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RESEARCH ARTICLE

Analytics on Future Talent Development in Middle Eastern Public Universities

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ABSTRACT

As countries around the world are accelerating their AI applications in human resource practices and some others are preparing for the disruption that this might cause, it is critical to identify how organizations in the region can get prepared. However, this paper aspires to provide direct insights into the application of AI technology and worker upskilling via assessment of a set of targeted focuses among low-and middle-income countries. This study used a survey-based methodology, with data collected from 356 respondents at the region's public universities, randomly selected to ensure they were representative. Data were analyzed using Structural Equation Modeling (SEM) via Smart PLS 4.0.4 and SPSS 29, allowing for the assessment of relationships between multiple constructs. The results indicate that employee perceptions of AI driven HR analytics influence the development of talent and work as mediating variables in turning results between these two aspects. Constructs with high potential impact Predicative analytics, employee monitoring Related to talent development Demonstrated moderate power in explaining big data Through the study, it enhances the current scientific knowledgebase regarding employee perceptions on AI adoption and application in HR practices while also stressing on how society needs strategies for a future-oriented workforce as well, and lastly this significance was offered to decision-makers with a reference pathway towards how they can integrate AI technologies within their respective systems through change management. Thus, this study is relevant to universities, policymakers, and organizations as it highlights the need for transparency, inclusivity as well as ethical AI practices.

INTRODUCTION

Artificial Intelligence (AI) has rapidly evolved and changed the landscape of industries including human resource management (HRM). Public university education is one of the main engines for education, invention and workforce training in the MENA region. Using AI-enabled HR analytics in these institutions would be a wonderful opportunity to evaluate talent pathways, optimize workforce productivity, and aggregate education and labour market objectives over time. However, the use and implementation of AI related technologies in HR processes in this region is less documented. AI has taken place in almost every function that utilizes data such as maximization recruitment, training, performance appraisal and succession planning (Al-Jarrah et al., 2024; Aloqaily et al., 2024; Al Obaidy et al., 2024). The power of AI in Human Resource analytics provides actionable insights using predictive analytics, machine learning and big data; help reduce biases in processes; and create efficiencies within the entire organization. Discerning and retaining academy talent in alignment with institutional goals are fundamental public university HR tasks that AI-enabled HR analytics informs. In addition, there are specific challenges faced by the Middle East in harnessing the potential of AI use in HR processes. If public universities are the bedrock of our future talent pool, traditional HR systems have too often been a drag on innovation and change in these same institutions embracing rapid technological advancement. In addition, differences in culture and institutional structure as well as varying degrees of technological readiness form additional barriers to AI adoption (Aloqaily and Al-Zaqeba, 2024; Shubailat et al., 2024; Murad et al., 2024). The need for AI-powered HR analytics to prepare future-ready talent with a unique edge is definitely more urgent for the region as it seeks to improve its global competitiveness and prepares talents to address national visions such as Saudi Arabia's Vision 2030, and the UAE Centennial Plan 2071. While there have been studies on the use of AI in HR, fewer papers have focused on this area at public universities in Middle East countries. Such a study is needed to determine how AI-driven HR analytics can leverage talent development without adequate supporting evidence for the role of employee perceptions and institutional readiness on effective implementation (Al-Zaqeba et al., 2024b; Al Rousan, 2024). Moreover, to prepare future leaders in a rapidly evolving global landscape, public universities in the Middle East find themselves at a crossroads. While there have been great advancements in AI technology, the majority of institutions are still using traditional HR systems that do not function efficiently at all and cannot cater to the properties of modern talent development. This dependence restricts them from recognising the talent with high potential, nurturing professional growth and ensuring employee retention.

As a solution, the implementation of AI-enabled HR analytics will permit data-driven decision-making and efficient strategies for talent development. Yet, the success of AI implementation depends on keeping up with technology; those innovations will fall flat without the employees willing and ready to embrace them. Public universities face several internal issues such as employee resistance, insufficient trust in AI systems and inadequate training to boost the large-scale use of AI for HR functions. Finally, even though the HR analytics (especially AI-enabled) prospect a dramatic change for talent development, the respective effect on future talent from public universities within Middle East is still uncertain. The role of how employees collectively perceive the employee value could also be an interesting area for future research. These gaps need to be addressed to understand the role of AI technologies underpinning HR practices that play a role in ensuring a sustainable and future-ready workforce in the region. However, this study aims to explore AI HR analytics transformation for the future talent development in public universities of the Middle-Eastern countries based on employee perceptions as mediator's variable. In doing so, it intends to provide institutional leaders and policy makers with actionable insights in designing interstitial strategies on how AI/ML based technologies might be adopted in practice.

