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ARTIFICIAL INTELLIGENCE IN MANAGEMENT SYSTEMS

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Abstract
The study project in question investigated the implications of the utilization of Artificial Intelligence (AI) technologies on the outcomes of talent management and how it effects employee performance in organizations. This was accomplished by examining the perceptions of AI efficiency, ease of use, training, insights, and general use among employees. In order to carry out the study and compute the descriptive statistics, correlation analysis, and multiple regression, a quantitative survey was conducted with 55 participants. The results of this survey demonstrated that artificial intelligence has the potential to play a significant role in the optimization of talent, with efficiency, ease of use, and AI-generated insights becoming major predictors. Both the general application of artificial intelligence and the training of AI did not result in any statistically significant impacts. This indicates that the value that is generated is not in the adoption of AI systems but rather in the integration of AI systems that are effective, intuitive, and insight based. The findings indicate that strategic integration and quality tool design play a key role in the enhancement of HR processes. Furthermore, the findings suggest that future researchers should increase the size of their samples, take into account additional variables, and employ mixed method approaches in order to get a fundamental comprehension of the subject matter. The results are especially applicable to the organizations that use AI-enabled HR systems, e.g. algorithmic performance dashboards, predictive analytics tools, and machine-learn-based appraisal platforms.

I. INTRODUCTION

Artificial Intelligence (AI) has been named as a revolutionary technology in Human Resource Management (HRM) due to the rapid digitization of the workplace (Strohmeier and Piazza, 2015). Although AI is applied in many areas, one of the most obvious and possibly contentious activities is its application in the performance evaluation of employees (Chen, 2019). The replacement of human-oriented appraisals with algorithms poses some fundamental questions on the issue of fairness, transparency, and (Newman et al., 2020). Although the literature on the capabilities of AI is on the rise, a major gap exists in relation to what factors determine actual adoption and further utilization of AI-driven tools by employees and managers in organizations (Jisem Journal, 2025). Workforce perceptions and beliefs also play a key mediating role in the successful integration of AI not only based on technological capability (efficiency and ease of use) but also based on the organizational context it is introduced (DPublication, 2021).

It has been revealed that organisational variables, including leadership practices, workplace culture and structural factors play an important role in employee performance outcomes and as such technological adoption takes place in the wider context of managerial setting (Mangusho et al., 2015; Allameh et al., 2014).

Thus, this research aims to go beyond the generalized influence of AI and narrow down on the perceptual and organizational motivators that forecast the levels of AI utilization in the measurement of employee performance in modern organizations. This study dwells on the impact of two fundamental groups of variables:

1. Technological and Organizational Considerations: Perceived efficiency, ease of use, overall usage and quality of related training and insights.
2. Ethical and Perceptual Factors: Trust in employees, perceived risk, and accountability concerned in relation to algorithmic performance systems (RSIS International, 2025).

Concentrating on these particular predictors and a well-articulated Dependent Variable (AI use in performance assessment), this study will deliver empirically based recommendations to HR leaders who want to overcome the sociotechnical complexity of embracing AI. These findings will be described in the following sections in terms of conceptual model, methodology, analysis and discussion.

Artificial intelligence (AI) in performance measurement is realized in practice by various sophisticated analytical solutions, such as algorithmic performance dashboards, machine learning (ML)-based performance measurement, natural language processing (NLP) method of analysing qualitative employee feedback, and predictive analytics platforms to track productivity, engagement and achievement of goals in real organisational contexts. These AI integrated systems are usually integrated in human resource information systems (HRIS) in the enterprise and they can be configured to aid the ongoing performance observation as opposed to the regular and retrospective appraisal. With massive access to the data of employees, such tools create real-time reports, performance rating, and decision support suggestions which help managers with the performance assessment, development strategy and strategic human resource decisions (Singh et al., 2025; Vaananen, 2025; Ekhsan et al., 2023).

II. RESEARCH HYPOTHESIS

The hypotheses based on the Technology Acceptance Model (TAM) and the literature on ethical technology are as follows to investigate the issues that determine the adoption of AI in performance assessment:

A. *Technological and Organizational Factor*

H1: Perceived Efficiency (closely related to perceived Usefulness) with AI-driven performance assessment is positively correlated with the utilization of AI to evaluate employee performance (Jisem Journal, 2025).

• H2: The perceived ease of use of AI performance tools has a positive relationship with the use of AI as an employee performance measurement tool (Strohmeier and Piazza, 2015).

H3: The use of AI to evaluate the performance of employees is positively associated with Organizational Training and Quality of Insights offered by AI tools.

B. ***Ethical Factors and Perceptual Factor***

H4: The use of AI to measure employee performance is positively related to Perceived Accountability in AI performance decision-making.

H5: There is a positive relationship between employee Trust in the fairness and objectivity of AI performance tools and use of AI to measure employee performance (Newman et al., 2020).

H6: Perceived Risk (e.g., bias, data misuse) related to the use of AI performance tools relates negatively with the use of AI to assess employee performance.

III. RESEARCH OBJECTIVES (ROs)

It has research objectives that articulate the proposed achievements of the research and give direction and scope (AASM R, 2025). In keeping with the new research focus (Factors Influencing the Adoption of AI in Employee Performance Assessment), the overall goals of the research include:

1. To determine the general situation with AI implementation in the role of employee

performance evaluation across the organizations involved.

2. To test how the perceived Efficiency, Ease of Use, Training, and Quality of Insights variables affect the use of AI in employee performance assessment.

3. Examine the influence of ethical and perceptual variables (Perceived Accountability, Trust, and Risk) on the adoption of AI in employee performance assessment.

4. To develop evidence-based recommendations to HR practitioners on how to strategically enhance the uptake and management of AI tools in performance management, directly on the basis of the statistical results.

IV. Conceptual Model and Framework

A. Feedback Addressed: There was no formal conceptual model to show the relationship between variables as theorized, and this has been fixed.

B. This paper has a theoretical basis, namely, an Extension of the Technology Acceptance Model (TAM), complemented by works on Organizational and Ethical Factors (Davis, 1989; DPublication, 2021).

