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AI-Augmented HRM and Organizational Performance: Examining the role of Job Performance and Quality of Work Life.

Ioannis Vasileiadis

Supervisor: Professor Niki Glaveli

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Supervising Committee

Supervisor:	Co-Supervisor:
Niki Glaveli	Barbara Myloni
Professor	Professor
University of the Aegean	University of Patras

Patras, Greece, September 2026

To my supervisors, Professors Glaveli and Myloni, for their educational work.

Abstract

One of the most significant technological developments of our days, influencing and affecting the way organizations work, Artificial Intelligence (AI) is transforming the way organizations are operated and managed. Human Resource Management (HRM) has been shifted from a traditional administrative function to a strategic organizational mechanism. On today's fast changing and competitive business environment, organizations increasingly rely on advanced technological systems to improve efficiency, productivity and sustainability.

This study investigates the relationship between AI-Augmented HRM practices and Organizational Performance and examines the association of Digital Culture, Job Performance and Quality of Work Life. It follows a quantitative research approach. Data were collected through an online questionnaire, designed to measure the variables of the research model: Digital Culture, AI-Augmented HRM practices, Quality of Work Life, employees' Job Performance and Organizational Performance. The collected data were analyzed using SPSS, including descriptive statistics, reliability analysis and Pearson correlation analysis to examine the relationships between the variables.

The sample consists of 112 employees working in organizations across various countries, sectors, and industries, all of whom have experience with digital HRM tools and AI-related technologies. The data were collected using a convenience sampling technique. The participants represent diverse age groups, professional levels, and organizational contexts, enhancing the variability of the dataset.

The findings indicate that Digital Culture is positively associated with AI-Augmented HRM practices, suggesting that organizations with higher levels of digital readiness are more likely to adopt and implement AI-based HRM solutions effectively. Furthermore, AI-Augmented HRM practices are positively related to Quality of Work Life; however, no statistically significant relationship was found between AI-Augmented HRM practices and Job Performance.

In addition, both Job Performance and Quality of Work Life are positively associated with Organizational Performance, with Quality of Work Life demonstrating the strongest relationship. These results highlight that AI-Augmented HRM contributes to Organizational Performance primarily through indirect pathways, particularly by improving employees' working conditions and well-being.

Finally, the study emphasizes the importance of maintaining a balance between technological advancement and human-centered HRM practices. From a managerial perspective, organizations should focus on strengthening Digital Culture, enhancing employees' Quality of Work Life, and effectively integrating AI-Augmented HRM systems in order to achieve improved organizational outcomes.

Keywords: AI-Augmented HRM, Digital Culture, Job Performance, Quality of Work Life, Organizational Performance

Περίληψη

Μία από τις σημαντικότερες τεχνολογικές εξελίξεις των τελευταίων ετών, η Τεχνητή Νοημοσύνη (ΤΝ), μετασχηματίζει ριζικά τον τρόπο με τον οποίο οι οργανισμοί λειτουργούν και διοικούνται. Στο πλαίσιο αυτό, η Διοίκηση Ανθρώπινου Δυναμικού (ΔΑΔ) έχει μεταβληθεί από μια παραδοσιακή διοικητική λειτουργία σε έναν στρατηγικό οργανωσιακό μηχανισμό. Στο σημερινό ταχέως μεταβαλλόμενο και ιδιαίτερα ανταγωνιστικό επιχειρηματικό περιβάλλον, οι οργανισμοί βασίζονται ολοένα και περισσότερο σε προηγμένα τεχνολογικά συστήματα για τη βελτίωση της αποδοτικότητας, της παραγωγικότητας και της μακροχρόνιας βιωσιμότητάς τους.

Η παρούσα μελέτη διερευνά τη σχέση μεταξύ πρακτικών ΔΑΔ ενισχυμένων με ΤΝ και Οργανωσιακής Απόδοσης, εξετάζοντας παράλληλα τον ρόλο της Ψηφιακής Κουλτούρας, της Εργασιακής Απόδοσης και της Ποιότητας Εργασιακής Ζωής. Υιοθετήθηκε ποσοτική ερευνητική προσέγγιση. Τα δεδομένα συλλέχθηκαν μέσω ηλεκτρονικού ερωτηματολογίου, το οποίο σχεδιάστηκε για τη μέτρηση των βασικών μεταβλητών του ερευνητικού μοντέλου: Ψηφιακή Κουλτούρα, πρακτικές ΔΑΔ ενισχυμένες με ΤΝ, Ποιότητα Εργασιακής Ζωής, Εργασιακή Απόδοση και Οργανωσιακή Απόδοση. Η ανάλυση των δεδομένων πραγματοποιήθηκε με τη χρήση του SPSS και περιλάμβανε περιγραφική στατιστική, ανάλυση αξιοπιστίας και ανάλυση συσχετίσεων Pearson για τη διερεύνηση των σχέσεων μεταξύ των μεταβλητών.

Το δείγμα αποτελείται από 112 εργαζόμενους που απασχολούνται σε οργανισμούς διαφόρων κλάδων και τομέων, οι οποίοι διαθέτουν εμπειρία στη χρήση ψηφιακών εργαλείων ΔΑΔ και τεχνολογιών Τεχνητής Νοημοσύνης. Η συλλογή των δεδομένων πραγματοποιήθηκε με τη μέθοδο δειγματοληψίας ευκολίας. Οι συμμετέχοντες εκπροσωπούν διαφορετικές ηλικιακές ομάδες, επαγγελματικά επίπεδα και οργανωσιακά περιβάλλοντα, ενισχύοντας την ετερογένεια του δείγματος.

Τα ευρήματα δείχνουν ότι η Ψηφιακή Κουλτούρα συσχετίζεται θετικά με τις πρακτικές ΔΑΔ ενισχυμένες με ΤΝ, υποδηλώνοντας ότι οι οργανισμοί με υψηλότερο επίπεδο ψηφιακής ετοιμότητας είναι πιο πιθανό να υιοθετήσουν και να εφαρμόσουν αποτελεσματικά λύσεις ΔΑΔ βασισμένες στην ΤΝ. Επιπλέον, οι πρακτικές ΔΑΔ ενισχυμένες με ΤΝ σχετίζονται θετικά με την Ποιότητα Εργασιακής Ζωής, ενώ δεν διαπιστώνεται στατιστικά σημαντική σχέση με την Εργασιακή Απόδοση. Αντιθέτως, τόσο η Εργασιακή Απόδοση όσο και η Ποιότητα Εργασιακής Ζωής σχετίζονται θετικά με την Οργανωσιακή Απόδοση, με την Ποιότητα Εργασιακής Ζωής να παρουσιάζει την ισχυρότερη συσχέτιση.

Τέλος, αναδεικνύεται η σημασία της ισορροπίας μεταξύ τεχνολογικής προόδου και ανθρωποκεντρικών πρακτικών ΔΑΔ. Από διοικητική σκοπιά, οι οργανισμοί θα πρέπει να εστιάσουν στην ενίσχυση της Ψηφιακής Κουλτούρας, στη βελτίωση της Ποιότητας Εργασιακής Ζωής των εργαζομένων και στην αποτελεσματική ενσωμάτωση πρακτικών ΔΑΔ ενισχυμένων με ΤΝ, προκειμένου να επιτύχουν βελτιωμένα οργανωσιακά αποτελέσματα.

Λέξεις-κλειδιά: Τεχνητή Νοημοσύνη, Διοίκηση Ανθρώπινου Δυναμικού, Ψηφιακή Κουλτούρα, Εργασιακή Απόδοση, Ποιότητα Εργασιακής Ζωής, Οργανωσιακή Απόδοση

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List of Abbreviations & Acronyms

AI	Artificial Intelligence
GDPR	General Data Protection Regulation
HR	Human Resources
HRIS	Human Resource Information Systems
HRM	Human Resource Management
JD-R	Job Demands-Resources model
NLP	Natural Language Processing
QWL	Quality of Work Life
RBV	Resource-Based View
SPSS	Statistical Package for the Social Sciences
ΔΑΔ	Διαχείριση Ανθρώπινου Δυναμικού
ΤΝ	Τεχνητή Νοημοσύνη

1 Introduction

1.1 Importance of the Topic and Research Context

Artificial Intelligence (AI) is one of the most significant technological developments of the modern era, which influences and affects substantially the way organizations operate, especially Human Resources Management (HRM). The rapid growth of digital technologies, Big Data, Machine Learning and the automated decision-making systems have transformed the role of HRM from a basic operational function to a strategic mechanism of organizational growth. Today's organizations are asked to work on environments of high uncertainty, advanced competition and rapid technological changes, a fact that makes necessary the use of technologically advanced tools in human recourse management.

The use of AI in HRM has led to the development of the concept of "AI- augmented Human Recourses Management", according to which the AI tools work as complementary systems to the human decision and not as a complete substitute. Through tools like People Analytics, Predictive Analysis and Algorithmic systems the organizations obtain the ability to process high data volumes and get more documented decisions regarding the personnel selection, performance evaluation, development of skills and talent management (Marler & Boudreau, 2017; Minbaeva, 2021). The use of these technologies allows the improvement of organization effectiveness, increases productivity and reinforces the competitiveness of the businesses (Vrontis et al., 2022).

At the same time, AI gives the possibility of producing more personalized HRM practices adjusted to the needs and the characteristics of each employee. The personalized learning systems, the continuous feedback and the forecast of skill development needs strengthen the work experience and professional development of the employees (Minbaeva, 2021). Additionally, the ability of forecasting employee resignations, occupational burnout or reduced commitment allows organizations the application of timely interventions for talent retention and improvement of the Quality of Work Life (QWL) (Tambe et al., 2019).

However, despite the significant benefits that AI offers, there are challenges applying it on HRM. The use of algorithmic systems is questioning regarding the transparency of the process, personal data protection, probable biases and ethical governance of the technologies. The opacity of the “black box” systems can reduce the trust of employees and produce feelings of insecurity and excessive control. At the same time, excessive dependence on automated processes might reduce human operational dimension and react negatively to emotional safety and organizational commitment of employees (Vrontis et al., 2022; Tambe et al., 2019).