LITERATURE REVIEW

The previous studies highlight a changing landscape for talent development characterized by interplays among technological innovation, changing workforce demographics, and HR strategy at different levels in the organization. The framework of Nurmala and Hermina (2024) in combination with Shan and Wang (2024) on how to shaped holistic versus strategic approaches while the meta-perspective created by Sono and Diputra (2024) mapping the proliferation of existences in this field. On the other hand, Gričnik and Poljašević (2024) discuss the importance of digital transformation in responding to the requirement of a new talent generation. Collectively, these pieces maybe point to a need for organizations response which is flexible, enabled by technology and/ or inclusive enough to become the new norm. However, as seen in the experimental studies reviewed here, success across domains depends increasingly on systemic approaches to talent development that are inclusive and enabled by technology. Critique and Need for Pathways to Address Bifurcation of Services Olszewski-Kubilius (2024) critiques current educational frameworks, emphasizing the importance of integrated pathways to prevent potentially harmful bifurcation of services. Muammar (2024) foresee an online platform-based future to provide better access and scalability, along with Nuriddinov (2023) state that collaborative approach in sports talent development should be long-term. Okatta et al. (2024) indicated that HR analytics and AI-driven technologies are heralding a new age of human resource management. Predictive analytics and data-driven insights could have great strategic potential to address workforce issues (Martin and McEwan, 2024) In the meantime, Padmavathi (2024), and Thangaraja et al. (2024) both outline the wider use of AI in bolstering agility, personalization and decision-making in HR-related events. A practical reading of the implementation of digital HR tools, Sharma and Sengupta (2023) emphasize their advantages for efficiency as well as employee engagement. These studies indicate that technological integration in HRM holds promise but also highlights ongoing issues such as data privacy, organizational readiness, and ethical dilemmas.

Based on the explored studies, AI-driven systems possess the potential to transform HR practices in a revolutionary way. Namperumal et al. (2024) and Sainila (2024) have compared AI with human work and highlighted improving the efficiency, accuracy, quality of work done using AI tools, able to make strategic decisions. (2022) found that big data and analytics have an integral part in making recruitment and running forecasting of workforce more effective now. A recent contribution by Allil (2024) and Al Samman. In addition, Al Obaidly (2024) identifies a set of ethical and practical considerations for AI usage, including the necessity for contextual fit with organizational aspirations, along human-centricity. Yahmadi et al. (2024) A concrete instance of this transformative potential for the workforce where both employee retention and economic stability is being realised through the effective use of AI. Additionally, Abdullah and Fakieh (2020) and Felemban et al. (2024) emphasize the importance of education and organizational support in fostering readiness for AI. In addition, Li et al. (2019) and Jerez-Jerez (2025) highlight the impact of AI on employee turnover, engagement, and alignment with strategic goals like sustainability. Singh and Tarkar (2022) and Ghaleche (2023) look at the emotional/psychological performance around AI which highlights communication and mental capabilities enabling transparency. Shah and Yagnik (2024) and Rožman et al. (2023) explore the broader implications of AI and e-HRM practices on employee engagement and organizational performance. Basri (2023) demonstrates the operational benefits of AI in SMEs, moderated by employee perceptions. Arora and Mittal (2024) and Milkus (2024) emphasize trust and perception as key mediators of AI acceptance, while Riaz and Ghanghas (2024) focus on AI's potential to revolutionize performance evaluations. Bagis and Yulianeu (2024) and Pillai et al. (2024) provide empirical evidence of the mediating and moderating factors that shape AI's impact on HRM. While these studies underscore AI's potential to enhance HR efficiency, fairness, and employee satisfaction, they also reveal challenges such as data privacy concerns, technological anxiety, and ethical dilemmas.

Future Talent Development

In today's competitive landscape, cultivating future talent has become one of the most critical elements for organizations to succeed. Human resource management (HRM) is a set of practices that aims to attract, develop, and retain employees with the skills and engagement required in the pursuit of organizational performance (Huselid 1995; Gričnik and Šarotar Žižek 2023). Employee loyalty and expertise is intangible (Gričnik and Šarotar, 2023) – as compared to products or services, they cannot be replicated easily making effective talent management a strategic priority. Human Resource Management had also witnessed a digital transformation that has changed the practices of talent management to help organizations find solutions to their workforce challenges through technology driven innovation. Traditional HR systems mostly provided administrative support; however, they have evolved into integrated solutions for improving organizational effectiveness and efficiency as well as evidence-based decision making (Mosca, 2020; Gorienšek, 2022). Most of the HR digitalization that is happening today in enterprises, talks about employee self-service systems, savings, better communication and a more engaged workforce (Crawshaw et al., 2020). Such innovations serve as an enabler to equip HR professionals in realigning employee goals and objective with the organizational chart. AI has revolutionized the HRM practices that, in one way or the other, have shaped up recruitment processes, appraisal systems and retention of employees. AI-enabled technologies (like, intelligent robotic process automation (RPA), smart analytics systems) simplify tasks from candidate screening to workforce analytics (Chugh, Macht & Hossain, 2022; Herm et al., 2022). On top of that, big data analytics boost HRM by analysing unstructured data to enhance recruitment strategies and through better retention plans (Cormarković et al., 2022). As new human-level intelligent systems come into play, HR process will likely adopt more advanced cognitive functions like emotional perception and adaptation (Cormarković et al. 2022). With these trends in mind, organizations need to leverage digital technologies for a competitive edge, and figure out industries to foster trust and engagement with personal interaction. A major transition in the composition and nature of work is taking place, as demographic changes, technological innovations and shifts in social priorities influence the future workforce. Evolution of Workforce Diversity Workforce diversity due to generational gap, cultural values and numerous other factors has been a crucial feature of the labor market nowadays (Kapoor and Solomon; 2011). Generation Z is a cohort identified as intelligent, independent and digitally-savvy (and yet also attention-deficit-disordered), soon coming into the workplace bringing new problems to HR departments as well as new opportunities (McCrindle, 2014; Rothman, 2016).