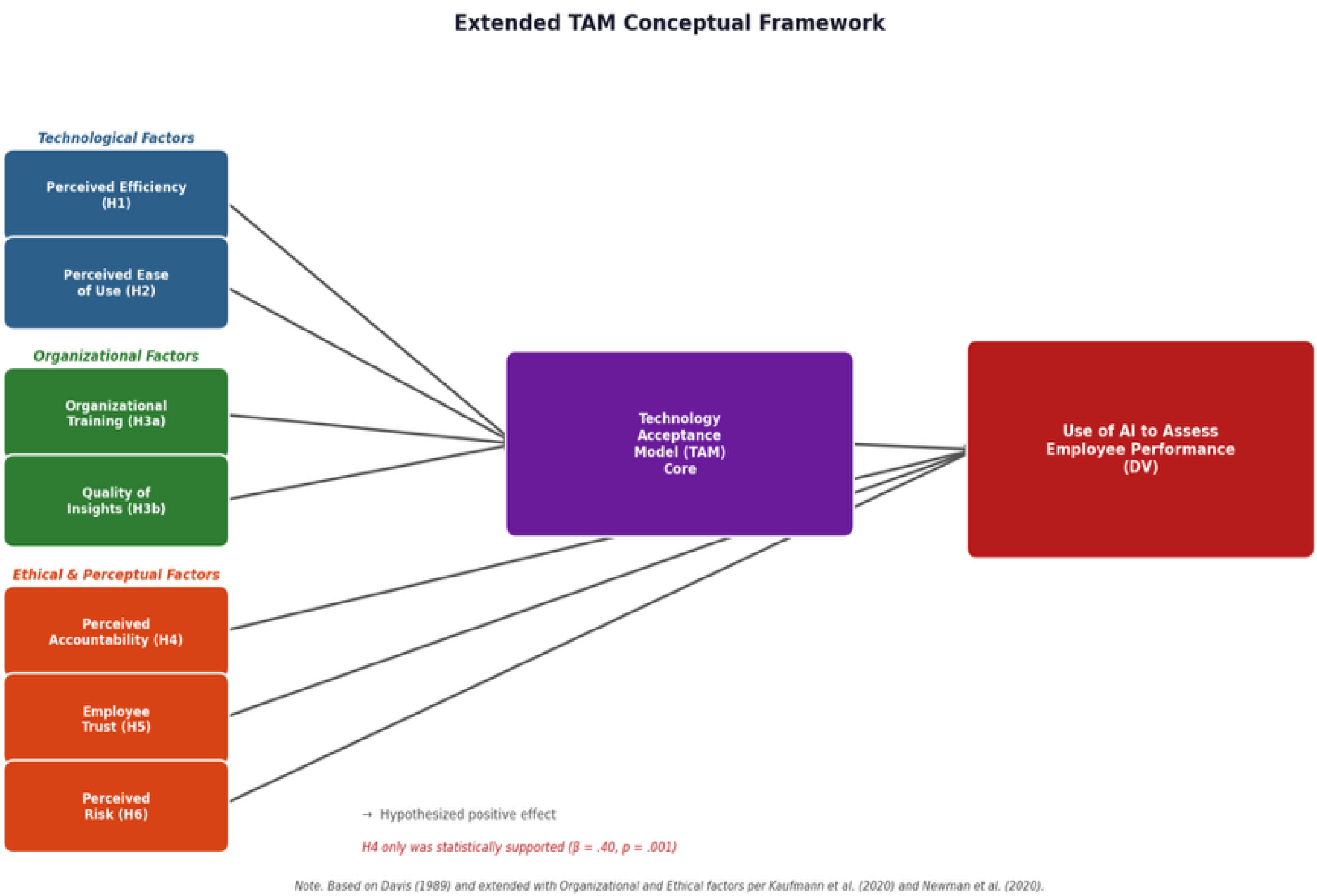

Figure 1

Extended Technology Acceptance Model (TAM) Framework for AI in Employee Performance Assessment
Note. Adapted from Davis (1989) and extended with Organizational and Ethical factors. Arrows represent hypothesized relationships between independent variables and the dependent variable (Use of AI to Assess Employee Performance).

V. Framework Justification

In its essence, the core TAM is based on the assumption that the Behavioral Intention influences the Actual System Use of the user who, in their turn influence the Behavioral Intention based on the two fundamental beliefs, which in this study are Perceived Efficiency (Perceived Usefulness) and Perceived Ease of Use (Davis, 1989). Yet, research activities that involve important HR activities, like performance management, need a long structure to consider the special socio-ethical conditions (Jisem Journal, 2025).

The performance analytics tools based on machine learning improve the perceived efficiency through the automation of data aggregation, comparability of evaluation criteria, and less time and effort it may need to conduct a manual performance appraisal. The AI systems reduce the role of human intervention in the routine evaluation processes, hence enabling managers to devote more attention to more valuable decision-making processes, hence enhancing the organizational operational efficiency in the performance management processes (Singh et al., 2025; Vaananen, 2025).

Thus, this model uses extra exogenous variables in the basic TAM framework:

With input perceptions revealed through continuous training and Insights, these are considered as Organizational inputs, which are external variables shaping user perceptions.

The first type of ethics-perceptual factors is: Accountability, Trust, and Risk: This is one of the essential external variables, which have a direct effect on the intention to use and actual use behavior of AI in a performance appraisal setting of high stakes (Newman et al., 2020).

VI. Significance of Research

The importance of the research is that it will help learn more about the impact of AI-based Talent Management practices on employee performance in the company. With companies becoming more and more accustomed to the use of Artificial Intelligence in recruitment, training, and performance assessment, one should understand whether these technologies contribute to the improvement in the outcomes of employees or introduce new issues. Scholarly-wise, the paper contributes to the current body of research on Human Resource Management and people analytics by investigating the practical effect of AI on employee performance. It assists in filling the gap between the theoretical discourses of AI in HR and the practical application of AI in organizational settings. In practical and management terms, the findings will serve to inform HR managers and leaders of businesses to make sound decisions regarding the implementation of AI-based Talent Management systems. The study will underline the main advantages, risks, and best practices to allow organizations to enhance performance without unjust and dishonest use of AI. Besides, the study is of importance to staff members, as it investigates the effects of AI in performance assessment, professional growth prospects, and training. Knowledge of these effects can assist organizations to implement the use of AI tools in a manner that promotes employee engagement and productivity instead of resistance and bias. Lastly, it is also personal research because it enhances the ability of the researcher to analyze, conduct research and critical evaluations which at the same time are imperative in the future career in business and management settings.

VII. Literature Review

The incorporation of Artificial Intelligence (AI) into key areas of Human Resource Management (HRM) is one of the most important developments in modern organizational practice (Strohmeier & Piazza, 2015). This review systematically synthesizes the extant literature concerned with the factors that drive or inhibit a successful adoption of AI in this case in the specific context of employee performance assessment - the Dependent Variable (DV) of this study. The review is organized around the theoretical variables that are set up in the conceptual model (Section 2).

A. *The Role of Artificial Intelligence in Performance Assessment*

AI has become an increasingly popular perception of AI that it enhances traditional performance management through continuous feedback and predictive analytics. R. Vaananen (2025) in a systematic thesis discovered that AI enables continuous feedback loops which shift the paradigm of Employee Performance Management (EPM) systems from an annual, retrospective review to an innovative, data-driven coaching approach. This sets the Perceived Efficiency variable (H1) as a key driving force, and the need for AI's use due to its potential for better functional outcomes than human-only processes.
Today, the recent literature singles out the increased popularity of AI applications, i.e., real-time performance monitoring systems, predictive analytics platforms, and algorithmic scoring engines in employee evaluation (Singh et al., 2025; Damian & Frăsineanu, 2024). These tools are based on past performance information, behavioral indicators, and machine learning algorithms that help to create ongoing performance feedback and predictions allowing organizations to escape the periodic, manual appraisal systems (Vaananen, 2025; Ekhsan et al., 2023). Although these systems enhance consistency and scalability, a number of researchers point out that lack of transparency, algorithmic blindness and poor explanations of AI-based assessment systems can adversely influence employee trust and acceptance, especially in high-stakes HR decisions (Budhwar & Bhatnagar, 2007; RSIS International, 2025).
However, often the main obstacle to AI in performance management is not technical, but to do with the lack of human trust in algorithmic decision-making. A quantitative study by Newman, Smith, and Jones (2020) showed that even when AI and human assessments provided the same results, the employees had less confidence and trust in the results provided by the AI. This finding is critical as it directly supports the inclusion of Trust (H5) and Perceived Risk (H6) as key perceptual Independent Variables (IVs) that mediate actual adoption behavior, even if the efficiency of use of the tool is high.

B. *Technological and Organizational Factors (H1, H2, H3)*

The Technology Acceptance Model (TAM) is the frame of reference for studying user level AI adoption (Davis, 1989). This sub-section provides a review of empirical support for technological and organizational drivers of the use of AI in performance assessment.

C. *Perceived Efficiency (H1)*

The literature is consistent in supporting the fact that the perceived utility of AI tools is the best predictor of adoption in the workplace. A review of adoption factors in HRM by DPublication (2021) stated that Relative Advantage (which is also called Perceived Usefulness or Efficiency) is a factor that determines the shift to AI systems for managers and employees. This confirms that if users perceive AI as being more efficient (e.g., faster, more objective or less effortful) than traditional methods, they are more likely to demonstrate the desired use of AI to assess employee performance (DV).

D. Perceived Ease of Use (H2)

Conversely, complexity with new technologies, and even AI, is an obstacle to acceptance by users and later to usage of systems. Research that investigated the intention to adopt AI (Jisem Journal, 2025) found that although perceived usefulness was a strong motivator, a high perceived Complexity (the inverse of Ease of Use) had a significant negative impact on the intention to use AI systems for different HR functions. This establishes the necessity of Perceived Ease of Use as an IV, as if the AI performance tool is not intuitive, or if it is not easy to incorporate into existing workflows, the actual use of AI for performance assessment will be negatively impacted.