1.2 Research Gap and Problem Statement

Previous research has examined the role of AI in HRM, focused mainly on AI adoption, technological capabilities and improvements in HR processes. Literature also highlights the contribution of AI in supporting HR decision-making, increasing efficiency and improving organizational capabilities (Marler & Boudreau, 2017; Vrontis et al., 2022).

The present work aims to contribute to the existing literature by examining the associations between AI-Augmented HRM practices and Organizational Performance, while considering the role of Digital Culture, employees’ Job Performance and Quality of Work Life. It attempts to promote that the successful utilization of AI is not only dependent on the technological capabilities of the systems, but also on the organizations’ skills to combine technological innovation with human-centered organizational practices and respect to the needs of the employees.

1.3 Research Objectives and Hypotheses

The main objective of this research is to examine the relationship between AI-Augmented HRM practices and Organizational Performance. Additionally, the study investigates the relationship of Digital Culture with AI-Augmented HRM practices and explore how these practices are associated with Job Performance and Quality of Work Life.

1.4 Brief description of methodology

This study follows a quantitative research approach. Data were collected through an online questionnaire from employees working in organizations in different sectors and industries. The collected data were analysed using SPSS through descriptive statistics, reliability analysis and Pearson correlation analysis to examine the relationships between the variables.

1.5 Structure of the Thesis

The thesis is organized into five main chapters:

Chapter 1 introduces the research topic, importance, objectives and methodology.
Chapter 2 presents the literature review regarding AI, AI-Augmented HRM, Digital Culture, Job Performance, Quality of Work Life and Organizational Performance.
Chapter 3 describes the research methodology, including the research strategy, sample, data collection procedure and analysis methods.
Chapter 4 presents the findings and discussion based on the collected data.
Chapter 5 provides the conclusions, implications, limitations and future research directions.

2 Literature Review

2.1 Introduction

The rapid evolvement of technology and incorporation of Artificial Intelligence (AI) have brought radical changes on the way modern organizations operate, directly affecting the management strategy of Human Resources. In this context, the AI-Augmented HRM is taking shape as a critical scope of application, where the synergy between the human decision and algorithmic support aim to reinforce the efficiency and organizational well-being (Mollah M.A. et al., 2024).

This chapter examines the relationship between Artificial Intelligence and Human Resource Management (HRM), with a particular focus on the emerging concept of AI-Augmented HRM. It begins by discussing the broader role of AI in HRM practices, highlighting its applications across key HR functions such as recruitment, selection, performance management, and employee development. Subsequently, the concept of AI-Augmented HRM is introduced and defined, emphasizing its role as a decision-support approach that enhances, rather than replaces, human judgment.

The chapter further explores the importance and role of AI-Augmented HRM in modern organizations, followed by an analysis of the key antecedents that facilitate its adoption. Finally, the outcomes of AI-Augmented HRM are examined at both the organizational and employee levels, focusing on performance, job satisfaction, organizational commitment, and well-being. The chapter concludes by setting the foundation for the development of the theoretical framework and hypotheses in Section 2.7.

2.2 AI and Human Recourses Management

AI is already one of the most transformative forces in modern HRM, significantly affecting core processes such as recruitment and selection, performance evaluation, training and development, and talent retention. The integration of machine learning systems and algorithmic decision-making tools enables organizations to make more data-driven decisions, improving efficiency while reducing operational costs. At the same time, AI technologies automate repetitive administrative tasks, allowing HR professionals to focus more on strategic activities related to human capital development and organizational change management (Jarrahi, 2018).

In recruitment and selection, AI-based systems apply algorithms for resume screening, natural language processing (NLP), and predictive analytics to identify suitable candidates more efficiently. By analyzing large volumes of applicant data, these tools can detect patterns associated with successful job performance, thereby improving the quality of hiring decisions. Additionally, automated interview systems and evaluation tools, including those that analyze behavioral and emotional indicators, aim to reduce subjectivity in human judgment (Kaplan & Haenlein, 2019). Chatbots and virtual assistants further enhance the recruitment process by improving communication with candidates, reducing response time, and improving overall candidate experience (Strohmeier, 2020).

Beyond recruitment, AI plays a critical role in employee retention and talent management. Predictive analytics allow organizations to identify employees at risk of turnover by detecting patterns of disengagement or reduced commitment, enabling early intervention strategies (Minbaeva, 2021). Similarly, AI-supported learning systems enable personalized training and development pathways, tailored to individual employee needs and organizational goals. Digital learning platforms enhance continuous learning and organizational adaptability, which is especially important in rapidly changing technological and economic environments (Marler & Boudreau, 2017).

However, the integration of AI into HRM also raises significant ethical and legal concerns. Algorithmic bias represents a major challenge, particularly when training data reflects historical inequalities. Research shows that AI-based recruitment systems may unintentionally reproduce gender or racial discrimination if not properly monitored and regulated (Raghavan et al., 2020). Issues related to data privacy and transparency are also critical, especially under regulatory frameworks such as the European Union's General Data Protection Regulation (GDPR). Moreover, excessive algorithmic monitoring may negatively affect employees' trust, psychological safety, and emotional well-being if not accompanied by clear ethical guidelines (Kellogg et al., 2020).

At a strategic level, AI adoption reshapes the role of HR professionals, shifting their focus from administrative tasks to strategic decision-making, data interpretation, and change management. Effective use of AI requires the development of digital competencies, the strengthening of digital culture, and the establishment of strong ethical governance mechanisms (Brynjolfsson & McAfee, 2017). Organizations are also increasingly required to invest in reskilling and upskilling initiatives to ensure that employees can adapt to digital transformation and effectively collaborate with AI-driven systems.

In conclusion, AI is fundamentally reshaping HRM by enhancing efficiency, improving decision-making, and enabling more strategic use of human capital. However, its successful implementation depends on addressing ethical challenges and ensuring that AI systems complement rather than replace human judgment

2.3 AI-Augmented Human Resource Management

The concept of AI-Augmented HRM refers to the integration of artificial intelligence systems into HRM processes in order to support and enhance human decision-making rather than replace it. In this framework, AI functions as a decision-support tool that provides predictive insights, automated recommendations, and data-driven analysis, while final decisions remain under human responsibility. This approach is grounded in the logic of Human-AI collaboration, where the combination of algorithmic precision and human judgment leads to improved organizational outcomes (Brynjolfsson & McAfee, 2017).

AI-Augmented HRM typically involves the use of machine learning, natural language processing, and predictive analytics across key HR functions such as recruitment, performance management, talent development, and organizational learning. Unlike fully automated HR systems, the augmented approach emphasizes transparency, accountability, and explainability, addressing concerns related to "black-box" algorithmic systems (Raghavan et al., 2020). This ensures that AI remains a supportive mechanism rather than an autonomous decision-maker.

The literature on digital HRM and algorithmic management highlights that the primary value of AI does not lie solely in automation, but in the creation of a hybrid human–machine model (Human-AI complementarity) (Brynjolfsson & McAfee, 2017; Jarrahi, 2018). In this sense, AI-Augmented HRM differs fundamentally from fully automated systems, as it preserves human oversight and emphasizes ethical governance and interpretability. Overall, AI-Augmented HRM represents a strategic integration of technology into HR processes that strengthens human judgment while maintaining responsibility and accountability at the human level.

2.4 Importance and Role of AI-Augmented Human Resource Management

AI-Augmented HRM is increasingly recognized as a critical development in modern organizations due to its ability to combine human judgment with data-driven insights, thereby improving both operational efficiency and strategic decision-making. Its importance lies not only in the automation of HR tasks, but primarily in the enhancement of decision quality, organizational responsiveness, and the alignment between human capital and business objectives.

From an operational perspective, AI-augmented HRM improves the efficiency of key HR processes such as recruitment, selection, performance evaluation, and employee development. Metrics such as time-to-hire, recruitment costs, and accuracy of performance prediction are commonly used to evaluate its effectiveness. Predictive analytics also enable organizations to anticipate workforce needs, identify skill gaps, and reduce voluntary turnover through early intervention strategies (Minbaeva, 2021). These capabilities enhance organizational agility and reduce uncertainty in HR decision-making.

At a strategic level, AI-Augmented HRM supports evidence-based human resource management by enabling more accurate workforce planning and better alignment between human capital and organizational goals. By transforming large volumes of employee data into actionable insights, AI systems contribute to improved strategic HR planning and increased organizational competitiveness (Kaplan & Haenlein, 2019). This data-driven approach enhances innovation capacity and strengthens long-term organizational performance. Furthermore, AI-Augmented HRM contributes to organizational flexibility and adaptability, which are essential in rapidly changing environments. Organizations that effectively integrate AI tools into HR processes are better equipped to respond to market volatility, technological disruption, and changing workforce expectations. This adaptability is closely linked to the development of digital capabilities within HR departments and across the broader organization.

However, the effectiveness of AI-Augmented HRM is not determined solely by technological capability, but also by employees' perceptions of fairness, transparency, and trust. The acceptance of AI-based HR systems plays a decisive role in their success. If employees perceive algorithmic processes as opaque or unfair, the effectiveness of these systems may be significantly reduced, regardless of their technical accuracy (Kellogg et al., 2020).

In summary, AI-Augmented HRM represents a hybrid model that enhances HR effectiveness by combining technological intelligence with human oversight. Its value lies in improving decision-making quality, increasing efficiency, and strengthening organizational adaptability, while maintaining the central role of human judgment in HR processes.

2.5 Factors Facilitating the Adoption of AI-Augmented HRM

The adoption of AI-Augmented HRM is driven by a set of organizational, technological, and environmental factors that increase the need for more advanced, data-driven human resource practices. One of the primary antecedents is the growing complexity of organizational environments, where rapid technological change and intense competition require faster and more accurate HR decision-making. In this context, AI enables organizations to transform large-scale employee data into strategic knowledge, supporting more informed and timely decisions (Marler & Boudreau, 2017).

A key driver of AI-Augmented HRM adoption is the shift toward data-driven HR strategies. Organizations increasingly rely on people analytics and machine learning tools to analyze employee behavior, performance patterns, and workforce trends. These technologies allow HR departments to identify hidden patterns that are difficult to detect through traditional methods, thereby improving recruitment accuracy, talent management, and workforce planning (Marler & Boudreau, 2017). In addition, predictive analytics support proactive HR interventions, such as identifying employees at risk of turnover or forecasting future skill requirements (Minbaeva, 2021).