Work-life balance, the millennials favour employers that share their values and prefer the working environments, which are flexible and technology-dominated (Dolot, 2018; Gabrielova & Bucho, 2021). As a result, organizations need to consider talent strategies that respond to these preferences and implement technologies befitting the digital-first mindset of Generation Z. Managing career expectations and retention issues alongside the insurgence of Generation Z into organized structures represent two sets of challenges that HRM professionals must contend with during this age. Given the common behaviour of Millennials leaving jobs for advancement, organizations need to be proactive in their approaches through workplace culture, mentorship opportunities and meaningful development (Magano et al., 2020; Snieska et al., 2020). Scullion et al. (2010: 118) define talent management as the 'set of integrated processes used to attract, develop and retain top talent in order to achieve long term success or competitive advantage'. Organizations have incorporated TM practices relying on its critical role in maintaining the competitive advantage via recruitment, performance management and career development initiatives that are aligned with objectives of firm (Heinen and O’Neill, 2004; Paradise, 2011).

Workforce planning stands at the core of talent management as it guarantees the future alignment between organizational objectives and manpower needs (Hay Group, 2005). In addition, organizations need to pay attention on the recruitment side by considering–branding, employee value propositions and processes (Michaels et al., 2001). Retention with the use of psychological contracts and cultural integration is also vital to curb attrition risks (Sušnik, 2018). In addition, Talent Development refers to the process of providing training, education and career development opportunities in a way that is customized for an individual workforce or employee. Job rotation, coaching, and mentoring as some examples add value to employee competencies whilst increasing morale (Berger & Berger, 2004). In support of this, comprehensive performance management systems offer organizational goal alignment and facilitate continuous improvement with feedback and evaluation (Zupan, 1999). Succession planning offers a necessary pipeline of competent leaders for essential positions within the organization, thereby reducing the risks involved in organizational leadership transitions (Huang, 2001). Such practice highlights the significance of applying future-ready HRM strategies to ensure organizational resilience. Talent development is seeing the impact of AI as well, with powerful tools to help HR professionals make data-driven decisions and offer highly personalized experiences. In recruitment, AI enabled algorithms help in screening candidates as well as reducing bias ensuring a fair hiring process (Murugesan et al., 2023). AI also makes the onboarding process easier by automating administrative tasks and helping whether new hires could easily integrate into the company or not (Trisca, 2024). Moreover, AI harnesses NLP for employee sentiment analysis, turnover risk prediction and personalized engagement efforts in talent retention and engagement. Support in Employee Development: Machine learning promotes employee development by helping you identify any skill gap and offer relevant training programs for each of your employees (Bhatt, 2022). Furthermore, predictive insights driven by AI in performance management systems can help identify not only the top performers but also predict who is likely to be awarded with a career advancement and/or a pay hike thus creating a culture of constant improvement (Oswald,2010). Identification of high-potential employees and aligning their career paths with organizational goals is also an area where AI can be extremely beneficial for succession planning (Trisca, 2024). Such capabilities highlight the power of AI in reshaping workforces to be nimble and ready for the future. In addition, Shan and Wang (2024) found striking geographic disparities, with Asia and the tech industry particularly committed to developing talent. They note trends like digital platforms, data-driven personalization, and collaborative learning networks as keys that will unlock the direction of talent strategies. Also supported by Nurmala and Hermina (2024) that good human resource management cannot be separated from preparing future leaders. The study also emphasizes the need for a diversity and inclusion program along with predictive analytics and collaboration tools to create an adaptive culture of performance.

Gričnik and Poljašević (2024), in their bibliometric analysis of talent development literature from 1952 to 2024) by delineate key themes and geographic collaborations. They showed the continued relevance of talent management and training in organizational and educational settings, but also its growing interdisciplinary complexity. Nevertheless, the focus on bibliometric approaches could restrict qualitative reflections regarding the implementation of such themes in practice. Olszewski-Kubilius (2024) also discusses the increasing acceptance of talent development frameworks for advanced learners, while also addressing debates about equity in access to and rearing of talent. This highlights a lack of identification systems both for different domains and stages of talent development, an absence that often results in many gifted skills going unrecognized and developing at school. They add that this programing should be ongoing, curriculum-based and have measurable outcomes. they also indicated that services could be split between talent development for underserved learners and "status quo" gifted programs for higher-achieving students. Muammar (2024) also asserts that utilizing the power of collective intelligence and sophisticated technologies can bring out the dormant potential within extraordinarily talented individuals, aligning talent development with knowledge-based economy needs. Muammar (2024) points out obstacles in the way such as resource scarcity, poor enablement, and a lack of agility due to legacy systems. For example, Nuriddinov (2023) discusses the complexity of talent development in sport and the multiple determinants impacting athlete performance. Key features such as developmental age, relative age effects, sex, training programs, social support and access to facilities were recognised in this framework of sports talent development pathways. Nevertheless, this paper underscores the necessity of sustained, systemic approaches to nurturing athletic talent.