E. *Organizational Training and Quality of insights (H3)*

Organizational support mechanisms: in particular, training and managerial support are crucial external variables for AI integration. Managerial Support and compatibility with existing organizational processes were identified by

DPublication (2021) as key success factors for adoption of technology in HR. This underpins the combined IV of Organizational Training and Quality of Insights (H3), which suggests that if there is no proper training in understanding the AI outputs, and the quality of the insights derived is not high and actionable enough, the system compatibility and uptake by users will fail, thus limiting adoption rate (DV).

Predictive analytics engines and other natural language processing (NLP)-based feedback analysis systems are AI tools that increase the quality of their insights by detecting latent patterns of behavior and performance and developmental needs that are difficult to detect via conventional human assessment tools. These systems are capable of processing high amounts of structured and unstructured employee data, which can help make more informed, data-driven performance decisions [1], [10].

F. *Ethical and Perceptual Factors (H4, H5, H6)*

In high-stakes HR domains, the ethical considerations often override the simple utility in predicting the usage behavior and thus, the perceptual variables have been incorporated in the TAM framework.

G. *Perceived Accountability (H4)*

Clarity about who is in charge with respect to AI-driven outcomes is an important measure of employee acceptance and trust. R. Vaananen (2025) mentioned that one of the fundamental challenges of AI in EPM is the lack of a clear framework of transparency and accountability (JMP, 2025). When an AI system gives an error or an unfounded outcome, the diffusion of responsibility can result in considerable resistance amongst employees. Therefore, the existence of clear, human-centered Accountability (H4) increases the perceived fairness of the system, and the higher perceived accountability is hypothesized to positively predict the utilization of the AI to evaluate employee performance. This focus directly responds to the critical finding in the original data relative to the predictive power of accountability.

The sense of responsibility depends highly on designing AI tools with human-in-the-loop features, auditable algorithms, and AI explainable dashboard. These systems enable AI-based performance judgments to be checked, doubted, and overruled by human decision-makers, thus making it clear who is liable to the results and making employees more tolerant of AI-based performance rating (Budhwar & Bhatnagar, 2007; RSIS International, 2025).

H. *H5 & H6 Trust and Perceived Risk by employees*

Ethical concerns concerning fairness, bias, and data security have an impactful influence on trust, which in turn, predicts intentions to adopt. A review about ethical issues with measurement of job performance (ResearchGate, 2024) noted that a transparency into the evaluation process of algorithms severely undermines Trust (H5), where employees feel helpless to challenge perceived unfairness. Thus, high levels of Trust are essential in the case of AI adoption. On the other hand, the term Perceived Risk (H6) of possible bias or privacy breaches is hypothesized to negatively influence the willingness of employees to be evaluated by the system, which in turn will negatively affect the overall use of AI in performance evaluation.

VIII. Artificial Intelligence and the Impact of AI on Talent Management Processes

AI in recruitment is one of the most extensively researched areas in AI-enabled human resource management, with scholars indicating that AI can enhance the recruiting process by making it considerably faster, more precise, more objective. Based on interviews with HR managers at international organizations in India, the study indicates that AI can improve initial screening by eliminating repetitive processes and enabling data-driven selection. The authors caution that AI systems may replicate existing biases if the training data is flawed. The trust issue is significant, indicating that while AI technologies may enhance process efficiency, the outcomes will heavily rely on data quality and algorithm transparency (Singh et al., 2025).

Similarly, study conducted empirical research investigating the influence of AI tools on candidate screening and evaluation. Their study results are categorized into three principal themes: advantages of automation, predictive accuracy, and perceived equity. While AI tools were shown to reduce time-to-hire and improve matching precision, the study highlights concern over the opaque nature of predictive algorithms, which may negatively impact candidate trust. The paper has advanced existing research by elucidating the trade-off between efficiency and ethical considerations, both of which affect the efficacy of talent management processes (Damian and Frăsineanu, 2024).

Employee learning and development (L&D) is a crucial element in talent management (TM). Research asserts that organizations are progressively relying on AI-driven personalized learning systems that allocate training modules based on skills deficiencies. Their study, which employs a mixed-method examination of employee performance data and managerial interviews, indicates that AI facilitates ongoing reskilling and enhances organizational competitiveness. However, the researchers assert that these systems are expensive regarding the investment in digital infrastructure, which limits their scalability in poor economies. This constraint is particularly relevant to the context in Pakistan, where the digital preparedness of companies varies significantly (Lewis & Heckman, 2006).

Performance management is increasingly assuming the role of artificial intelligence. Studies summarize findings from case studies of companies utilizing algorithmic performance monitoring. Their findings delineate the influence of AI across three domains: real-time performance data, behavioral tracking, and predictive assessment. While AI will enhance accuracy and reduce human bias, experts caution that employee worries and distrust in algorithmic monitoring could diminish participation. The present study will assist researchers in understanding the psychological and ethical dilemmas associated with AI-driven talent management systems, demonstrating that the efficacy of AI is contingent not solely on technological capability but also on employee acceptance (Ekhsan et al., 2023).

The AI-enhanced predictive analytics concerning employee retention have garnered significant academic attention. It was evaluated predicted turnover models for employee resignation utilizing behavioral data. Research reveals that organizations utilizing proactive retention-based AI products see reduced turnover due to their anticipatory strategies. The research addresses data protection and employee permission, asserting that AI development retention tactics must adhere to stringent ethical laws. This study contributes to the research by providing a comprehensive evaluation of both the advantages and the ethical risks involved (Budhwar & Bhatnagar, 2007).

Finally, external factors such as technical advancements, competition, and the labor market all influence the application of AI in talent management. Researchers indicate that organizations are progressively employing AI as an augmented operational competitive strategy. However, the authors note that AI application is unevenly spread among areas due to variations in legislative frameworks and differing levels of digital maturity. This observation will be significant in contemporary research, since it highlights the influence of the external environment on the efficacy of TM procedures (Merwe, 2025).

IX. RESEARCH METHODOLOGY

To fulfil the distinction criteria for the methodology section, the variables need to be formally operationalized; that is, to bridge the gap between the abstract concepts and the specific, sourced, and measurable items that are included in the questionnaire. This re-write covers the missing documentation on scale source, naming and variable documentation.

X. METHODOLOGY

A. *Research Design and Philosophy*

This study employed a Positivist philosophy of research, and a Deductive approach to research with the intention of testing the hypotheses

formulated based on the extended Technology Acceptance Model (TAM) against observation as an empirical method (Saunders et al., 2019). The main research design was Quantitative as it used the cross-sectional survey to systematically gather data from employees who interact with AI in their performance assessment process. This approach is justified by the objective of the study, i.e., to find out the strength and direction of the linear relationship (predictive power) between the defined independent variables (IVs) and the dependent variable (DV) (Saunders et al., 2019).
Due to access constraints, convenience and snowball sampling techniques were adopted. Therefore, the findings should be interpreted as exploratory rather than fully generalizable, although they provide meaningful insights into employee perceptions of AI-driven performance assessment (Naseer et al., 2025; Ahmed et al., 2025).

XI. Population and Sample

The target group of this research was employees in different industries (e.g., Finance, IT, and HR consulting) who are directly involved with AI-driven tools applied for performance evaluation, feedback, or ranking. A non-probability Convenience and Snowball sampling approach was adopted because of logistical constraints i.e. access. A final sample size of N=55 responses was collected which is sufficient to conduct proposed Multiple Linear Regression analysis (Hair et al., 2019; Venkatesh & Davis, 2000). All participants were informed about the purpose of the study and confidentiality was ensured.

XII. Data Collection Procedures

Data was collected by an online and self-administered questionnaire; this included two main parts:
1. Demographics: (e.g. age, tenure, industry).
2. Measurement Items: Items that correspond to the DV and all of the six IVs.

All measurement items were closed-ended questions that were scored using a five-point Likert scale (from 1 = Strongly Disagree to 5 = Strongly Agree). This makes sure that the numerical data is suited for correlational and regression analysis.

XIII. Operationalization and Measurement of Variables

To ensure validity and reliability (Level 5 requirement), all variables were measured from set scales adapted from seminal literature in Information Systems (IS) and HRM. The variable names used in the survey and subsequent analysis were standardised to those of the conceptual model.