Another important antecedent is the emergence of hybrid and geographically dispersed workforces. The rise of remote and hybrid work models, particularly following the COVID-19 pandemic, has increased the need for digital HR systems capable of monitoring engagement, performance, and well-being in real time (Strohmeier, 2020). In such contexts, AI tools provide critical support by enabling continuous monitoring and data-driven coordination across distributed teams.

From a strategic perspective, the Resource-Based View (RBV) suggests that human capital can generate sustainable competitive advantage when effectively aligned with organizational objectives (Barney, 1991). AI-Augmented HRM strengthens this alignment by improving the matching of skills to job requirements, supporting talent development, and enhancing workforce planning. This enables organizations to better integrate HR practices with long-term strategic goals.

In addition, the need to reduce bias in HR decision-making represents a significant driver for AI adoption. Human judgment in recruitment, promotion, and evaluation processes is often influenced by subjective biases and stereotypes. AI systems, when properly designed and governed, can help mitigate these biases by providing standardized and data-driven evaluation criteria (Raghavan et al., 2020). However, this benefit is contingent upon the existence of strong ethical frameworks and transparent algorithmic governance.

Finally, the development of digital culture and HR digital competencies is a critical enabling factor. The successful implementation of AI-Augmented HRM requires HR professionals to possess digital literacy skills and the ability to interpret data-driven insights. Organizations that invest in reskilling and upskilling initiatives, as well as in fostering a culture of innovation and continuous learning, are more likely to successfully adopt and sustain AI-augmented HR practices (Brynjolfsson & McAfee, 2017).

In conclusion, the adoption of AI-Augmented HRM is driven by a combination of environmental pressures, technological advancements, strategic needs, and organizational readiness factors, all of which collectively increase the relevance of AI in modern HRM systems.

2.6 AI-Augmented HRM Outcomes

The implementation of AI-Augmented HRM generates significant outcomes at both the organizational and employee levels. These outcomes reflect the dual nature of AI as both an efficiency-enhancing tool and a mechanism for improving human resource experiences and organizational effectiveness.

At the organizational level, AI-Augmented HRM strengthens evidence-based decision-making and enhances the accuracy of strategic human resource planning. By leveraging data analytics, organizations can improve workforce forecasting, optimize talent allocation, and increase the alignment between HR practices and business objectives. This data-driven approach contributes to improved organizational performance, innovation, and competitiveness (Kaplan & Haenlein, 2019). In addition, organizations that effectively integrate AI into HR processes tend to exhibit higher levels of adaptability and resilience in dynamic environments.

At the employee level, AI-Augmented HRM produces multiple outcomes across different dimensions. In terms of job satisfaction, the use of AI systems can improve employee experience through personalized feedback, faster HR responses, and tailored development opportunities. However, satisfaction is strongly influenced by employees' perceptions of transparency and fairness, as non-transparent systems may generate distrust and dissatisfaction (Marler & Boudreau, 2017).

Regarding organizational commitment, perceived fairness in AI-driven HR processes enhances employees' emotional attachment to the organization. When employees perceive that AI systems provide equal opportunities for development and career progression, their trust and commitment tend to increase. Conversely, excessive reliance on automated decision-making and lack of human interaction may weaken organizational identification (Kellogg et al., 2020).

In terms of job performance and adaptive behavior, AI-Augmented HRM supports improved performance through better role matching, continuous feedback, and targeted skill development. It also promotes adaptive behavior by enabling employees to respond more effectively to changing job demands through continuous learning and data-driven insights

(Minbaeva, 2021). However, excessive monitoring and performance tracking may increase stress and reduce motivation if not properly balanced.

Finally, AI-Augmented HRM can positively influence employee well-being and psychological safety by identifying early signs of burnout and supporting workload management. At the same time, concerns about surveillance and data privacy may negatively affect psychological safety if AI systems are perceived as intrusive or overly controlling (Kellogg et al., 2020). Therefore, the balance between support and control remains a critical factor in determining the overall impact of AI on employee well-being.

2.7 Research framework and hypotheses

2.7.1 Theoretical rationale for the expected relationships with employee outcomes

2.7.1.1 Social Exchange Theory

According to the Social Exchange Theory (Blau, 1964), employees return the perceived organizational support with increased commitment and performance. This theory is based on the idea that the relationship between employees and organizations is based on mutual obligations and exchanges, where the positive practices of the organization build an expectation of a return from employees' side. When AI is used though HRM to offer personal training, transparent evaluation, and fair selection processes, the perception of organizational support is being strengthened, leading to positive outcomes such as organizational commitment and job satisfaction. Furthermore, the utilization over AI tools to provide personalized feedback and skill development can enhance further the sense that the organization is investing genuinely in the professional development of the employees. That has as a result the improved trust in the organization and a stronger emotional bond between employee and employer.

In parallel, the use of AI on processes like performance evaluation, can reduce human biases and reinforce the perception of meritocracy. When the employees realize that the decisions are made using objective and consistent criteria, it's more luckily to develop positive attitude towards the organization and to demonstrate higher levels of organizational commitment and performance. However, if this technology is used in a non-transparent way or without enough communication, there might be feelings of distrust and alienation.

2.7.1.2 Organizational Justice Theory

Organizational Justice Theory (Colquitt et al., 2001) supports that the perception of justice in all forms significantly influences the attitude and behavior of employees. AI-Augmented HRM can enhance justice through consistent and evidence-based decisions, as the algorithms have the capability to apply uniform criteria for personnel evaluation and selection. Automation in some of the processes can reduce the influence of personal biases and enhance the perception of objectivity.

However, if the algorithmic systems are considered as “black boxes”, they may undermine employee trust (Raghavan et al., 2020). The inability of understanding the way decisions are taken can create a sense of uncertainty and reduced perception of fairness. Furthermore, the presence of potential algorithmic biases may lead to discrimination against specific social groups, affecting negatively organization’s culture and the commitment of the employees. For that reason, literature emphasizes the importance of accountability and human judgment during implementation of AI systems on HRM.

2.7.1.3 Self-determination Theory

Self-determination Theory (Deci & Ryan, 2000) highlights that meeting the needs for autonomy and competence, enhances employees’ intrinsic motivation and psychological well-being. Personalized learning systems which are based on AI can enhance the sense of competence, targeted skill development and tailored training programs. By analyzing performance data and needs’ learning data, these systems provide personalized development aid, allowing employees to advance professionally in the most efficient way.

However, excessive automation might reduce human interaction, and impact negatively the sense of connection of the employees. If the employees perceive that decisions are made exclusively from algorithms without human judgment, it can lead to a sense of alienation and reduced emotional safety.

2.7.1.4 Job Demands-Resources (JD-R) Theory

According to JD-R model (Bakker & Demerouti, 2007), job resources reduce burnout and strengthen the commitment and performance of the employees. AI can work as an organizational resource, providing role clarity, immediate feedback, access to information and development opportunities. Through People Analytics tools and automated decision support systems, employees can receive more targeted guidance and manage their professional demands more effectively.

Furthermore, AI can help reduce administrative burdens and repetitive tasks, allowing employees to focus on more creative and strategic tasks. That can enhance job satisfaction and reduce levels of burnout. However, when AI is used as a tool of algorithmic surveillance, it might increase job demands leading to stress and emotional pressure. The continuous performance monitoring and the sense of being constantly evaluated, can create conditions of job insecurity and can negatively impact the emotional well-being of the employees (Kellogg et al., 2020). Thus, the outcome of using Artificial Intelligence depends a lot on the way it is applied, and whether or not it is utilized as a support tool rather than exclusively a control mechanism.

2.7.2 The theoretical framework and hypotheses development

The proposed conceptual model is presented in Figure 1.

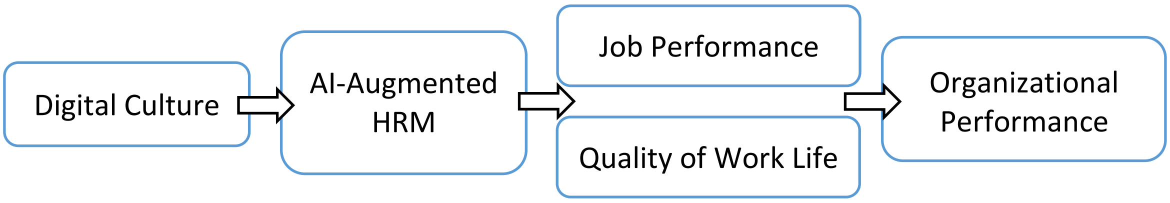

Figure 1: Conceptual Model

The proposed research model is grounded in the view that Digital Culture functions as a key enabling mechanism that facilitates the effective implementation of AI-augmented HRM practices. Within digitally mature organizational environments, employees and managers are more likely to adopt and effectively utilize AI-driven HR tools, such as people analytics and predictive systems, which in turn shape core HR outcomes. In this context, AI-Augmented HRM practices are expected to positively influence employees' job performance and quality of work life.

More specifically, the effective use of people analytics enhances the quality of HR decision-making by improving accuracy, consistency, and fairness in HR processes. At the same time, it enables the provision of personalized development opportunities and supports evidence-based HR practices. As a result, organizations are better able to identify behavioral patterns and workforce trends, strengthening the strategic alignment between human resource management practices and broader organizational objectives (Strohmeier, 2020). Based on this conceptual foundation, the following hypotheses are developed:

2.7.2.1 Digital Culture and AI-Augmented HRM Practices

Digital Culture plays a fundamental role in enabling the successful adoption and implementation of AI-augmented HRM practices. Organizations characterized by strong digital values, openness to technological innovation, and high levels of digital literacy are more likely to integrate AI tools effectively into HRM processes.

Within such environments, employees and HR professionals are more willing to trust, adopt, and utilize AI-based systems such as people analytics, predictive HR tools, and algorithmic decision-support systems. Consequently, digital culture acts as a facilitating condition that strengthens the integration of AI into HRM processes and enhances their effectiveness.