AI-Driven HR Analytics

The AI-Powered HR Analytics harnesses artificial intelligence to examine and interpret enormous amounts of human resource data so that companies can base their decisions on data. AI-powered HR analytics boost processes including recruitment, talent management, performance assessment and workforce planning by incorporating tools such as machine learning, predictive analytics and natural language processing into them. They help to reduce redundancy, offer analytics that uncover insights about potential top talent and trends in the workforce, and align human resource management strategies with organizational change. This approach modernises and aids the innovative planning process, whilst encouraging long-term success within human resource management. For example, Okatta et al. (2024) confirm that HR Data can use to understand the trend and take advantage of skills for selection process and retention of employee. They emphasize major obstacles such as data quality and privacy issues that could impede effective deployment. However, their work highlights the double-edged sword nature of HR analytics as both a bullet point for organizational triumph or the catalyst on highlighting its weak link. In addition, Alabi et al. (2024) on predictive analytics in HR, such as predicting turnover, skill gaps and high-potential talent. Using machine learning and AI algorithms, organizations can improve hiring processes while also enhancing HR strategies with overall business goals. Unlike traditional analytics, predictive analytics enables humans to make real-time decisions that can drastically improve the productivity of manpower as well as reduce turnover –both good talent management. This highlights the need for AI-driven HR analytics to cultivate workforce agility, and access relevant data in Padmavathi (2024) along with strategical approaches it helps make. He points out the potential of AI in predicting trends and spotting opportunities for taking pre-emptive measures, enabling HR to become a business partner to help organizations grow. Padmavathi (2024) on the other hand points out that AI integration into traditional HR systems can be quite a challenge due to several hurdles, such as existing technological infrastructure and human adaptability.

Thangaraja et al. (2024) explains AI based HR technologies in the Industrial 5.0 aspect such as recruitment, talent management and workforce utilization. Their research also emphasizes the convergence of AI with IoT and automation that can help empower employees, thereby driving data-led decision making. Digital HR tools are increasingly being adopted across organizations (Sharma and Sengupta, 2023). However, Sharma and Sengupta (2023) concluded that digital HR tools aid in boosting efficiency, productivity and employee experience alongside data-driven decision-making. As discussed in Manoharan (2024), there is a potential to leverage AI as an innovative agent, which can help in minimising inefficiencies and biases but also data management issues within HR functions. These, when combined with data analytics and automation, make AI-driven HR practices superior to the conventional means of hiring candidates, performance management as well as employee engagement. Manoharan (2024) indicates that AI can elevate the accuracy of decision-making, enhance operational efficiency while driving a workforce to be more competitive and agile. Namperumal et al. (2022) explore the nexus between big data and analytics in cloud-enabled systems of Human Capital Management (HCM), which are changing the way recruitment, performance appraisal, and workforce forecasting is done. With big data analytics, these practices are well established – cultural fit, performance potential and turnover risk can all be predicted with some accuracy. Also, performance evaluations have always been in the spotlight, and using analytic driven performances evaluations ensure that the system is objective and transparent as opposed to traditional evaluation methods. Workforce forecasting models allow organizations to identify potential skill gaps and develop strategies that complement long-term goals, thereby ensuring agility in rapidly evolving business climates. However, Namperumal et al. (2022) emphasizes that an ideal HR analytics should be a comprehensive one, taking data-metrics from several areas into account to allow for strategic human resource talent management and improvement on continuous basis. Business analytics is radically changing recruitment, retention and employee engagement, enabling alternative business structure from HRM perspective in Asia (Allil, 2024). Allil (2024) focusing on How can AI help create a Future Ready Workforce & point of view in the context of losing business ethics with practices that violate law or core principles that people themselves have embraced. Sainila (2024) focuses on the advantages of implementing artificial intelligence technologies in HRM, such as the automation of the routine work and strategic engagement. AI enables HR professionals to embrace more strategic initiatives by minimizing redundant processes like resume sorting, payroll management and performance tracking. Nonetheless, some issues like dependence on AI, budgetary restrictions, and data protection are apprehended. Insights centers on the use of AI in e-HRM and implications for employee performance and organization productivity by Al Samman and Al Obaidly

(2024), as they reveal that AI-powered e-HRM systems play significant positive role in HR activities like recruitment, performance appraisal and employee development. Clearly, they emphasize a hybrid approach towards technology and human-beings to retain engagement level and satisfaction. Moreover, Al Yahmadi et al. (2024) demonstrates the power of the tool to examine expiring contracts, track gaps in skills, and provide customized training and job placement support. The results show how pro-active workforce management and data-based decision-making supports sustainability and foster work force agility. Success of the tool is a testament to AI power for transformation of workforce; however, aerospace or oil and gas is just small portion of economy and there are other industries where applicability could be explored.

