025*. https://www.netguru.com/blog/ai-adoption-statistics

Noerman, T., Riyadi, Yuliaji, E. S., & Natasha, C. A. M. (2025). The impacts of social influence and hedonic motivation on experience and continuance intention of using AI in SMEs' HRM. *Cogent Business & Management*, *12*(1), 2542422.

Noy, C. (2008). Sampling knowledge: The hermeneutics of snowball sampling in qualitative research. *International Journal of social research methodology*, *11*(4), 327-344.

OECD. (2025). *The adoption of artificial intelligence in firms*. https://www.oecd.org/publications/the-adoption-of-artificial-intelligence-in-firms_8fab986b-en.htm

Oh, J. C., & Yoon, S. J. (2014). Predicting the use of online information services based on a modified UTAUT model. *Behaviour & Information Technology*, *33*(7), 716-729.

Oliveira, T., Faria, M., Thomas, M. A., & Popovič, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International journal of information management*, *34*(5), 689-703.

PricewaterhouseCoopers (PwC). (2024). *2025 AI business predictions*. https://www.pwc.com/us/en/tech-effect/ai-analytics/ai-predictions.html

Rathnayake, A. S., Nguyen, T. D. H. N., & Ahn, Y. (2025). Factors Influencing AI Chatbot Adoption in Government Administration: A Case Study of Sri Lanka's Digital Government. *Administrative Sciences*, *15*(5), 157.

Shahid, M. K., et al. (2024). Exploring the relationship of psychological factors and AI adoption in performance assessment. *Computers in Human Behavior Journal, 148*, 107617. https://doi.org/10.1016/j.chb.2023.107617

Sadler, G. R., Lee, H. C., Lim, R. S. H., & Fullerton, J. (2010). Recruitment of hard-to-reach population subgroups via adaptations of the snowball sampling strategy. *Nursing & health sciences*, *12*(3), 369-374.

Sharma, N. P., Sharma, T., & Agarwal, M. N. (2016). Measuring employee perception of performance management system effectiveness: Conceptualization and scale development. *Employee Relations*, *38*(2), 224-247.

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter business technology journal*, *31*(2), 47.

Soulami, M., Benchekroun, S., & Galiulina, A. (2024). Exploring how AI adoption in the workplace affects employees: a bibliometric and systematic review. *Frontiers in Artificial Intelligence*, *7*, 1473872.

Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California management review*, *61*(4), 66-83.

Stanford Institute for Human-Centered Artificial Intelligence (2025). The 2025 AI index report. https://hai.stanford.edu/ai-index/2025-ai-index-report

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Šumak, B., Heričko, M., & Pušnik, M. (2011). A meta-analysis of e-learning technology acceptance: The role of user types and e-learning technology types. *Computers in human behavior*, *27*(6), 2067-2077.

Sun, H., & Zhang, P. (2006). The role of moderating factors in user technology acceptance. *International journal of human-computer studies*, *64*(2), 53-78.

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. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178.

Wang, X., Khan, M. U., & Mir, F. W. (2025). Artificial intelligence as heterogeneous agents in environmental performance: The mediating role of energy transition and the moderating effect of green technology adoption in Belt and Road Initiative countries. *Journal of Cleaner Production*, *523*, 146331.

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in human behavior*, *26*(4), 760-767.