H1: *Digital culture is positively associated with AI-augmented HRM practices.*

2.7.2.2 AI-Augmented HRM Practices, Job Performance and Quality of Work Life

AI-Augmented HRM practices are expected to positively influence both employee job performance and quality of work life through more accurate, data-driven, and personalized HR processes.

On the one hand, the use of AI and people analytics improves decision-making processes related to recruitment, task allocation, and performance evaluation. This leads to better person–job fit, more effective skill utilization, and more targeted employee development. In addition, real-time data analysis allows organizations to quickly identify performance gaps and training needs, ensuring continuous alignment between employee capabilities and organizational demands (Mollah M.A. et al., 2024). These mechanisms collectively enhance individual job performance.

On the other hand, AI-Augmented HRM contributes to employees' quality of work life by promoting fairness, transparency, and personalized development opportunities. Algorithmic and data-driven HR systems can reduce subjective biases in evaluation processes and provide more consistent feedback. Furthermore, predictive and well-being analytics allow organizations to anticipate burnout risks and implement preventive interventions, improving employees' psychological and professional well-being (Minbaeva, 2021).

However, these positive effects depend on how AI systems are implemented. If AI is perceived as a control and surveillance mechanism, it may negatively affect trust, engagement, and psychological safety (Kellogg et al., 2020).

Based on these arguments:

H2a: *AI-Augmented HRM practices are positively associated with job performance.*

H2b: *AI-Augmented HRM practices are positively associated with QWL.*

2.7.2.3 Job Performance and Organizational Performance

Job performance represents a key mediating mechanism through which AI-Augmented HRM contributes to overall organizational performance.

Through predictive analytics and people analytics tools, organizations can identify factors associated with high productivity and design targeted employee development interventions. These systems enable continuous collection and analysis of data related to performance, skills, behavior, and employee engagement, allowing organizations to make more informed and effective HR decisions (Mollah M.A. et al., 2024). Real-time analytics further support the rapid identification of performance gaps and training needs.

A critical mechanism is improved person–job matching. AI-based systems enable more accurate assessment of employees fit with job roles, leading to better utilization of skills and increased individual performance. In addition, personalized learning and development programs enhance employees’ professional growth and strengthen their ability to meet organizational expectations.

Furthermore, AI-Augmented HRM enhances adaptability and innovation by providing continuous feedback and data accessibility, enabling employees to improve decision-making, develop new skills, and respond effectively to changing job demands. This is particularly important in dynamic environments characterized by uncertainty and rapid technological change (Minbaeva, 2021).

At the organizational level, higher job performance contributes to improved productivity, innovation, and profitability. It also strengthens talent management, reduces turnover rates, and enhances the strategic alignment between human resources and organizational objectives. In turn, this contributes to sustained competitive advantage and organizational resilience. However, these positive effects are contingent upon the responsible use of AI. Lack of transparency, poor data quality, or excessive surveillance may reduce trust, increase stress, and negatively affect employee engagement (Kellogg et al., 2020).

Accordingly:

H3: *Job Performance is positively associated with Organizational Performance.*

2.7.2.4 Quality of Work Life and Organizational Performance

Quality of Work Life (QWL) represents a central dimension of contemporary HRM, as it reflects employees' well-being, satisfaction, psychological safety, and overall work experience. Within the context of AI-Augmented HRM, QWL is shaped by how digital HR systems influence fairness, personalization, and employee well-being.

AI can enhance QWL through several mechanisms. First, personalized development opportunities allow employees to receive tailored learning and training programs based on their skills, performance data, and career goals. This strengthens employees' sense of competence and growth, which is positively associated with job satisfaction and organizational commitment (Minbaeva, 2021).

Second, AI-based performance evaluation systems can improve perceptions of organizational justice. By applying consistent and data-driven criteria, algorithmic systems reduce the influence of subjective bias and promote fairness. Transparent and evidence-based evaluations enhance trust and psychological safety, both of which are key components of QWL (Colquitt et al., 2001).

Third, AI-supported people analytics enables early identification of burnout risks and well-being issues. This allows organizations to implement preventive interventions before serious problems arise, particularly in high-demand or rapidly changing work environments. Such support contributes to improved well-being and reduced turnover intentions.

According to the Job Demands–Resources (JD-R) model, higher levels of QWL lead to increased organizational commitment, which in turn positively affects organizational performance (Bakker & Demerouti, 2007). Employees who perceive adequate support and resources are more likely to demonstrate higher motivation, creativity, and engagement, thereby enhancing productivity and overall performance.

Nevertheless, excessive monitoring and algorithmic surveillance may negatively affect QWL by reducing trust, increasing stress, and creating perceptions of control and insecurity (Kellogg et al., 2020). Therefore, the impact of AI depends heavily on its design and implementation.

Overall, theoretical perspectives from the Resource-Based View (RBV), Job Demands–Resources model, Organizational Justice theory, and Social Exchange theory support the idea that QWL plays a critical role in enhancing organizational performance.

So:

H4: *QWL is positively associated with Organizational Performance*.

3 Research Methods

3.1 Introduction

This chapter presents the methodological approach adopted to investigate the impact of AI-Augmented HRM practices on Organizational Performance. The study develops an empirical model that examines both direct and indirect relationships among the key variables through correlation analysis.

Specifically, the research examines Digital Culture as an antecedent of AI-Augmented HRM practices, while also exploring the roles of Quality of Work Life and employees' Job Performance in relation to AI-augmented HRM and Organizational Performance.

The structure of the chapter is as follows. First, the research strategy is presented and the rationale for adopting a quantitative approach is discussed. This is followed by an overview of the aim and scope of the study, the population and sampling strategy, and the data collection procedure. Subsequently, the research instruments and variables are described, and the chapter concludes with the presentation of the data analysis techniques employed.

3.2 Research Strategy

This study adopts a quantitative research approach, which is particularly suitable for testing theoretical models and empirically examining hypotheses using statistical techniques (Creswell, 2014). The quantitative method enables the systematic collection of numerical data and the analysis of relationships among variables.

The choice of this approach is justified by the nature of the study, which aims to examine relationships between variables such as the effect of AI-Augmented HRM on employees' Job Performance and Organizational Performance. According to Saunders et al. (2019), quantitative methods are especially appropriate for deductive research designs, where hypotheses are derived from theory and subsequently tested empirically.

In addition, the quantitative approach offers several advantages, including objectivity in data collection and analysis, the ability to generalize findings, statistical testing of complex relationships, and replicability of results. It also allows the use of advanced analytical techniques (Hayes, 2018). However, limitations include reduced depth in capturing subjective experiences, reliance on questionnaire design quality, and potential response bias. Despite these limitations, the advantages are considered to outweigh the drawbacks for the purposes of this study.

3.3 Aim and scope of the research

The main aim of this study is to investigate how HRM practices enhanced by AI influence Organizational Performance. More specifically, the research seeks to: examine the relationship between Digital Culture and AI-Augmented HRM, analyze the impact of AI-Augmented HRM on employees' QWL and Job Performance, and explore how these variables collectively contribute to Organizational Performance. The scope of the study is limited to employees working in organizations where AI-Augmented HRM practices are either implemented or under consideration.

3.4 Population and Sampling

The population of this study consists of employees from various organizations and industries who have experience with digital HRM tools or AI-based technologies.

A convenience sampling technique was applied, which is widely used in organizational research (Etikan et al., 2016). The sample includes employees of different ages, educational backgrounds, and hierarchical levels. Although this method limits the generalizability of the findings, it is considered appropriate given the practical constraints of the study.

3.5 Data Collection Procedure

Data were collected through an online questionnaire distributed to participants in order to ensure accessibility and maximize response rates. This method was considered appropriate as it enables efficient data collection from a geographically diverse sample while reducing both time and cost.

Prior to completing the questionnaire, participants were informed about the purpose of the study, which is to examine the impact of AI-Augmented HRM on Organizational Performance, as well as the roles of Job Performance and Quality of Work Life. Participation was entirely voluntary, and respondents could withdraw at any stage without any consequences.

Anonymity and confidentiality were fully ensured, as no personal identifying information was collected. The online platform used did not allow the recording of personal data, ensuring that participants could not be identified. The collected data were used exclusively for research purposes. The entire procedure followed established ethical guidelines in line with the relevant literature (Bryman, 2016).

3.6 Research Tools

The questionnaire consisted of structured items designed to measure the key variables of the conceptual model in a systematic and reliable manner. The instrument was divided into sections to improve clarity and ease of completion.

The first section collected demographic information, including gender, age, educational level, work experience, and job position, which were used to describe the sample and identify potential subgroup differences. The subsequent sections measured the main study variables: Digital Culture, AI-Augmented HRM practices, Quality of Work Life, employees' Job Performance, and Organizational Performance.

All items were adapted from previously validated scales in international literature, enhancing the validity and reliability of the study. Minor wording adjustments were made to ensure contextual relevance while maintaining theoretical consistency (see Appendix A).

3.7 Measures

All variables were measured using a 5-point Likert scale, which is widely used in social sciences to assess attitudes and perceptions. The scale ranges from 1 (“Strongly disagree”) to 5 (“Strongly agree”), allowing respondents to indicate their level of agreement with each statement.

The main constructs include Digital Culture, AI-augmented HRM practices, Job Performance, Organizational Performance, and QWL. Each construct was measured using multiple items to capture its different dimensions. More precisely:

Digital Culture was operationalized with 7 items adapted from Mollah M.A. (2024).

AI-Augmented HRM practices were measured with 8 items developed by Mollah M.A. (2024).

Job Performance was operationalized using 5 items adopted from Koopmans, L. (2015)

Organizational Performance was measured using 6 items from Mollah M.A. (2024).

QWL was measured using 10 items from Walton, R. E. (1973).

Using multiple items per construct is essential for improving measurement reliability and internal consistency. As noted by Hair et al. (2019), multi-item scales enhance measurement stability and reduce error variance, thereby improving the robustness of statistical analysis.

3.8 Data Analysis Methods

Data analysis was conducted using SPSS (Statistical Package for the Social Sciences), a widely used software package for quantitative analysis in social sciences. SPSS was selected due to its capacity to perform a broad range of statistical procedures, from descriptive statistics to correlation and reliability analysis.