Employee Perception of AI Implementation

Employee perception of AI implementation is the way employees feel about and react to the addition of artificial intelligence technologies in workplace operations. Such perceptions will depend on trust in AI systems, awareness of the benefits of using AI, and the extent to which there are concerns over potential risks including job displacement or data privacy. On the other hand, hold negative views can cause resistance that blocks implementation successfully. Awareness of employee interpretation is essential to the successful onboarding of AI technologies and utilizing their capabilities to help maintain a competitive edge in organizational performance. Jerez-Jerez (2025) highlighting a direct route from NFP employee engagement with AI towards SDG adoption and ultimately to positive sustainability metrics for the organisation, including satisfaction and optimism. The research emphasizes that employee attitudes can be leveraged for better outcomes when AI is connected to larger organizational goals such as sustainability. At the same time, its focus on the hospitality industry restricts experiments in different contexts. Felemban et al. (2024) explored elements that may determine the organizational readiness for AI adoption in construction firms operating, as they place great emphasis on the importance of government and top management support, as well as employee mentality/attitudes being necessary facilitating factors by seamless AI integration. Arora and Mittal (2024) analyse the influence of AI on specific HR functions like talent acquisition, training and development, performance evaluation and pay & rewards in the digital workplace while focusing on the mediating role of trust-in-order to derive information for technology (AI-tech trust; a person-centered conceptualization). It means employees' perception of AI as a potential enhancer for HR functions plays a crucial role in the process of adoption.

According to Arora and Mittal (2024), how employees perceive AI as it hits the workplace, will be the key factor in how successful this transformation becomes. Clear outlines of benefits in terms of employee development (increased skill and knowledge) were identified as facilitating acceptance, while fear of being replaced by a machine were seen as severely inhibiting desired engagement. Thus, Arora and Mittal (2024) call for tailored organizational efforts to counter adverse imagery and instil credibility of AI. Nonetheless, this expansive approach to technology adoption within the workplace is too general with respect to the challenges presented by AI integration and calls for additional empirical studies. According to Milkus (2024), whether AI in the workplace is accepted or rejected is largely based on employee perception of why, where and how we use it, when organizations demonstrate clear value and easy skill building, they stimulate adoption and engagement. While, as a fear of replacement and technology anxiety, it galvanizes resistance. Despite the importance of perception, most prior work has focused on other technologies is timely because it explores perceptions in the context of AI adoption. These findings emphasize the fact that organizations need to proactively manage and exploit negative perceptions about AI systems in order to enhance user confidence. Nonetheless, a general focus on adoption of workplace technology is less helpful in identifying the specific impediments associated with AI integration and this presents further areas for empirical research.

Bagis and Yulianeu (2024) found that AI analytics have the effect of improving job crafting, and job crafting has the role of improving employee performance and engagement. Identifying perceived risk and engagement as moderators in the study, the researchers suggest focused efforts to minimize perceived risks, but also encouraging psychological safety through a broader workplace culture initiative. Riaz and Ghanghas (2024) examine the application of AI/ML tools in reviewing employee performance. They suggest that the incorporation of such tools has the potential to increase fairness, accuracy, and real-time assessment among HR practices. According to their research, assessments using AI help in strategic decision-making talent outcomes, enhanced employee performance, commitment and satisfaction. Nonetheless, this research highlights a lack of research on the reliability and (un)intended ethical consequences of these systems. Although the managerial implications are favorable, algorithmic bias and overexploitation of AI provide causes for concern. Shah and Yagnik (2024) explores electronic HRM (e-HRM) practices from the perspective of employees in IT sector. Regarding the impact of e-HRM on employees, most views are positive in that e-HRM is perceived to enhance accessibility, efficiency and transparency; however, concerns remain over the impersonal nature of e-HRM and privacy issues. This growth is further emphasized, noting that new developments in e-HRM also are still in their infancy as quantum and edge computing revolutionizes HR functions. The findings reflect the opportunities that e-HRM opens up for organizations to deliver better HR services, but at the same time, they highlight that companies need to be proactive and control ethical and security risks. Pillai et al. (2024) indicate that personalization, interactivity and perceived intelligence positively drive adoption intention while the technological anxiety and language barriers negatively predict it. They outline key themes to elucidate the path towards chatbot adoption, namely that organizations should promote an openness to change and mitigate perceived risks.