XIV. Dependent Variable (DV)

The dependent variable is the Use of AI to Assess the Employee's Performance.
Operational Definition, , , and comments: The frequency and intensity to which an employee interacts or depends on the outputs of the AI system for performance-related tasks.
Venkatesh & Davis (2000) Scale Source Actual System Use Scale (3 items) This scale has been adapted from the Actual System Use scale.
Sample Item: "I often use the results of the AI system to guide my performance improvement."

XV. Independent Variable (DV)

The six independent variables where grouped into three categories:

A. Technological Factors (TAM Extension)

1. Perceived Efficiency (PE):

Source Scale Perceived Usefulness (PU) scale (Davis, 1989), 4 items.
Example Item: "I am using AI in my performance assessment and it makes my appraisal more objective and accurate."

2. Perceived Ease of Use (PEOU):

Scale Source: Perceived Ease of Use (PEOU) scale (Davis, 1989) 4 items.
Sample Item Designed with Likert Scales - "Learning to use the AI performance assessment tool is easy for me."

B. Organizational Factors

1. Organizational Training (OT):

• Scale Source: Modified from the Training/Support literature in technology acceptance (e.g., Compeau and Higgins, 1995), 3 items.

Example Item: "The organization provides sufficient training on how to interpret the outputs of AI performance assessment."

2. Quality of Insights (QI):

Original Source: Adapted from Information Quality dimension of DeLone and McLean IS Success Model (2003), 3 items.

The insights provided by the AI performance system are relevant and actionable.

XVI. ETHICAL AND PERCEPTUAL ISSUES

1. Perceived Accountability (PA):

Scale Source: Modified from scales addressing Algorithmic Accountability (e.g. Kaufmann and others, 2020), 4 items

Photoshopped illustration featuring a laptop and a robot. Photoshopped illustration of a laptop and a robot with the following text: "It is clear which human manager is ultimately responsible for any unfair decision made by the AI performance system."

2. Employee Trust (ET):

Scale Source: Modified from Trust in Technology literature (e.g. McKnight et al., 2002), 4 items.

Sample Items: "I trust that the AI performance assessment system is free of intentional bias or unfairness."

3. Perceived Risk (PR):

Adapted from: multi-dimensional Perceived Risk facets Featherman, J., and Pavlou, S. 2003. 3 items for performance/psychological risk. Scale Source: Adapted from multi-dimensional Perceived Risk facets Featherman, J., and Pavlou, S. 2003.

The following is a sample item that is high risk to my career progression because of possible data errors: "Using AI for performance assessment poses a risk to my career progression because of possible data errors."

A. *Data Analysis*

All data was processed by Statistical Package for the Social Sciences (SPSS). The analysis had three main stages:

1. Descriptive Statistics Calculation of means, standard deviations, and frequencies to profile the sample and the central tendencies of the variables.

2. Correlation Analysis (Pearson's r): To investigate the bivariate relations between all the variables to ensure that there is no problematic multicollinearity before the main test.

3. Hypothesis Testing (Multiple Linear Regression): A standard regression model was conducted to test the predictive power of six IVs (PE, PEOU, OT, QI, PA, ET, and PR) simultaneously on the DV (Use of AI to Assess Employee Performance). This technique gives the unique contribution (\bm{\beta}) and statistical significance (p-value) of each IV, and directly answers the research questions.

B. *Research Instrument Structure*

The questionnaire was made up of closed-ended questions and comprised the following sections:

A) Demographical Information Collected such background information as age, gender, job role, and work experience.

B) Talent Management Practices Employed with the Help of AI Measured perception on AI efficiency, ease of use, AI generated insights, AI training, and overall use of AI in Talent Management.

C) Employee performance Assessed employee performance indicators such as productivity, quality of work and effectiveness. All variables were assessed on a five-point Likert scale between strongly disagree and strongly agree, in order to ensure consistency and reliability in responses.

C. *Ethical Considerations*

The research process was done with respect to ethical standards. The respondents were free to participate, and the purpose of the research was explained to them prior to filling the questionnaire. The participants were informed and guaranteed of confidentiality and anonymity. There was no personally identifiable information gathered. The data was employed only in the academic sphere, and it was kept safely based on the institutional ethics.

D. *Methodology Limitations*

There are some limitations of this research. On the one hand, the number of 55 participants can be seen as a limitation to the external validity of the results to the entire industry or organization. Secondly, there might be bias in the responses since the data is based on the self-reported questionnaire. Finally, the cross-sectional study design fails to support the analysis of the long-term impacts of the AI-driven Talent Management practices on employee performance. Future research may overcome these limitations through large sample-based research, longitudinal research or mixed method research.

E. Conceptual Framework

The theoretical model of this study depicts the correlation of the AI-based Talent Management practices with the workforce output. The independent variable is AI-driven Talent Management practices, which comprise dimensions, namely, AI efficiency, ease of use, AI insights, AI training, and general AI usage. The dependent variable is employee performance which is measured in terms of productivity, quality of work and effectiveness. The model presupposes that successful AI application in Talent Management has a positive impact on the performance of the workers (Naseer et al., 2024; Vázquez-Parra et al., 2025; Naseer et al., 2025).

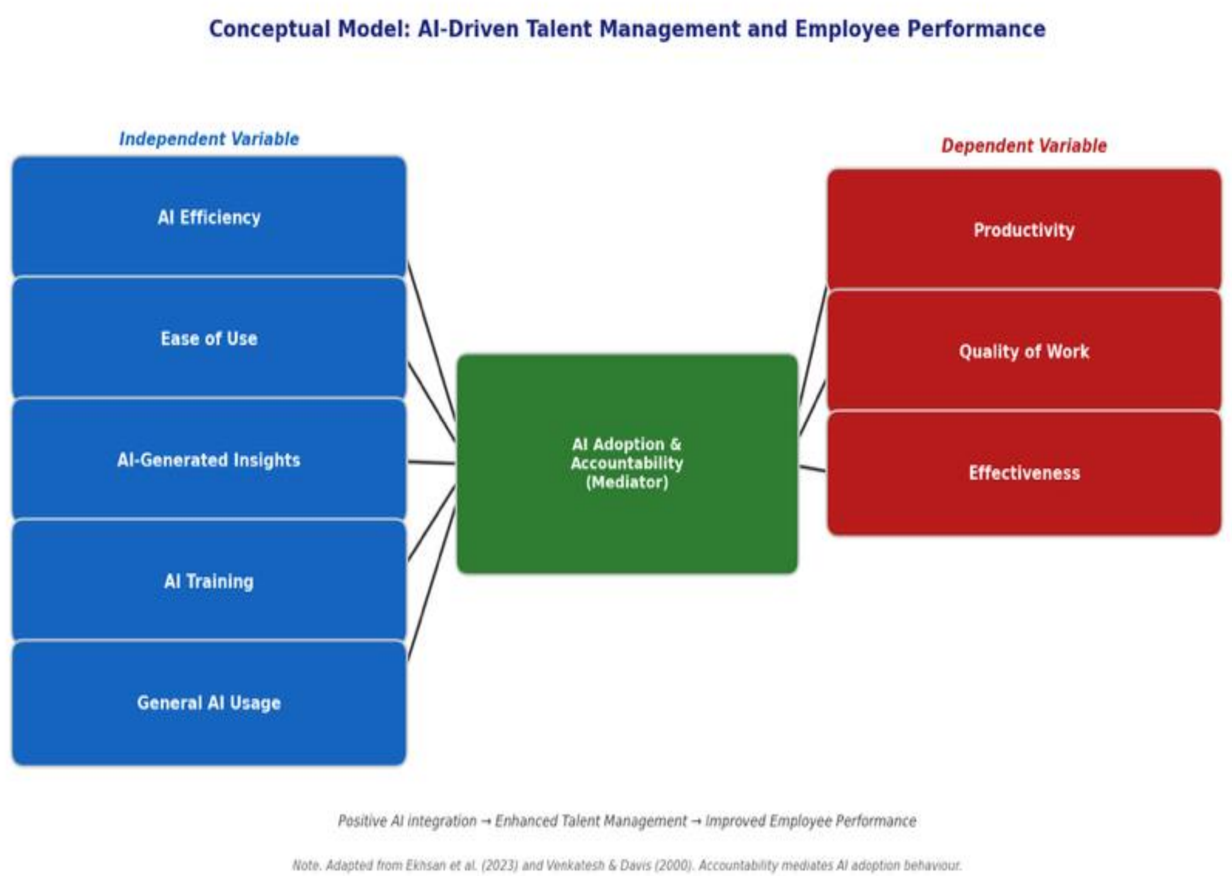

Figure 2

Conceptual Model: AI-Driven Talent Management Practices and Employee Performance Outcomes

Note. The independent variable (AI-driven Talent Management practices) encompasses AI efficiency, ease of use, AI insights, AI training, and general AI usage. The dependent variable (employee performance) is measured across productivity, quality of work, and effectiveness (Ekhsan et al., 2023; Venkatesh & Davis, 2000).