Initially, data were coded and imported into SPSS, and checks were performed for missing or invalid responses. Subsequently, descriptive statistics were applied to explore the distribution of variables. Reliability and correlation analyses were then conducted to examine relationships among the key constructs and to support hypothesis testing.

3.9 Descriptive Statistics

Descriptive statistics were used to summarize the characteristics of the sample and the distribution of variables. Means were calculated to provide an overall indication of respondents' evaluations for each construct, enabling comparisons across variables.

Standard deviations were also computed to assess the degree of variation in responses around the mean, indicating whether perceptions among respondents were homogeneous or dispersed. Additionally, percentages were used primarily for demographic variables to describe the distribution of the sample in terms of gender, age, and work experience.

3.10 Reliability and Validity

Reliability was assessed using Cronbach's Alpha, one of the most widely accepted measures of internal consistency in quantitative research. This indicator evaluates the extent to which items within each construct measure the same underlying concept. In this study, values above 0.70 were considered acceptable, indicating satisfactory reliability.

The measurement scales were adapted from previously validated instruments widely used in the literature, ensuring both face and content validity.

3.10.1 Correlations

The relationships between variables were examined using Pearson's correlation coefficient, a widely used statistical technique for assessing linear relationships between continuous variables. The coefficient ranges from -1 to +1, where positive values indicate a positive relationship, negative values indicate an inverse relationship, and values close to zero indicate no linear relationship.

Pearson correlation was considered appropriate since the study variables, measured using Likert scales, can be treated as continuous for analytical purposes. This analysis provides an initial understanding of the direction and strength of relationships among key constructs, including AI-Augmented HRM, QWL, Job Performance, and Organizational Performance, thereby contributing to hypothesis testing.

4 Findings and Discussion

4.1 Introduction

This chapter presents and discusses the empirical findings of the study, which investigates the impact of AI-Augmented Human Resource Management (HRM) practices on Organizational Performance. The analysis is based on data collected through a structured questionnaire and processed using SPSS statistical software.

The purpose of this chapter is twofold. First, it provides a systematic presentation of the descriptive characteristics of the sample, offering an overview of the respondents' demographic and organizational profiles. Second, it presents the results of the statistical analysis, including descriptive statistics, reliability analysis, and Pearson correlation analysis used to test the research hypotheses formulated in Chapter 2.

The chapter is structured as follows. Initially, the sample characteristics are presented. Then, descriptive statistics of key demographic variables are reported. This is followed by an assessment of the reliability of the measurement scales. Finally, correlation analysis is conducted to test the hypotheses and the findings are interpreted in relation to the theoretical framework of the study.

4.2 Description of the Sample

The sample of this study consists of employees working in a variety of organizations across different sectors (see Appendix B). All participants reported either direct experience or familiarity with Human Resource Management practices that incorporate Artificial Intelligence technologies.

The analysis of demographic characteristics was conducted using frequency distributions and percentages. This approach allows for a clear understanding of the composition of the sample and supports the evaluation of its representativeness.

The variables examined include gender, age, educational background, years of professional experience, and job position. The results indicate that the sample includes respondents from diverse occupational and hierarchical levels (see Appendix C), which strengthens the heterogeneity of the dataset.

This diversity is particularly important, as it allows the study to capture perceptions from individuals operating in different organizational environments. Consequently, it enhances both the internal robustness and the external relevance of the empirical findings, especially in relation to the adoption and impact of AI-Augmented HRM practices.

4.3 Descriptive Statistics

4.3.1 Gender

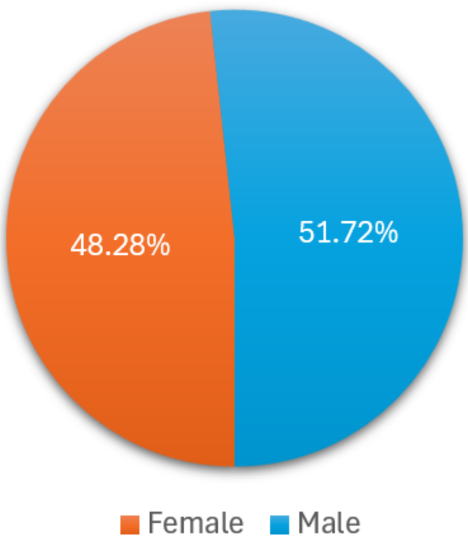

Figure 2: Gender

The gender distribution of the sample (Figure 2) indicates a highly balanced composition, with 49.1% female and 50.9% male respondents. This near-equal representation significantly reduces the likelihood of gender-related sampling bias.

Such balance is important for the validity of the study, as it ensures that the findings are not disproportionately influenced by one gender group. Furthermore, it provides the opportunity for future research to conduct gender-based comparative analyses regarding perceptions of AI-Augmented HRM practices, QWL, Job Performance, and Organizational Performance.

4.3.2 Years of experience

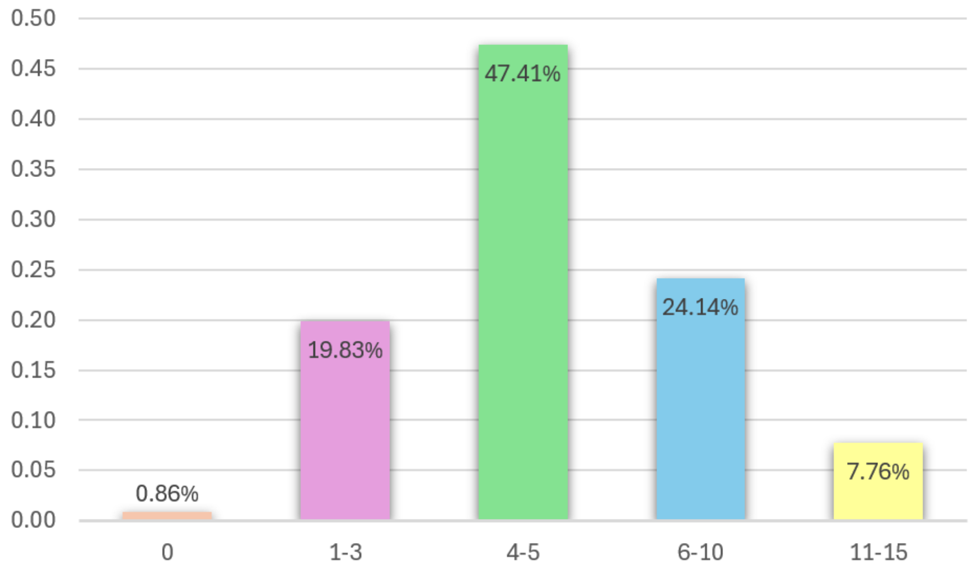

Figure 3: Years of experience

The distribution of respondents based on years of professional experience (Figure 3) shows that the largest proportion (47.41%) has 4–5 years of experience. This suggests that the sample is primarily composed of mid-level professionals.

This is followed by employees with 6–10 years of experience (24.14%) and 1–3 years of experience (19.83%). Smaller proportions are observed in the categories of 11–15 years (7.76%), while only 0.86% report no professional experience.

Overall, the sample reflects a workforce with moderate professional experience, which is particularly relevant for evaluating HRM practices and technological integration, as these individuals are likely to have sufficient exposure to organizational systems and digital tools.

4.3.3 Organizations' Size

The distribution by organization size (Figure 4) indicates that the majority of respondents (56.9%) are employed in large organizations with more than 250 employees. This is followed by medium-sized organizations (51–250 employees: 12.06%), small organizations (11–50 employees: 19.83%), and very small organizations (up to 10 employees: 11.21%).

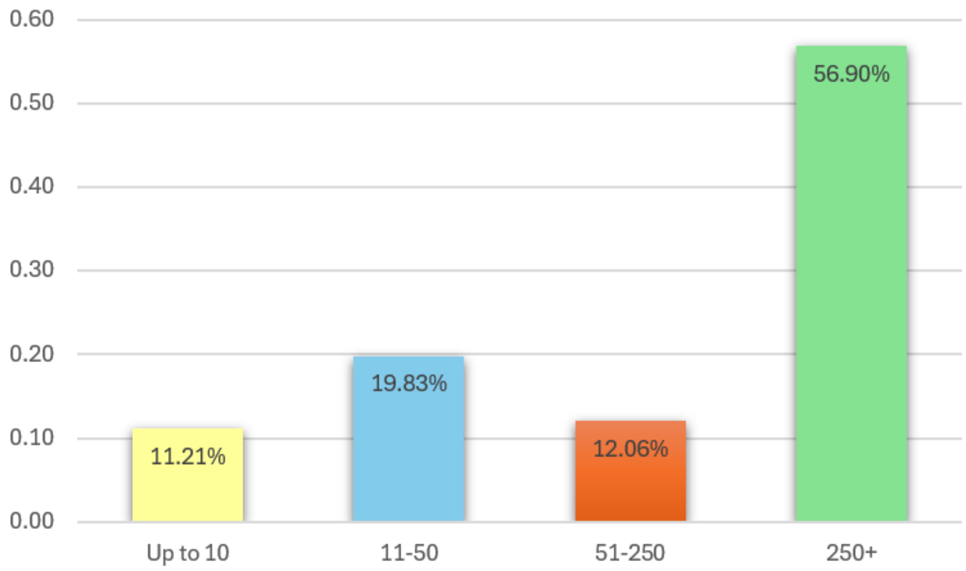

Figure 4: Organization's Size

This distribution suggests that the dataset is predominantly drawn from large-scale organizations, which are more likely to adopt advanced HRM systems, including AI-based solutions. While this enhances the relevance of the findings to the study context, it also implies that caution should be exercised when generalizing the results to smaller organizations with limited technological infrastructure.

4.3.4 Use of AI Tools

The results regarding the use of AI tools (Figure 5) indicate a relatively high level of adoption among respondents. The majority report using Google AI-based tools (57.89%), followed by OpenAI tools (20.18%).

A smaller proportion of respondents reported the use of other platforms such as Microsoft, Amazon Web Services, and Google Cloud. Notably, 12.28% of respondents stated that they do not use AI tools at all.

This distribution highlights that while AI adoption is relatively widespread, there remains a significant minority of employees with limited or no exposure to such technologies. This variation is important, as it may influence perceptions of AI-augmented HRM practices and their perceived effectiveness.