Rožman et al. (2023) suggested that AI-mediated HR practices like leadership, training, and organisational culture help lower employee workload while increasing engagement using a multidimensional mode. The results suggest that employee engagement and performance will benefit from lower workloads enabled by AI-assisted technologies especially in times of turmoil and instability. The research enhances the conceptualization of AI as a force to boost productivity while preventing burnout with sustainable work through focusing on how AI is an enabler. Moreover, Ghaleche (2023) identifies several major themes related to AI in workplace decision-making including, but not limited to: the effectiveness of using AI, the impact on human emotions and reactions, and organizational effects. The other thing that came out is trust in AI and also then the resistance to change, which was an important factor for acceptance. The research stresses ethical practice and transparent communication to lessen negative perceptions. In addition, Basri (2023) investigated the influence of AI adoption to improve operational efficiency in small medium enterprises (SMEs) moderated by employee readiness, cybersecurity and infrastructure Adoption of AI is strongly and positively associated with e-operational performance, a relationship moderated by employee perception toward usefulness of AI. The study points to the need for creating an acceptable organizational culture. Although informative, its application to other sectors may be constrained because it addresses SMEs engaged in e-business. Singh and Tarkar (2022) explore the dynamics of employee satisfaction in this era of post-pandemic workforce under AI-enabled work culture. However, digitalization and automation are being adopted quicker than ever before because of remote work specific demands. While it is clear that AI has the potential to improve satisfaction, fear around lack of skills and job displacement remain challenges. As mentioned by Bhargava et al. (2021), Successful RAIA adoption relies on positive perceptions of RAIA as being an opportunity rather than a threat. These findings highlight the key role of organizational readiness, continuous learning and working together to ensure that any risks and concerns about RAIA implementation are reduced, and its full potential can be harnessed. Abdullah and Fakieh (2020) highlights the need for specific training courses aimed at raising awareness and acceptance of AI use cases. While the study focused on a healthcare culture and profession that may have specific adoption barriers, its findings would be well served by related work in other disciplines or locations. While they do not highlight the important fact that education of employees may help provide a supportive environment for AI adoption. Li et al. (2019) study the effects of awareness of AI and robotics on turnover intention of hospitality employees. Diverging from those findings, their study shows that awareness is the single most important contributor for turnover over and above perceived organizational support and competitive psychological climate. Although thy showed the importance of support to overcome negative descriptions related to new space ventures, it is focused on one industry and a single city limiting generalisability.

RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

AI-Driven HR Analytics and Employee Perception of AI Implementation

AI-driven HR analytics in workplace settings has dramatically changed the practice of human capital management with far-reaching consequences on employee's perception of AI deployment. AI enables more meaningful characteristics though of driving HR analytics by utilizing advanced algorithms, machine learning, and data-driven insights to help organizations improve its most important functions inclouds recruitment, training assessment strategy development, performance management plans and employee engagement (Bagis & amp; Yulianeu 2024). HR analytics powered by AI can have a major impact on how employees perceive them positively or negatively, concerning fairness, transparency & inclusivity. It results in reduced biases and improved impressions of fairness of appraisal processes, for example, analytics-powered performance evaluation systems (Riaz & Ghanghas, 2024). Also, predictive analytics enables pro-active career planning and tailored development opportunities, promoting trust and feeling of value among employees (Basri, 2023). Employees are more prone to back AI systems if they sense that those systems resonate with their personal growth and professional objectives as well as the goals of their organisation. AI trust is an important variable determining employee attitude towards its adoption (Arora and Mittal, 2024). Transparent and explainable AI-based HR analytics systems can counteract skepticism and inspire more faith in the technology. For instance, if employees understand how decisions are made and can see clear evidence of fairness and efficiency, they will be more likely to view AI in a positive light (Ghaleche, 2023). AI-enabled HR analytics systems can ease resistance to change and improve acceptance by enhancing trust. However, while that's all well and good in principle, there are still some hurdles to leap over before AI's HR analytics capabilities lead to the type of perception changes. Job displacement anxiety, a poor AI system understanding, and worries about data security can harm staff attitudes (Abdullah and Fakieh, 2020; Singh and Tarkar, 2022). This suggests the empirical evidence of association of HR analytics powered by AI and employee perceptions. As an example, Bagis and Yulianeu (2024) showed that the use of AI for analytics leads to personalization in job crafting and minimizes work inefficiency leading to employee engagement and job satisfaction. In accordance, employee readiness and acceptance of AI positively augment organizational adoption of AI technologies (Jerez-Jerez, 2025) further validating the implication that positive perceptions are relevant for implementation success. It indicates a pathway to leveraging AI powered HR analytics that facilitate employees in feeling comfortable with technology as using the right channels will ease employee engagements and prove to give benefits. According to the above discussion, it is hypothesized that employee perceptions of AI implementation are positively influenced by AI-driven HR analytics. These factors include improved trust, equity and transparency in HR processes along with personalized experiences by focusing on employee needs and expectations. Companies can promote positive perceptions of AI and drive the broader adoption of this technology in HR by touching on some likely challenges it may face and reinforcing that AI is meant to complement not replace human input. Thus, the following hypothesis is proposed:

H1: AI-Driven HR Analytics positively affect the Employee Perception of AI Implementation.