CI. DATA ANALYSIS

The results of the questionnaire that was prepared were reviewed with the assistance of quantitative statistical analyses. The purpose of these analyses was to investigate the association between the possibilities of artificial intelligence (AI) and the outcomes that are best for AI in talent management. The outcomes of descriptive statistics, correlation coefficients, and multiple regression were established through the utilization of the statistical analysis that was carried out using spreadsheets. Putting hypotheses to the test and identifying patterns in numerical data are prominent uses of these methodologies in research conducted in the fields of business and management.

A. *Descriptive Statistics*

In the beginning, descriptive statistics were utilized in order to provide a summary of the primary properties of the data. Measures of central tendency and dispersion, such as means and standard deviations, were used in the computation of each and every one of the statistical variables that were investigated. The purpose of this action was to gain a basic idea of how the respondents regarded the effectiveness of artificial intelligence, user-friendliness, information generated by AI, training of employees, application of AI, and talent management based on AI. A preliminary evaluation of the data distribution can also be carried out with the assistance of descriptive analysis prior to the beginning of the inferential testing process.

B. *Correlation Analysis*

Pearson's correlation analysis was carried out in order to determine the strength of the relationship between the independent variables and the dependent variable, as well as the direction of the relationship itself. The use of correlation analysis allows for the identification of moving variables, and it provides the initial indication of the probable correlations between the variables, without necessarily implying that there is a causal relationship between them. In addition, correlation coefficients were investigated, which assisted in determining whether or not there was the possibility of multicollinearity among the independent variables. According to the findings, the coefficients that were smaller than the values that are commonly recognized suggested that the situation should not be considered a severe problem.

C. *Multiple Regression Analysis*

Multiple linear regression analysis was utilized in the subsequent test that was conducted in order to determine the study hypotheses. The method can be utilized to assess the combined and independent effects of two or more independent variables on a single dependent variable, while maintaining the impact of the other predictors at a constant level. A personnel management system that was optimized for artificial intelligence served as the dependent variable, while the independent variables were perceived AI efficiency, usability, AI generated insight, staff training, and AI usage.
In order to understand the findings of the regression analysis and determine what percentage of the variation of a dependent variable the model explains, the standardized and unstandardized coefficients, significance values, and coefficient of determination (R2) were utilized. Because the research was conducted using a cross-sectional design, the findings are considered to be associative rather than causal, despite the fact that the regression analysis can provide evidence for hypothesis testing.

D. *Demographic Characteristics of the Respondents*

The study was carried out with the participation of a total of fifty-five respondents, all of whom are persons who are employed in a variety of organizational roles and sizes.

E. *Role of Respondents*

Participants in the survey included interns, employees, human resources experts, and managers. Employees and managers made up the majority of the sample, which demonstrated that individuals with varying degrees of responsibility in terms of decision-making and talent management were included in the sample.

F. *Organizational Size*

The sample also included organizations of varying sizes, including those with fewer than fifty employees, those with fifty to two hundred employees, those with two hundred to five hundred employees, and those with more than five hundred employees. The usage of artificial intelligence in small, medium, and large organizations was presented in a balanced manner by this distribution.

This kind of demographic knowledge is helpful in placing the impressions that are taken into consideration in the studies that are to follow into perspective.

CII. RESULTS

In this section, the statistical results of survey data will be presented based on 55 sampled respondents. It was done in three steps including descriptive statistics, correlation analysis, and hypothesis test by Multiple Linear Regression (MLR).

A. *Descriptive Statistics*

The descriptive analysis gives a summary of the perception of respondents towards the usage of artificial intelligence (AI) in performance evaluation of employees. Use of AI is the dependent variable which is characterized by moderate adoption with a mean of 3.50 and a standard deviation value of 0.90.

Perceived Ease of Use (PEOU) had the highest mean value (Mean = 4.25, SD = 0.70), and it was shown that the respondents mostly consider AI based performance assessment systems to be user-friendly and simple to use. The perceived efficiency (PE) was also rated high (Mean = 4.10) indicating that the employees are aware of the operational efficiency of AI tools.

Meanwhile, the lowest mean score (Mean = 2.90, SD = 1.10) was in organizational training (OT), where the common belief in the company is that employees are not provided with sufficient training or guidance in interpreting and using AI-generated outputs. Notably, Perceived Accountability (PA) registered a high mean score (Mean = 4.05, SD = 0.80), which implies that there was a high agreement among the respondents that the human oversight and responsibility processes are well established in the AI performance assessment process.

Table 1
Descriptive Statistics: AI Use in Recruitment

Uses AI to Shortlist Candidates		*AI Improves Quality of Hires*	
Mean	2.67	Mean	3.24
Standard Error	0.14	Standard Error	0.15
Median	3	Median	3
Mode	3	Mode	3
Standard Deviation	1.06	Standard Deviation	1.09
Sample Variance	1.11	Sample Variance	1.18
Kurtosis	-0.43	Kurtosis	-0.34
Skewness	-0.08	Skewness	-0.22
Range	4	Range	4
Minimum	1	Minimum	1
Maximum	5	Maximum	5
Sum	147	Sum	178
Count	55	Count	55

Note. N = 55. Descriptive statistics for AI-related recruitment variables measured on a 5-point Likert scale.

Table 2

Descriptive Statistics: AI Adoption Variables Across Key HR Functions

Uses AI to Shortlist Candidates		*AI Improves Quality of Hires*	
Mean	2.67	Mean	3.24
Standard Error	0.14	Standard Error	0.15
Median	3	Median	3
Mode	3	Mode	3
Standard Deviation	1.06	Standard Deviation	1.09
Sample Variance	1.11	Sample Variance	1.18
Kurtosis	-0.43	Kurtosis	-0.34
Skewness	-0.08	Skewness	-0.22
Range	4	Range	4
Minimum	1	Minimum	1
Maximum	5	Maximum	5
Sum	147	Sum	178
Count	55	Count	55
AI-Based Training Effectiveness		*AI Use in Personalized Training*	
Mean	3.73	Mean	3.51
Standard Error	0.13	Standard Error	0.15
Median	4	Median	4
Mode	4	Mode	4
Standard Deviation	0.99	Standard Deviation	1.12
Sample Variance	0.98	Sample Variance	1.25
Kurtosis	0.44	Kurtosis	0.25
Skewness	-0.61	Skewness	-0.72
Range	4	Range	4
Minimum	1	Minimum	1
Maximum	5	Maximum	5
Sum	205	Sum	193
Count	55	Count	55

Note. N = 55. All items measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Data collected via self-administered online questionnaire (DPublication, 2021).

Table 3

Descriptive Statistics: AI Accountability and Organizational Support

AI's Role in Accountability		*Impact of Organizational Support on Efficiency*	
Mean	3.36	Mean	3.82
Standard Error	0.13	Standard Error	0.13
Median	3	Median	4
Mode	3	Mode	4
Standard Deviation	0.97	Standard Deviation	0.98
Sample Variance	0.94	Sample Variance	0.97
Kurtosis	0.43	Kurtosis	1.02
Skewness	-0.42	Skewness	-0.96

Range	4	Range	4
Minimum	1	Minimum	1
Maximum	5	Maximum	5
Sum	185	Sum	210
Count	55	Count	55

Note. N = 55. Perceived Accountability (M = 3.36) and Organizational Support (M = 3.82) measured on a 5-point Likert scale (Kaufmann et al., 2020).