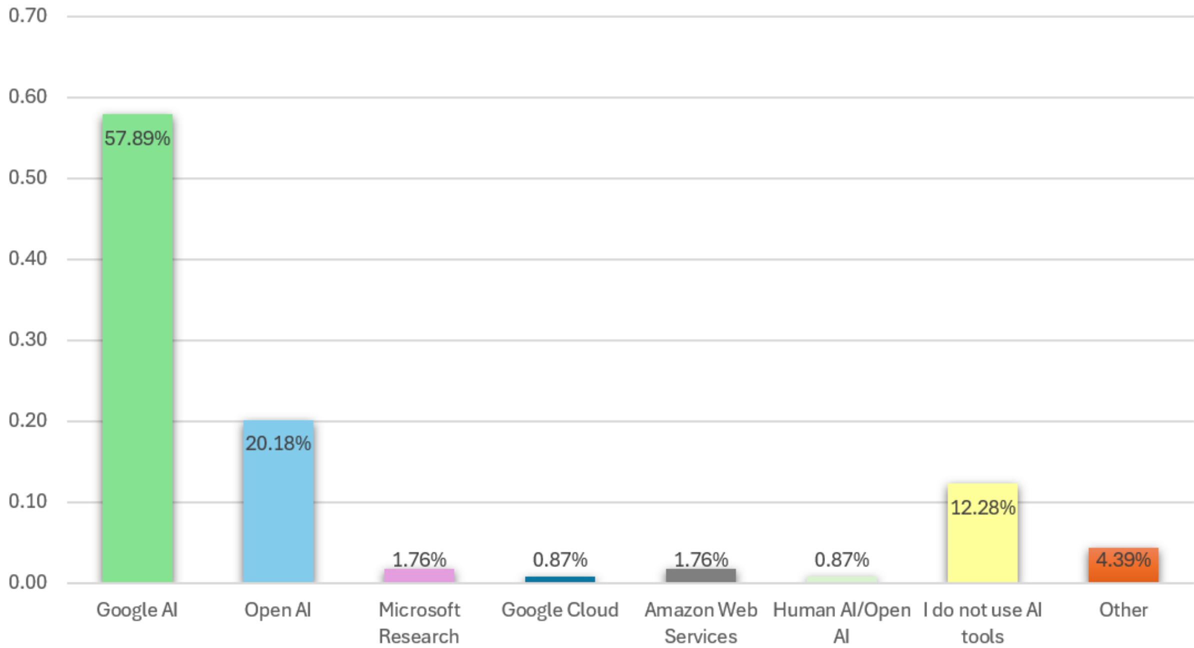

Figure 5: Use of AI tools

4.4 Reliability

4.4.1 Digital Culture

Table 1: Digital Culture reliability analysis

Cronbach's Alpha	Number of Items
0.897	6

The outcome of the reliability analysis for the group of questions related to Digital Culture, is that Cronbach's Alpha is 0.897 (Table 1). This value is considered particularly high and indicates very good internal consistency among the individual items that synthesize the variable.

According to the relevant literature, values of Cronbach's Alpha over 0.80, are considered as very good, a fact that means that the items of the scale measure with consistency and reliability the concept of Digital Culture. The use of six (6) questions (items) allows fair representation of different dimensions of the variable, such as employee commitment, participation and enthusiasm.

Overall, the findings confirm that the Digital Culture scale shows that it is suitable for further statistical analyses, such as correlation and regression, in the context of this study.

4.4.2 AI-Augmented HRM

Table 2: AI-Augmented HRM practices reliability analysis

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	Number of Items
0.944	0.944	8

The results of that liability analysis for the set of questions regarding AI-Augmented HRM practices, show that Cronbach's Alpha is 0.944 (Table 2). This value is considered extremely high and indicates very strong internal consistency among the individual questions that synthesize this variable.

Particularly, the values of Cronbach's Alpha above 0.90, are classified as excellent, meaning that the scale items consistently measure the same concept, the AI-Augmented HRM practices. Furthermore, the fact that Cronbach's Alpha based on standardized items (0.944) is identical to the initial one, further reinforces the scales reliability.

The use of eight (8) questions to measure this specific variable contributes to the accuracy and stability of the results. Overall, the findings confirm that the AI-augmented HRM scale is reliable and suitable for further statistical analysis, such as correlations and regression.

4.4.3 Job Performance

Table 3: Job Performance reliability analysis

Cronbach's Alpha	Number of Items
0.796	5

The results of the reliability analysis for the set of questions regarding employees' Job Performance show that Cronbach's Alpha is 0.796 (Table 3). This value is considered satisfactory and indicates an acceptable level of internal consistency among the individual items that synthesize this variable.

According to the literature, Cronbach's Alpha values above 0.70 are considered acceptable for research purposes, meaning that the scale items measure the concept of employees' Job Performance with sufficient consistency. The use of five (5) questions helps capturing relevant dimensions of performance, such as productivity efficiency and task management.

Although the index value 0.796 is not as high as the other variables in the survey (for AI-Augmented HRM practices and QWL, it remains within the acceptable limits and does not indicate a reliability issue. Thus, the employees' Job Performance scale is considered sufficiently reliable and suitable for further statistical analysis.

4.4.4 Quality of Work Life

Table 4: Quality of Work Life Validity Analysis

Cronbach's Alpha	Number of Items
0.854	9

The reliability analysis results regarding the questions related to the QWL, shows that the indicator of Cronbach's Alpha is 0.854 (Table 4). This value is considered particularly satisfactory and indicates a high internal consistency among the individual questions that synthesize this variable.

According to the relevant literature, values of Cronbach's Alpha over 0.80 are considered very good, a fact that means that the scale items, measure consistently and reliably the concept of Quality of Work Life. The use of nine (9) questions contributes to a more successful representation of the variables dimensions, enhancing the validity and stability of the results.

Overall, the findings confirm that the QWL scale shows high reliability and can be safely used for further statistical analysis, such as correlation and regression, in the context of this study.

4.4.5 Organizational Performance Reliability Analysis

Table 5: Organizational Performance Reliability Analysis

Cronbach's Alpha	Number of Items
0.792	6

The results of the reliability analysis for the group of questions regarding the Organizational Performance show that the indicator Cronbach's Alpha is 0.792 (Table 5). This value is considered satisfactory and indicates an acceptable level of internal consistency among the individual items that synthesize this variable.

According to the relevant literature, values of Cronbach's Alpha indicator over 0.70, are considered acceptable for research purposes, meaning that the scale items measure the concept of Organizational Performance with sufficient consistency. The use of six (6) questions allows the fair representation of key dimensions of the variable, such as efficiency, competitiveness and quality of services provided.

Although the value of the indicator is not particularly high, it remains within the acceptable limits and does not indicate reliability issues. Thus, the Organizational Performance scale is considered reliable and suitable for further statistical analysis in the context of this study.

4.5 Descriptive Statistics of the Study Variables

This section presents descriptive statistics for the main study variables (Digital Culture, AI-Augmented HRM, Job Performance, QWL and Organizational Performance. Mean values and standard deviations were calculated to assess respondents' perceptions regarding each variable. The mean scores provide an indication of the overall tendency of responses, whereas standard deviations indicate the extent of variability among participants. Overall descriptive analysis offers a preliminary understanding of the data and serves as a basis for subsequent inferential analysis.

4.5.1 Digital Culture

Table 6: Digital Culture means and standard deviations

Items	Mean	Standard Deviation
Employees in my organization are…		
1. Encouraged for innovation and adopt new technologies.	3.88	0.95

2. Comfortable for sharing ideas and providing feedback openly.	3.88	0.88
3. Feeling encouraged to participate digitally.	3.88	1.01
Our organization…		
4. Has a dynamic environment which is quick to respond to technological developments.	3.59	1.16
5. Works in an integrated method for sharing information and ideas by using digital tools.	3.67	1.21
6. Uses virtual collaboration system.	3.72	1.13
7. Respects the responsible use of technology.	3.72	1.20
Total Mean:	**3.76**	

The findings indicate that respondents perceived the level of Digital Culture within their organizations positively. The overall mean score of 3.76 suggests that employees generally agree that digital adoption, practices and technologies are embedded within their organization. The highest mean values were observed for items 1, 2 and 3 (M = 3.88), indicating a strong perception that digital transformation initiatives and practices are present in their workplaces. In contrast, item 4 (*"Quick respond to technological development."*) recorded the lowest mean score (M = 3.59), although it still reflects a relatively favorable evaluation.

Standard deviations ranged from 0.88 to 1.20, indicating moderate variability in responses. This suggests that while employees share broadly similar views regarding Digital Culture, some differences exist in the way digital initiatives are experienced across departments or job positions.

Overall, the results imply that organizations included in the study have developed a relatively strong Digital Culture, which may facilitate innovation, knowledge sharing and the adoption of advanced technologies.

4.5.2 AI-Augmented HRM

Table 7: AI-Augmented HRM means and standard deviations

Items	Mean	Standard Deviation
My organization uses AI tools to:		
1. To support recruitment and selection processes.	2.59	1.37
2. For searching candidate data acquisition from resumes.	2.72	1.37
3. In re-skilling and upskilling.	2.58	1.39
4. For performance management and career planning.	2.64	1.35
5. For job design and workforce planning.	2.65	1.39
6. As an expert method for the job evaluation system.	2.53	1.28
7. For employee turnover forecasting.	2.36	1.30
8. For decision making in crisis situations.	2.33	1.28
Total Mean:	**2.55**	

The descriptive statistics for AI-Augmented HRM reveal comparatively lower scores than those observed for the other study variables. Specifically, the overall mean score of 2.55 indicates that respondents tend to disagree or remain neutral regarding the widespread use of AI technologies in HRM processes. Item 2 (*"Searching candidate data acquisition from resumes")* exhibited the highest mean score (M = 2.72), whereas item 8 (*"For decision making in crisis situations."*) presented the lowest score (M = 2.33).

The relatively high standard deviations, ranging from 1.28 to 1.39, demonstrate substantial variability among respondents. Such variability may indicate that some organizations have already implemented AI-Augmented HRM practices, whereas others remain at an early stage of adoption.

The findings therefore suggest that AI integration within HRM processes is still limited and uneven across organizations. These results are consistent with previous studies indicating that although AI technologies are increasingly recognized as strategically important, their practical implementation in HR functions often remains underdeveloped (Marler & Boudreau, 2017; Vrontis et al., 2022).

4.5.3 Job Performance

Table 8: Job Performance means and standard deviations

Items	Mean	Standard Deviation
In the past 3 months…		
1. I was able to plan my work so that I finished it on time.	3.92	0.88
2. I kept in mind the work result I needed to achieve.	4.24	0.77
3. I was able to set priorities.	3.95	0.90
4. I was able to carry out my work efficiently.	4.04	0.79
5. I managed my time well.	3.81	0.91
Total Mean:	**3.99**	

Respondents reported high levels of Job Performance, as evidenced by the overall mean score of 3.99. This finding suggests that employees perceive themselves as performing effectively and successfully fulfilling their work responsibilities. Item 2 *("I kept in mind the work result I needed to achieve.")* recorded the highest mean score (M = 4.24), indicating particularly strong agreement. On the other hand, item 5 (*"I managed my time well."*) obtained the lowest mean score (M = 3.81), although it still reflects positive perceptions.

Standard deviations ranged between 0.77 and 0.91, suggesting a high degree of consensus among participants. The relatively limited dispersion of responses indicates that employees share similar perceptions regarding their performance levels.

Overall, the findings demonstrate that Job Performance is evaluated positively across the sample, which may be associated with supportive organizational conditions, supportive management practices and the existence of an enabling work environment.

4.5.4 Quality Of Work Life

Table 9: QWL means and standard deviations

Items	Mean	Standard Deviation
In your organization, how satisfied are you with…		
1. Your salary?	3.51	0.87
2. Your salary, if you compare it to your colleague's salary?	3.44	0.84
3. The quantity or working hours?	3.48	1.01
4. The tiredness that your work causes to you?	3.19	1.07
5. The work responsibility given to you?	3.49	0.89

6. Your opportunity of professional growth?	3.62	1.06
7. The discrimination: social, racial, religious, sexual etc.?	3.73	1.01
8. The work influence on your family life?	3.37	1.02
9. Your schedule of work and rest?	3.42	1.01
10. The image this company has to the society?	3.92	0.89
Total Mean:	**3.52**	

The results concerning QWL indicate moderate to high levels of employee satisfaction regarding their work environment and employment conditions. The overall mean score was 3.52, suggesting that respondents generally hold positive views about their quality of work life.

Among the items, 10 (*"The image this company has to the society."*) displayed the highest mean score (M = 3.92), while item 4 (*"The tiredness that your work causes to you."*) recorded the lowest value (M = 3.19). Although all mean values exceeded the midpoint of the scale, differences among items indicate that some dimensions of work life are perceived more positively than others.

Standard deviations varied from 0.84 to 1.07, reflecting moderate heterogeneity in employees' responses. These findings suggest that organizations provide reasonably satisfactory working conditions; however, specific aspects related to employee well-being, work-life balance or organizational support may still require improvement. Enhancing these dimensions could further strengthen employee satisfaction and organizational effectiveness.

4.5.5 Organizational Performance

Table 10: Organizational Performance means and standard deviations

Items	Mean	Standard Deviation
Our organization…		
1. Provides high-quality services.	3.42	0.98
2. Has lower production and service operational cost compared to our competitors.	4.09	0.77
3. Performs well providing effective delivery services.	3.81	0.85
4. Adapts quickly to adjust with unanticipated changes.	3.73	0.90
5. Can compete properly in the contemporary market.	3.93	0.94
6. Is considered profitable in the industry.	4.04	0.82
Total Mean:	**3.84**	

The descriptive analysis revealed relatively high perceptions of Organizational Performance among respondents. The overall mean score of 3.84 suggests that employees generally consider that their organizations perform effectively. Item 2 (*"Has lower production and service operational cost compared to our competitors.")* obtained the highest mean score (M = 4.09), closely followed by item 6 (*"Is considered profitable in the industry."*) (M = 4.04), indicating strong agreement concerning the profitability of their organization

In contrast, item 1 (*"Provides high-quality services."*) demonstrated the lowest mean value (M = 3.42), although the score remains above the midpoint of the scale.

Standard deviations ranged from 0.77 to 0.98, indicating relatively low variability and substantial agreement among respondents. Overall, the findings imply that employees perceive their organizations as successful in achieving objectives, maintaining productivity and delivering satisfactory outcomes. These positive perceptions may be associated with the existence of supportive organizational practices, effective leadership and an advantageous organizational climate.

4.6 Correlations – Hypotheses testing

4.6.1 Digital Culture and AI-Augmented HRM practices.

4.6.1.1 Hypothesis 1

H1: Digital culture is positively associated with AI-Augmented HRM practices.

Table 11: Digital Culture correlation with AI augmented HRM practices

	Digital Culture	AI-Augmented HRM practices
Digital Culture	1	0.499**
AI-Augmented HRM practices	0.499**	1

* $p < 0.05$ ** $p < 0.01$ (two-tailed).

The Pearson correlation analysis indicates a positive and statistically significant relationship between Digital Culture and AI-augmented HRM practices ($r = 0.499$, $p < 0.001$). This finding provides strong empirical support for Hypothesis H1.

This suggests that organizations with a stronger digital culture are more likely to adopt and implement AI-enhanced HRM systems. Digital Culture appears to function as a foundational enabler for technological integration within HRM processes, facilitating openness to innovation and digital transformation.

4.6.2 AI-Augmented HRM Practices, Job Performance and Quality of Work Life.

4.6.2.1 Hypothesis 2

H2: AI-Augmented HRM practices are positively associated with Job Performance (H2a) and QWL (H2b).

Table 12: AI-Augmented HRM, Job Performance, and QWL

	AI-Augmented HRM practices	Job Performance	Quality of Work Life
AI-augmented HRM practices	1		
Job Performance	0.046	1	
Quality of Work Life	0.260**	0.566**	1

* p < 0.05 ** p < 0.01 (two-tailed).

The results show a differentiated pattern of relationships. No statistically significant relationship was found between AI-Augmented HRM practices and Job Performance ($r = 0.046$, $p = 0.627$). Therefore, Hypothesis H2a is not supported.

In contrast, a positive and statistically significant relationship was found between AI-augmented HRM practices and QWL ($r = 0.260$, $p = 0.005$), supporting Hypothesis H2b.

These findings suggest that AI-Augmented HRM practices are more strongly associated with employee well-being and perceived work quality than with direct performance outcomes. This may indicate that AI systems primarily influence psychological and perceptual dimensions of work before translating into measurable performance improvements.

4.6.3 Employees' Job Performance and Organizational Performance

4.6.3.1 Hypothesis 3

H3: Job Performance is positively associated with Organizational Performance.

Table 13: Job Performance and Organizational Performance

	Job Performance	Organizational Performance
Job Performance	1	
Organizational Performance	0.274**	1

* $p < 0.05$ ** $p < 0.01$ (two-tailed).

A Pearson correlation analysis was conducted to examine the relationship between Job Performance and Organizational Performance. The results show that there is a positive and statistically significant correlation between the two variables ($r = 0.274$, $p = 0.003$).

These findings suggest that the higher the levels of Job Performance, the higher the Organizational Performance. Thus, Hypothesis 3, according to which Job Performance is positively associated with Organizational Performance, is confirmed.

4.6.4 Quality of Work Life and Organizational Performance

4.6.4.1 Hypothesis 4

H4: Quality of Work Life is positively associated with Organizational Performance.

Table 14: Quality of Work Life and Organizational Performance

		Quality of Work Life	Organizational Performance
Quality of Work Life	Pearson Correlation	1	0.533**
Organizational Performance	Pearson Correlation	0.533**	1

* $p < 0.05$ ** $p < 0.01$ (two-tailed).

The strongest relationship in the model was observed between QWL and Organizational Performance ($r = 0.533$, $p < 0.001$), supporting Hypothesis H4. This finding highlights the critical role of employee well-being, satisfaction, and work-life balance in shaping organizational effectiveness and competitiveness.

4.6.5 Discussion

The empirical findings provide overall support for the proposed conceptual model, confirming most of the hypothesized relationships.

Hypothesis H1 is strongly supported, confirming that Digital Culture is a key enabler of AI-Augmented HRM practices. This aligns with existing literature emphasizing that digital readiness is a prerequisite for successful AI adoption in HRM contexts (Vrontis et al., 2022; Marler & Boudreau, 2017).

Hypothesis H2 presents a more nuanced picture. While AI-Augmented HRM practices are positively associated with Quality of Work Life, no significant relationship was found with Job Performance. This suggests that AI-driven HRM systems may first influence employee perceptions, well-being, and satisfaction before translating into measurable performance outcomes.

A possible explanation is that AI systems are currently more effective in improving transparency, fairness, and personalization of HR processes rather than directly enhancing task performance. This finding highlights the importance of implementation maturity and organizational integration of AI systems.

Hypothesis H3 is confirmed, reinforcing the established theoretical link between individual Job Performance and Organizational Performance.

Hypothesis H4 is also strongly supported, with Quality of Work Life emerging as the most influential predictor of Organizational Performance among the examined relationships. This is consistent with the Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2007), which emphasizes the importance of employee well-being in driving organizational effectiveness.

Overall, the findings confirm the relevance of the conceptual model, while also highlighting that the relationship between AI-Augmented HRM and performance outcomes is indirect and mediated by employee well-being and work experience factors.

5 Conclusions, Implications, Limitations and Future Research Directions

5.1 Conclusion and Summary of Key Findings

This study examined the impact of AI-Augmented HRM practices on Organizational Performance, with particular attention to the mediating role of employees' Job Performance and QWL, as well as the antecedent role of Digital Culture.

The empirical findings provide overall support for the proposed conceptual model, while also revealing important nuances regarding the mechanisms through which AI influences organizational outcomes.

First, the results confirm that Digital Culture is positively associated with the adoption of AI-Augmented HRM practices. This finding highlights that organizations with higher levels of digital maturity are more likely to integrate Artificial Intelligence into HRM processes, reinforcing the idea that cultural readiness is a key enabler of technological transformation.