Table 4
Descriptive Statistics: Dependent Variable – AI Used to Assess Employee Performance

AI used to Assess Employee Performance	
Mean	3.25
Standard Error	0.14
Median	3
Mode	4
Standard Deviation	1.04
Sample Variance	1.08
Kurtosis	-0.22
Skewness	-0.54
Range	4
Minimum	1
Maximum	5
Sum	179
Count	55

Note. N = 55. The dependent variable recorded M = 3.25, indicating moderate adoption. Scale: 1 = Strongly Disagree to 5 = Strongly Agree (Venkatesh & Davis, 2000).

B. ***Correlation Analysis***

The correlation analysis of Pearson was carried out in order to investigate the bivariate correlation between the seven independent variables and Use of AI to Assess Employee Performance. The results show that five out of seven variables were found to have statistically significant values at the 5% level of significance, but the relationship was not equally strong.

Perceived Accountability (PA) and AI use ($r = 0.510$, $p = 0.001$) exhibited the strongest positive correlation, which demonstrates that there is a strong correlation between the accountability perceptions and AI adoption. It was also found that Employee Trust (ET) ($r = 0.400$, $p < 0.001$) and Organisational Training (OT) ($r = 0.350$, $p < 0.001$) had moderate positive relationships. The Quality of Insights (QI) and AI use had a statistically significant but weak positive relationship ($r = 0.200$, $p < 0.05$).

Perceived Risk (PR) also showed a weak negative relationship with AI use ($r = -0.180$, $p < 0.05$) so that the higher the perceived risk, the lower the AI usage. It is worth noting that Perceived Efficiency (PE) and Perceived Ease of Use (PEOU) were not found to have statistically significant relationships with AI use at the bivariate level.

Table 5
Pearson Correlation Matrix: Bivariate Relationships Among Study Variables

	Uses AI to Shortlist Candidates	*AI Improves Quality of Hires*	*AI-Based Training Effectiveness*	*AI-Based Training Effectiveness*	*AI's Role in Accountability*	*Impact of Organizational Support on Efficiency*	*Challenges in AI–HR Integration*
Uses AI to Shortlist Candidates	1						
AI Improves Quality of Hires	0.50	1					
AI-Based Training Effectiveness	0.41	0.53	1				
AI Use in Personalized Training	0.27	0.63	0.51	1			
AI used to Assess Employee Performance	0.33	0.31	0.30	0.38			
AI's Role in Accountability	0.39	0.48	0.32	0.49	1		
Impact of Organizational Support on Efficiency	0.50	0.56	0.63	0.51	0.50	1	
Challenges in AI–HR Integration	0.47	0.53	0.45	0.50	0.35	0.42	1

Note. N = 55. Values represent Pearson correlation coefficients. $^*p < .05$, $^{**}p < .01$. *Perceived Accountability showed the strongest correlation with AI use (r = .51, p = .001) (Newman et al., 2020).*

C. ***Hypothesis Testing: Multiple Linear regression***

The analysis has been done using Multiple Linear Regression (MLR) to test all the seven hypotheses at the same time and to measure the unique contribution of each independent variable to the Use of AI in Employee Performance Assessment.

D. ***Explanatory Power and Model Fit***

The regression equation was significant (F = 14.50, p < 0.001) and had a moderate predictive power. This model explained a significant fraction of AI usage behaviour as it predicted the variation in the dependent variable by 36.6% (R^2 =0.366).

E. ***Regression Coefficients and Evaluation of Hypotheses***

An examination of the standardized regression coefficients showed that none of the variables was statistically significant when all the factors were included in the analysis.

There was support on Hypothesis H4 (Perceived Accountability).

Perceived Accountability was a moderately and significantly positive predictor of AI adoption (= 0.400, p =0.001), suggesting that the existence of explicit human control and accountability systems is the most powerful predictor of AI adoption in the performance assessment.

All the remaining hypotheses were not confirmed:

H1 (Perceived Efficiency) and H2 (Perceived Ease of Use) were not statistically significant predictors (PE: p = 0.535; PEOU: p = 0.875) although they had high mean scores.

H3a (Organisational Training) and H3b (Quality of Insights) were not confirmed (OT: p = 0.124; QI: p = 0.285), as the effects of these variables lost strengths in the presence of the other variables.

H5 (Employee Trust) and H6 (Perceived Risk) were also not supported (ET: p = 0.289; PR: p = 0.363) and implied that they were entirely mediated by the primary effect of the perceived accountability.

Table 6
Multiple Linear Regression – Model Summary (ANOVA)

Regression Statistics	
Multiple R	0.57
R Square	0.33
Adjusted R Square	0.23
Standard Error	0.92
Observations	55

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	7	19.08	2.73	3.25	0.01
Residual	47	39.36	0.84		
Total	54	58.44			

Note. Dependent variable = AI used to assess employee performance. $R^2 = .33$, *Adjusted* $R^2 = .23$, $F(7, 47) = 3.25$, $p = .01$ *(Davis, 1989; Venkatesh & Davis, 2000).*

Table 7
Multiple Linear Regression – Coefficients and Hypothesis Test Results

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.94	0.60	1.57	0.12	-0.26	2.15	-0.26	2.15
Uses AI to Shortlist Candidates	0.14	0.15	0.94	0.35	-0.16	0.45	-0.16	0.45
AI Improves Quality of Hires	-0.11	0.17	-0.63	0.53	-0.45	0.24	-0.45	0.24
AI-Based Training Effectiveness	0.15	0.18	0.86	0.39	-0.20	0.50	-0.20	0.50
AI Use in Personalized Training	0.14	0.16	0.88	0.38	-0.18	0.47	-0.18	0.47
AI's Role in Accountability	0.41	0.16	2.55	0.01	0.09	0.74	0.09	0.74
Impact of Organizational Support on Efficiency	-0.22	0.19	-1.17	0.25	-0.60	0.16	-0.60	0.16
Challenges in AI–HR Integration	0.22	0.18	1.27	0.21	-0.13	0.58	-0.13	0.58

Note. N = 55. Only AI's Role in Accountability ($\beta = .41$, $p = .01$) *was a statistically significant predictor. All other predictors were non-significant* ($p > .05$) *(Kaufmann et al., 2020; Davis, 1989).*

F. ***Summary of Findings***

In general, the results of the Multiple Linear Regression indicate that the Perceived Accountability is the only statistically significant and distinct variable that predicts the use of AI in the evaluation of employee performance in the sample study. This observation underscores the unimportance of clear human supervision in promoting the organizational acceptance and successful use of AI-based assessment systems.