Second, the analysis shows that AI-Augmented HRM practices are not directly related to employees' Job Performance. However, they are positively associated with Quality of Work Life. This suggests that AI-based HRM systems primarily influence employee perceptions, well-being, and working conditions rather than immediate performance outcomes.

Third, both Job Performance and QWL are positively associated with Organizational Performance, with QWL demonstrating the strongest relationship. This indicates that employee well-being plays a more central role than individual performance in explaining organizational effectiveness within the context of AI-supported HRM systems.

Overall, the findings suggest that the impact of AI-Augmented HRM on Organizational Performance is largely indirect, operating through improvements in employees' working conditions and well-being rather than through direct performance enhancement.

5.2 Theoretical and Practical Implications

5.2.1 Theoretical Implications

The findings of this study make several contributions to the growing body of literature on AI in HRM. First, the results confirm that AI-Augmented HRM does not directly enhance Job Performance but rather operates through intermediate mechanisms such as Quality of Work Life. This aligns with contemporary theoretical perspectives emphasizing the mediating role of human and contextual factors in determining organizational outcomes (Tambe et al., 2019).

Second, by incorporating Digital Culture as an antecedent variable, the study extends existing theoretical models by demonstrating that AI adoption in HRM is not purely technological but is significantly shaped by organizational culture and digital readiness (Vrontis et al., 2022). This strengthens the argument that cultural and contextual conditions are essential for understanding technological integration in HRM systems.

Finally, the results contribute to a more nuanced understanding of AI in HRM by supporting the view that its value lies not only in automation, but primarily in its capacity to reshape employee experience and organizational processes through data-driven decision-making.

5.2.2 Practical Implications (Suggestions)

From a managerial and practical perspective, the findings highlight several important implications for organizations implementing AI-Augmented HRM systems.

First, organizations should not focus exclusively on technological investment in AI tools, but should also prioritize the development of a strong Digital Culture. A supportive digital environment is essential for ensuring successful adoption and effective utilization of AI in HRM processes.

Second, the findings emphasize the critical role of Quality of Work Life as the primary pathway through which AI contributes to Organizational Performance. This suggests that organizations should design AI systems that enhance employee well-being, fairness, transparency, and work-life balance.

Human Resource professionals should therefore focus on leveraging AI not merely as a performance optimization tool, but as a mechanism for improving employee experience, engagement, and organizational support systems.

5.3 Research Limitations and Future Research

Despite its contributions, this study is subject to several limitations.

First, the use of non-probability convenience sampling limits the generalizability of the findings. Although the sample includes respondents from diverse sectors and organizational levels, it may not fully represent the broader population of employees.

Second, the reliance on self-reported questionnaire data introduces the possibility of response bias, including subjective interpretation and social desirability effects.

Third, the study focuses on linear relationships between variables and does not examine potential mediation or moderation effects in depth, which may oversimplify the complexity of AI-Augmented HRM processes.

5.4 Conclusion

The findings of this study are strongly supported by existing literature, which highlights that Artificial Intelligence is fundamentally transforming Human Resource Management by enabling a shift toward data-driven and hybrid decision-making systems (Brynjolfsson & McAfee, 2017; Marler & Boudreau, 2017).

AI-Augmented HRM extends beyond automation of administrative tasks and represents a broader transformation of HRM into a strategic, analytics-driven function. Through tools such as people analytics, machine learning, and predictive modelling, organizations are able to enhance decision-making quality, improve talent management, and strengthen strategic alignment with organizational goals (Minbaeva, 2021).

The literature further confirms that AI's impact on Organizational Performance is largely indirect. Rather than directly increasing performance, AI influences intermediate employee-level outcomes, particularly Job Performance and Quality of Work Life. These mechanisms are consistent with the Resource-Based View (RBV), Social Exchange Theory, Organizational Justice Theory, Self-Determination Theory, and the Job Demands–Resources (JD-R) model (Barney, 1991; Deci & Ryan, 2000; Bakker & Demerouti, 2007).

A key insight from both the literature and empirical findings is the central role of organizational justice, transparency, and trust. While AI systems can reduce human bias and increase consistency in decision-making, their effectiveness is highly dependent on transparency and interpretability. The presence of "black-box" systems without human oversight may negatively affect employee trust, psychological safety, and organizational commitment (Mollah M.A. et al., 2024).

Moreover, the findings emphasize that Digital Culture and continuous skill development are essential prerequisites for successful AI integration. Organizations that invest in digital literacy, learning-oriented environments, and employee trust-building are more likely to realize the full potential of AI-Augmented HRM systems (Jarrahi, 2018).

Overall, this study confirms that AI should be understood not as a replacement for human judgment, but as a complementary mechanism within a Human–AI collaborative model. While algorithmic systems enhance efficiency and analytical capability, human judgement, ethical reasoning, and interpersonal understanding remain essential for effective HRM practices (Kaplan & Haenlein, 2019).

In conclusion, AI-Augmented HRM can act as a strategic catalyst for Organizational Performance, primarily through its positive influence on employees' Job Performance and Quality of Work Life. However, these effects are not automatic. Their realization depends on data quality, transparency, ethical governance, and organizational culture. Therefore, AI should be viewed not merely as a technological tool, but as part of a broader organizational transformation that integrates technological innovation with human-centered management principles.

6 Appendix A: Questionnaire

6.1 Demographic Information

Table 15: Questionnaire's Demographic Questions

	18-25	26-35	36-45	46-55	56-65	65+
Your age range:	○	○	○	○	○	○

	Male	Female	Other/ Prefer not to say
Gender:	○	○	○

Department/Function	

	Low-level management	Middle-level management	Hi-level management	Other
Your position in the organization:	○	○	○	

Years of experience	1-3	4-5	6-10	11-15	15+
In current organization	○	○	○	○	○
In total	○	○	○	○	○

Nationality (Optional question)	

Number of employees	Up to 10	11-50	51-250	250+
Your organization size	○	○	○	

Sector	

Country (Optional question)	

	Yes	No
Does your organization use AI-based Human Resource Management?	○	○

AI tools used by you:	
☐	Google AI
☐	Open AI
☐	Microsoft Research
☐	Google Cloud
☐	Amazon Web Service
☐	Human AI/Open AI
☐	I do not use AI tools
☐	Other:

6.2 AI-Augmented Human Resource management (HRM) practices

Table 16: Use of AI Tools

My organization uses AI tools to:					
	Never	Rarely	Sometimes	Often	Always
To support recruitment and selection processes.	○	○	○	○	○
For searching candidate data acquisition from resumes.	○	○	○	○	○
In re-skilling and upskilling.	○	○	○	○	○
For performance management and career planning.	○	○	○	○	○
For job design and workforce planning.	○	○	○	○	○
As an expert method for the job evaluation system.	○	○	○	○	○
For employee turnover forecasting.	○	○	○	○	○
For decision making in crisis situations.	○	○	○	○	○

6.3 Quality of Work Life

Table 17: Quality of Work Life

In your organization, how satisfied are you with…					
	Very Dissatisfied	Dissatisfied	Neutral	Satisfied	Very Satisfied
Your salary?	○	○	○	○	○
Your salary, if you compare it to your colleague's salary?	○	○	○	○	○
The quantity or working hours?	○	○	○	○	○
The tiredness that your work causes to you?	○	○	○	○	○
The work responsibility given to you?	○	○	○	○	○
Your opportunity of professional growth?	○	○	○	○	○
The discrimination: social, racial, religious, sexual etc.?	○	○	○	○	○
The work influence on your family life?	○	○	○	○	○
Your schedule of work and rest?	○	○	○	○	○
The image this company has to the society?	○	○	○	○	○

6.4 Job Performance

Table 18: Employees' Job Performance

In the past 3 months…					
	Never	Rarely	Sometimes	Often	Always
I was able to plan my work so that I finished it on time.	○	○	○	○	○
I kept in mind the work result I needed to achieve.	○	○	○	○	○
I was able to set priorities.	○	○	○	○	○
I was able to carry out my work efficiently.	○	○	○	○	○
I managed my time well.	○	○	○	○	○

6.5 Digital Culture

Table 19: Digital Culture

Employees in my organization are…					
	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Encouraged for innovation and adopt new technologies.	○	○	○	○	○
Comfortable for sharing ideas and providing feedback openly.	○	○	○	○	○
Feeling encouraged to participate digitally.	○	○	○	○	○

Our organization…					
Has a dynamic environment which is quick to respond to technological developments.	○	○	○	○	○
Works in an integrated method for sharing information and ideas by using digital tools.	○	○	○	○	○
Uses virtual collaboration system.	○	○	○	○	○
Respects the responsible use of technology.	○	○	○	○	○

6.6 Organizational Performance

Table 20: Organizational Performance

Our organization…					
	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Provides high-quality services.	○	○	○	○	○
Has lower production and service operational cost compared to our competitors.	○	○	○	○	○
Performs well providing effective delivery services.	○	○	○	○	○
Adapts quickly to adjust with unanticipated changes.	○	○	○	○	○
Can compete properly in the contemporary market.	○	○	○	○	○
Is considered profitable in the industry.	○	○	○	○	○

7 Appendix B: Questionnaire recordings on Working Sector

The sample of this study consists of employees working in organizations of various sectors, as recorded in the questionnaire and presented alphabetically below:

Academic	General Trading
Accounting Services	Health and Social Care
AI	Hospitality
Apparel	HR
Architectural and Interior Design Services	Industrial / Manufacturing / Engineering
Automotive	Services
B2C / C2C / Distribution / Delivery / IT	IT / Consulting
Platform	Logistics
BPO	Manufacturing
Business Consulting	Maritime
Career Counseling	Marketing Consultancy
Construction	Mechanical Engineering
Consulting	Oil and Gas / Energy
Defence	Pharmaceutical
E-commerce	Private Sector
Education	Public Sector
Energy	Sales
Energy Sector – Natural	Service
Gas	Speech Therapy
Engineering	Sports Equipment
Engineering – Construction	Supply Chain
Enterprise IT and Business Consulting	Technical
Services	Technology
Fashion	Tech – Amazon
Finance	Tourism
Financial Department	Trading
Financial Services	Travel and Tourism
FMCG	Wellness
Food Industry	Workforce – Internet Services

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