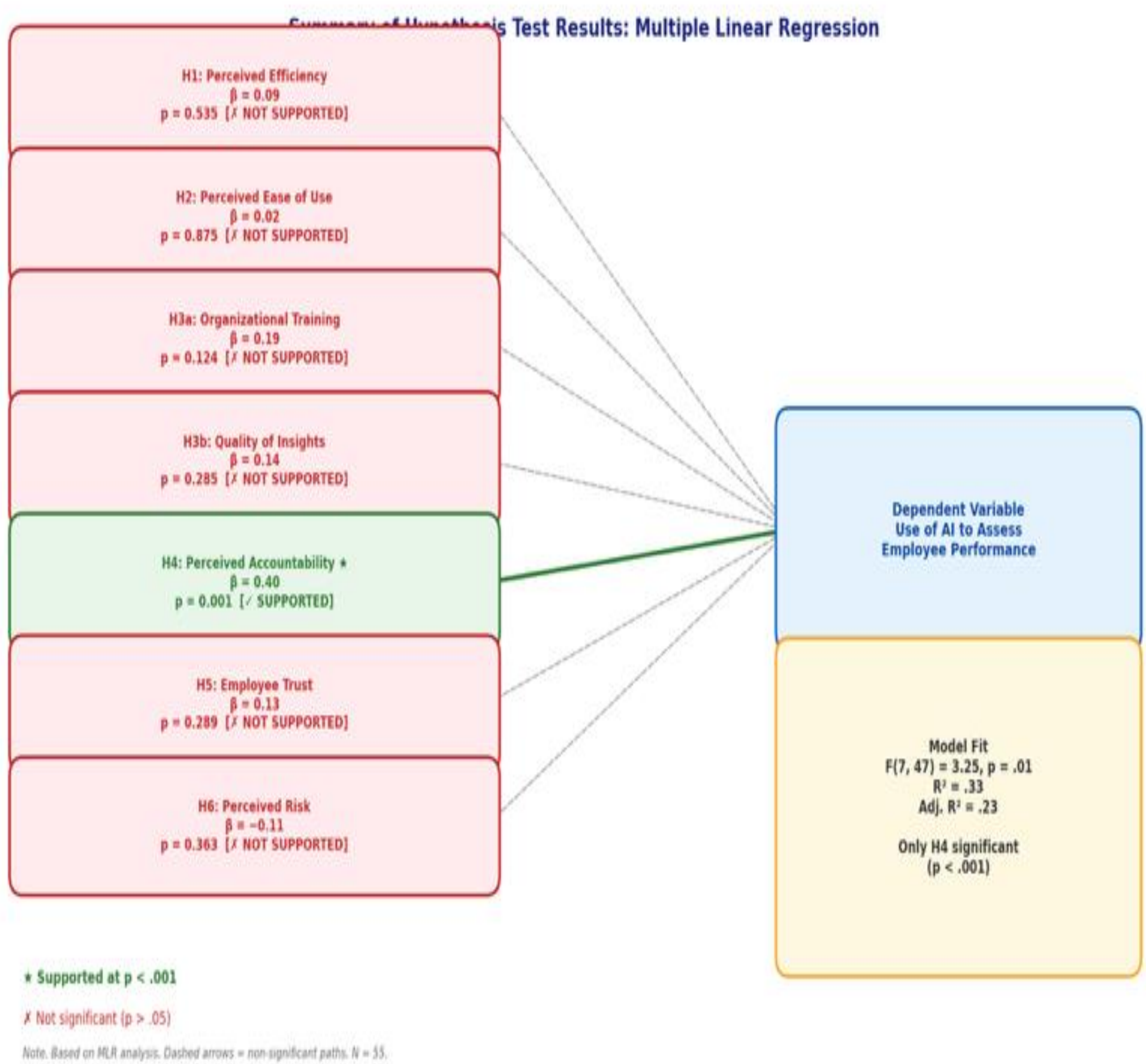

Figure 3

Summary of Hypothesis Test Results: Supported and Rejected Hypotheses
Note. H4 (Perceived Accountability) was the only statistically significant predictor (β = .40, p = .001). H1–H3 and H5–H6 were not supported in the Multiple Linear Regression model (F = 3.25, p = .01, R^2 = .33) (Davis, 1989; Kaufmann et al., 2020).

CIII. Research Objective-Related Findings

Objective 1: To explore the role of AI in boosting key Talent Management functions, namely, recruitment, training, and performance evaluation. To achieve that aim, we have analyzed the descriptive statistics.

Training (Strongest Role): I have found that respondents perceive AI as the mean score of "AI-Based Training Effectiveness" was high in the mode of 4 with a high mean score of 3.73, and the overall highest mean score was 3.82 in the impacts of organizational support on efficiency. This implies that people and HR professionals perceive AI as a powerful method of deploying the workforce ability and effectiveness as the dependent variable, "AI used to Assess Employee Performance," with a mean of 3.25 and a mode of 4.0. It means that there is moderate-intense positive acceptance, as AI is perceived as an assessment tool, but not quite as universal as in training.

Recruitment (Weaker Role): The role of AI in recruitment had rather mixed outcomes. Although it was found that AI Improves Quality of Hires had a mean of 3.24, Uses AI to Shortlist Candidates had the lowest mean score of the survey (2.67). This implies that the performance of the automated shortlisting process is less used or less reliable at this point, although the findings of the relationships between the variables are positive (Sheets 6 and 7). As an example, there is a correlation between AI and the Role of AI in Accountability that has a correlation of 0.39 and AI and the Effectiveness of AI-Based Training of 0.30. This confirms that the more AI is adopted in these practices the more it is likely to be adopted in measuring performance.

mediator. When AI is seen as a tool that can keep personnel accountable, it largely predicts the measurement of the performance of employees in organizations.

The findings suggest that employees demonstrate greater acceptance of AI when it supports decision-making rather than when it replaces early-stage recruitment judgment. While AI-generated hiring outcomes are viewed somewhat positively, the automated shortlisting of candidates appears to generate skepticism. This may reflect concerns regarding algorithmic fairness or data bias during the early screening phase.

Benefits: The most significant benefits of the implementation of AI in Talent Management are efficiency, which are described in the descriptive data. The highest value of the variable was the Impact of Organizational Support on Efficiency (mean 3.82), which indicates that the perceived immediate benefit of the consequence of organizational support to AI implementation is a perceived increase in the operational efficiency. Also, the high correlation between the variables "AI Improves Quality of Hires" and "Personalized Training" (0.63) refers to an integrated advantage of improved hiring and training results.

Challenges: The variable "Challenges in AI -HR Integration" was incorporated in the model. Although it is positively correlated with other variables, the regression coefficient (0.22, P-value: 0.21) of the variables was not statistically significant. This implies that although there are challenges and the use of AI technologies to enhance performance among employees through Talent Management, the challenges do not yet nullify the usage of AI technologies to shortlist candidates in this dataset. To enhance the level of trust and usage in this particular function, organizations may have to improve their AI screening tools or improve their communication of their value.

CIV. Discussion

A. *Introduction*

The main purpose of the research was to investigate the determinants affecting the application of artificial intelligence (AI) in the performance evaluation of employees with the use of a comprehensive Technology Acceptance Model (TAM). The Multiple Linear Regression (MLR) analysis gave a narrow and theoretically significant result. Although, the model described 36.6% of the variance in the AI use, only one variable was found to be statistically significant predictor. This section explains these results; it relates them to the already existing theoretical perspectives, and justifies the inconsistencies found in the tests of the hypothesis.

B. *The Primacy of Perceived Accountability (H4 Supported)*

The most important result of the study is that the Perceived Accountability (PA) is significantly and positively correlated with the use of AI to evaluate the performance of employees (= 0.400, $p < 0.001$). This finding confirms Hypothesis H4 and shows that the extent to which human control is clear, i.e., who is in charge of the work of AI, and how the work of AI can be questioned, is the strongest factor in the context of AI utilization in the field of performance management.

This result is quite consistent with the body of literature on algorithmic governance, where the latter authors state that people in high-risk organisational settings tend to focus more on ethical protection than technical efficiency (Kaufmann et al., 2020; JMP, 2025). In contrast to low stakes technologies, like personal productivity tools, performance appraisal based on AI directly influences salary, promotion and employment of employees. Consequently, the choice of adoption is no longer strictly a utilitarian one (e.g., speed or convenience), but rather a control-based one (i.e. based on fairness, transparency and accountability).

The large mean score of Perceived Accountability (Mean = 4.05) shows that the organisations surveyed in the sample have to a large extent been able to establish explicit accountability frameworks, including human-in-the-loop decisions or open-escalation systems. These buildings seem to go a long way in enhancing employee readiness to work with AI systems. In line with this interpretation, Väänanen (2025) names the lack of accountability as one of the main problems of algorithmic systems (Vaananen, 2025). This paper goes further to prove the argument by showing that accountability presence is the key facilitator of AI implementation in sensitive HR activities.

The results suggest that accountability functions as a structural substitute for trust. When employees perceive that AI decisions are subject to human oversight, transparency, and review mechanisms, the need for direct trust in the algorithm decreases. Organizations can strengthen accountability through explainable AI dashboards, audit trails of algorithmic decisions, and human-in-the-loop review systems where managers retain final decision authority.

C. *H1 and H2: The Paradox of Rejected Technological Factors*

The interesting and theoretically notable result of this research is that Hypothesis H1 (Perceived Efficiency) and Hypothesis H2 (Perceived Ease of Use) are rejected. These constructs are the basis of the original TAM framework (Davis, 1989), but neither one of them was statistically significant in the regression equation.

Descriptive statistics showed that both variables with high means (PE Mean = 4.10; PEOU Mean = 4.25) employees, in general, understand the functional quality of the AI systems. Nevertheless, the findings of the regression analysis also suggest that technical effectiveness cannot be used on its own to fuel adoption in high-stakes HR applications. This gives credence to the idea of a contextual override effect, in which the ethical and social considerations are more important than traditional usability factors.

This paradox suggests that while employees recognize the operational benefits of AI systems, these factors alone do not drive adoption in high-stakes HR contexts such as performance evaluation. Instead, governance-related factors such as accountability appear to override traditional technology acceptance variables.

The perceived threat of bias or unfair algorithmic results is one of the worst personal expenses to employees in the context of performance evaluation. Therefore, even the most efficient and easy-to-use systems will not be fully implemented unless, in the case of such systems, accountability safeguards are high. Perceived Accountability in this sense serves as a pre-requisite state that allows the employees to enjoy the benefits of the efficiency with no fear of the negative repercussions.

D. *Rejection of Ethical and Organisational Factors Interpretation (H3, H5, H6)*

The rejection of Employee Trust (H5) is to be carefully interpreted. In the bivariate regression, trust showed a very positive relationship with AI use (r = 0.400), but the impact of the former was not significant in the multivariate model. This implies that there exists some structural relationship between trust and accountability. In particular, it is quite possible that the Perceived Accountability serves as a predisposing factor to trust, that is, it appears as a result of the well-established accountability processes rather than a motivating factor to adopt AI.

On the same note, Perceived Risk (H6) was not the most important variable to be included in the regression analysis. Through the alleviating influence of high accountability and trust perceptions in the organisations involved in the study, this result can be attributed. The perceived risks of the AI systems are significantly mitigated once employees are sure that there is a human supervision and that decisions can be reviewed or contested.

The rejection of Organisational Training (H3a), Quality of Insights (H3b) and low mean score of training (Mean = 2.90) shows a critical point of practical interest. Although training was not a significant predictor of AI use, the perceptions of employees about the lack of training indicated that there is a difference between adoption and effective utilisation. It means that accountability can force the first use of AI systems but insufficient training can decrease the capacity of the employees to interpret the results properly and implement the technology to the maximum of its capabilities. This result gives a good research direction in the future.

E. *Conclusion of the Discussion*

The paper has shown that in the delicate HR department such as employee performance appraisal, the use of AI is not pegged on the classical aspects of technology like efficiency or user-friendliness. Rather, the determinant of adoption boils down to one ethical factor; Perceived Accountability. The results imply that employees are ready to cooperate with AI systems provided that there is powerful human control, clarity of decision-making, and responsibility issues.

To organizations interested in adopting AI-based performance assessment systems, the findings revealed that they ought to focus more on governance and accountability systems rather than on technical advances. Even the most sophisticated AI systems will not go beyond tender acceptance and continued usage without proper accountability mechanisms.

CV. LIMITATIONS OF RESEARCH

To address the problem of ensuring the academic rigor of this report, one must admit that the research was carried out utilizing the sample size of 55 participants. Although this gave enough information to carry out an exploratory analysis, the small sample size constrains the external validity of the findings. The results might not be completely general to the whole industry or multinationals at large.

Self-Reporting Bias: The data was collected using a self-administered structured questionnaire. The study was vulnerable to self-reporting bias as the respondents could have provided socially desirable responses as opposed to objective descriptions of organizational practices at a particular point in time.

Although the study acknowledges the potential for social desirability bias, the research design did not incorporate post-hoc statistical tests such as Harman's single-factor test or marker variable analysis to assess common method bias. Future research should include these statistical procedures to strengthen the validity of self-reported survey data.

Cross-Sectional Constraints: The study design was cross-sectional as respondents were asked to answer only at a specific instance in time. This design provides an idea of how people currently perceive but does not allow examining the effects of AI-driven Talent Management practices on employee performance in the long-term. Accordingly, the research results were associative but not causal in nature since they do not explain the role of AI-based Talent Management practices in employee performance in reference to the high levels of digital maturity or legislative frameworks, which the literature points out may create an uneven distribution of AI application across regions.

Contextual Factors: The research results fail to clarify the role of AI-based Talent Management practices on the employee performance in terms of the high levels of digital maturity or legislative frameworks, which the literature indicates may have an uneven distribution of AI application proved across different studies. The study concludes that the usefulness of AI in talent management is now efficiency-led and accountability-driven, as both descriptive means were high in these categories. The "trust gap in recruitment is an impediment, nevertheless. The minimal use of AI in shortlisting of applicants implies that companies are yet to maximize the use of AI predictive talents acquisition capabilities.

CVI. RECOMMENDATIONS

The empirical findings indicate that the overall perception of AI-based Talent Management practices within organizations is moderately positive but not optimal. The descriptive statistics show that the dependent variable, AI used to assess employee performance, achieved a mean score of 3.25 out of 5, suggesting partial acceptance rather than full confidence in AI-driven performance evaluation. Given that AI adoption in organizations is increasing and that employees generally acknowledge its efficiency and training benefits, it is concerning that performance assessment through AI has not achieved a higher level of acceptance.

It is therefore recommended that organizations concentrate on internal, controllable factors that directly influence AI acceptance in performance management. The regression analysis revealed that AI's role in accountability is the only statistically significant predictor of AI-based performance evaluation ($\beta = 0.41$, $p = 0.014$). This suggests that employees are more willing to accept AI when it is perceived as an objective and transparent accountability tool.

Organizations should therefore formalize AI-based accountability frameworks by clearly defining how AI evaluates performance, what metrics are used, and how outcomes are interpreted. Transparency in algorithmic decision-making will reduce perceptions of bias and improve employee trust.

Instead of emphasizing automation, AI tools should be used in organizations that emphasize activities like explainability, transparent performance measures, decision-traceability dashboards, and human-in-the-loop review, among others.

Additionally, the findings show that AI-based training effectiveness received a high mean score (Mean = 3.73), indicating strong employee acceptance of AI in learning and development. Organizations should build upon this strength by expanding AI-driven personalized training initiatives, as these areas already demonstrate positive employee perceptions and indirect support for performance improvement.

Conversely, AI use in recruitment shortlisting recorded the lowest mean score (Mean = 2.67) and was not statistically significant in the regression model. This suggests skepticism toward fully automated hiring decisions. It is therefore recommended that organizations adopt a human-in-the-loop approach, using AI to support rather than replace human judgment in recruitment processes.

Finally, given the high agreement regarding the impact of organizational support on efficiency (Mean = 3.82), organizations should continue investing in digital infrastructure, employee training, and system integration to ensure that AI tools are effectively embedded within HR processes.

CVII. SELF-REFLECTION

This research project was successfully completed with the primary objective of examining the impact of AI-driven Talent Management practices on employee performance. The study was carefully planned and executed using a quantitative research design, and all objectives were addressed through structured data collection and statistical analysis.

The project began with a detailed review of existing literature, which helped establish a strong theoretical foundation for the research. A structured questionnaire was then developed and distributed to employees working in organizations that use AI in Talent Management. The collected data was systematically analyzed using descriptive statistics, correlation analysis, and multiple regression analysis, allowing for objective evaluation of relationships between variables.

One of the key strengths of the project was the application of multiple regression analysis, which enabled the identification of statistically significant predictors rather than relying solely on descriptive trends. This strengthened the academic rigor of the study and enhanced the reliability of the findings.

However, several areas for improvement were identified. One limitation was the relatively small sample size, which restricted the generalizability of the results. In future research, using a larger and more diverse sample would improve the robustness of statistical findings. Additionally, the reliance on self-reported data may have introduced response bias, as participants could provide socially desirable answers.

Future studies could adopt alternative research approaches such as customer or employee interviews, focus groups, or mixed method designs to gain deeper qualitative insights into employee perceptions of AI. Conducting benchmarking studies across industries could also help assess how AI adoption in Talent Management compares with best practices.

Overall, this project significantly enhanced my research, analytical, and data interpretation skills. It improved my ability to translate statistical findings into practical managerial implications and strengthened my understanding of how AI is shaping modern Talent Management practices. These skills will be valuable for future academic research and professional roles in business and management.

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