Employee Perception of AI Implementation and Future Talent Development

Maintaining the trust employees have on adoption of AI is crucial for organizations in their future talent building endeavours. With organizations increasingly implementing AI to revolutionize HR practices, employee beliefs about these technologies are foundational determinants of whether they will succeed in creating a future-ready workforce. A favourable outlook for AI deployment has the potential to influence engagement, trust, and collaboration which are essential elements of building effective talent pipelines that can be aligned to evolving organizational needs. In addition, AI technologies facilitate personalized learning, predictive skills analytics, and workforce planning, making them indispensable for talent development. AI-enabled learning management systems design and customize training programs based on employee need, minimizing skill gaps and accelerating professional development (Bagis and Yulianeu, 2024). Third, AI-enabled analytics help in workforce forecasting, enabling organizations to forecast required skilling needs and preparing employees for the future through tailored skilling interventions (Felemban et al., 2024; Sohail and Ruikar, 2019). These innovations demonstrate the ability of AI to create talent that can thrive in fast-changing business environments. However, the effectiveness of AI in talent development largely depends on how the employees perceive it when implemented. When employees have a positive perception of AI, they become more accepting and participate more proactively in the development programs driven by AI, thereby making optimal use of what it has to offer. Singh and Tarkar (2022) highlight that employees perceive AI as an enhancement to human effort, therefore they have more likely focus on the AI-enabled learning and development initiatives. On the other hand, if participants are sceptical or afraid of being replaced by AI (Abdullah and Fakieh, 2020), it will be difficult for AI to meet future staffing requirements. The relationship between perception and talent development outcomes is mediated by employee trust in AI based systems they have to work with. By showcasing openness in AI practices and clarity about how decisions are made, the confidence of employees increases which urges them to go for development opportunities driven by AI (Arora and Mittal, 2024). In addition, good impressions boost employee engagement which is very important talent development success driver. The investing of more time and effort in continuous learning, upskilling, and adapting to technological advancement by engaged employees expedites to having a strong talent pipeline (Jerez-Jerez 2025). Even though there are benefits from the positives, organizations find it difficult to instill positive perceptions among employees. Ghaleche (2023) states that worries around data privacy, algorithmic bias and not understanding how AI fits in the development pathways can lead to pushback. Furthermore, involving employees in the design of AI systems ensures that the information system fits their needs and is consistent with their expectations, which can help further improve perceptions of AI and strengthen participation. Existing empirical evidence suggests that how employees perceive the implementation of AI within their organizations may create talent development outcomes. For example, the results ofJerez-Jerez (2025) suggest that employee acceptance or readiness to use AI plays a critical role in the adoption of AI technologies for driving strategic goals, including Sustainable Development Goals (SDGs) and non-financial performance outcomes. Likewise, Bagis and Yulianeu (2024) showed that when AI-enabled HR analytics is viewed positively, job crafting takes off (which in turn leads to engagement) a necessary ingredient of developing future talent. However, when the perception of AI is positive, such strategic initiatives are trusted, engaged with, and actively participated in. Thus, creating future-ready skills and capabilities. Organizations can also strengthen this connection by addressing employee concerns, ensuring that they trust AI systems to work well, and showing the increased value of AI-driven talent development in practice. However, the following is the hypothesis:

H2: Employee Perception of AI Implementation positively affect the Future Talent Development.

AI-Driven HR Analytics and Future Talent Development

AI-based HR analytics is a game-changer that is transforming the talent development process by providing data-based insights while also embracing personalization. Utilizing algorithms and ML, these systems can deliver relevant information regarding workforce dynamics by pinpointing skill deficiencies in talent and maximizing developmental programs to match the future requirement of an organization workforce (Bagis and Yulianeu, 2024). This gives organization a unique opportunity to take an early start in getting their workforce ready for the future. In addition, AI-powered HR analytics provide an opportunity to predict future skill needs and help in workforce planning. Predictive analytics allows organisations to spot new labour market trends and align their strategies to foster the development of necessary talent (Felemban et al., 2024). Moreover, based on employee performance data, career trajectories, and industry standards figures AI can recommend bespoke development programs that cultivate employees' capabilities and ready them for their next roles. This process helps organizations to be competitive in more dynamic existent. HR analytics powered by AI enables organizations to create customized L&D programs based on an individual needs anyone and everyone (Jerez-Jerez 2025). This enabling of a customized focus optimizes the efficiency of developments, also incentivizes employee interest and retention, which is integral for an agile future workforce. Data-driven insights in HR analytics powered by AI allow the professionals to make informed decision and manage their budget allocation as well as high-impact development areas effectively. For example, analytics could recognize the employees with highest potential and suggest specific inputs to accelerate their development to help an organization building a strong Leadership Pipeline (Riaz and Ghanghas, 2024). Moreover, these systems are capable of tracking development program results and through real time monitoring enables organizations to continue improving both their strategies and impact. While the potential of AI-driven HR analytics in talent development is substantial, challenges remain. Concerns about data privacy, algorithmic bias, and over-reliance on technology can hinder its implementation (Basri, 2023). Ethical considerations, such as equitable access to development opportunities and the avoidance of bias in talent identification, are critical for the sustainable use of AI in HR functions (Ghaleche, 2023). Moreover, Empirical research underscores the positive impact of AI-driven HR analytics on talent development. Bagis and Yulianeu (2024) demonstrated that AI analytics significantly enhances job crafting and engagement, fostering a culture of continuous learning and development. Similarly, Felemban et al. (2024) highlighted the role of AI-driven predictive analytics in identifying future skills and aligning workforce strategies with long-term organizational goals. These findings validate the efficacy of AI-driven analytics in creating personalized and impactful talent development pathways. Based on the above discussion, it is hypothesized that AI-Driven HR Analytics positively affects Future Talent Development. The ability of AI analytics to anticipate skill needs, personalize development programs, and support strategic decision-making ensures that organizations are well-equipped to cultivate a future-ready workforce. By addressing ethical concerns and fostering trust in AI systems, organizations can maximize the potential of HR analytics to drive sustainable talent development. This highlights the strategic role of AI-driven HR analytics in shaping talent development initiatives, providing a foundation for future research to explore its implications across industries and cultural contexts. Thus, this paper proposes the following hypotheses:

H3: AI-Driven HR Analytics positively affect the Future Talent Development

Mediating effect of Employee Perception of AI Implementation

Artificial intelligence implementation perception represents a significant role in determining how employees respond to AI-based HR analytics as opposed to their intended future talent development. AI-powered HR analytics offers the technical underpinnings for a complete transformation of talent strategies, but employee perceptions are what ultimately dictates how much these systems will be adopted, trusted and used. Employees will trust the outcomes of using AI-powered systems for their talent development only if they perceive these systems positively. With the help of AI in HR analytics, it improves decision-making capabilities, ensures automation of processes with efficiency at work behavioural level along with personalizing programs packages to nurture the individual employee development programs making employees hold a positive perception towards their value from AI. They mitigate chronic HR issues such as bias or inefficiency with predictive insights and fairness in decision-making (Bagis and Yulianeu, 2024). Since AI can shape the thoughts of employees in either way, its impact on employee perceptions regarding AI implementation and usage can be positive when it increases transparency of operations and offers tangible value (specialized training or skills development opportunity & career path etc.) using AI analytics to lessen human biases around AI adoption (Arora & Mittal, 2024). This favourable perception is vital to ensuring that employees buy in, trust one another and you if you plan on deploying AI-based analytics resourcefully to help drive talent development outcome.

The lens of Employee perception about AI implementation translates the attractiveness of benefits from AI-based HR analytics in talent development. Engagement in AI-powered developmental or training initiatives increases when employees see AI as complementing, and not competing with them. To illustrate, an AI in personalized learning programs works better when the employees trust and embrace the technology solutions provider (Jerez-Jerez, 2025). On the other hand, negative perceptions (such as fear of losing a job or doubts about fairness) can bring into question the effectiveness of even the best-designed AI-powered analytics systems (Abdullah and Fakieh, 2020).

The mediation effect of perception is also closely connected with the trust and the engagement. A positive view translates to trust in AI systems, leading to better engagement among employees with the AI-enabled talent development opportunities (Riaz & Ghanghas, 2024). Employee engagement is very crucial for future talent development goals, as when employees have faith in systems, they tend to be more resilient in upskilling programmes and technology adoption and alignment towards organizational objectives (Singh and Tarkar, 2022). This means that the technical capabilities of AI-enabled HR analytics can only be transformed into actionable development outcomes through employee perception serving as a mediator. While its importance can hardly be overstated, getting employees to think positively about it has never been easy. The impersonal nature of AI-driven systems, as well as concerns about data privacy and algorithmic bias can erode trust, which is detrimental to engagement (Ghaleche, 2023). Organizations will need to take these matters into their own hands, through an emphasis on transparency, by involving employees in the design and deployment of AI systems, and through strong training to demystify such tools. When organizations couple AI-driven analytics with the values and expectations of employees, they can strengthen favorable perceptions and thereby optimize their mediating role within talent development. For instance, Bagis and Yulianeu (2024) showed that employee engagement affects talent outcomes significantly based on positive perceptions of AI-enabled HR analytics. In line with this research, Arora and Mittal (2024) suggested that the influence of AI-based systems on different HR functions is mediated by belief in AI technology stressing on how actualization of these technologies depend upon perception. Jerez-Jerez (2025) underlines how acceptance and readiness for AI among employees affect the introduction of AI as well as the effectiveness of talent development initiatives.

Against the backdrop of this discussion, it is being posited that Employee Perception of AI Implementation will mediate the relationship between AI-Driven HR Analytics and Future Talent Development. In fact, the role of positive employee perceptions remains critical and a necessary precursor translating technical capabilities offered by AI-driven HR analytics into meaningful outcomes in terms of talent development. When organizations build trust, get employees engaged and aligned with the expectations, they can leverage AI-powered HR analytics to unleash the true potential of tomorrow's workforce. Consequently, the following hypothesis is proposed:

H4: Employee Perception of AI Implementation mediate the effect of AI-Driven HR Analytics on Future Talent Development

The interplay between AI-driven HR analytics, employee perceptions, and talent development illustrates a dynamic relationship where technology and human factors complement each other. AI-driven HR analytics provides predictive and actionable insights, but its success in talent development relies on employee perceptions, which mediate the adoption and engagement with these systems. Transparent and explainable AI systems foster positive perceptions of their value, functionality, and trustworthiness, as they showcase the ability to enhance fairness, efficiency, and personalization in HR processes (Arora & Mittal, 2024). For instance, AI-powered performance management systems reduce subjective biases and deliver data-driven insights, enhancing trust in HR processes (Riaz & Ghanghas, 2024), while predictive analytics in recruitment and workforce planning promotes transparency and proactivity, shaping favorable employee views toward AI (Bagis & Yulianeu, 2024). Positive perceptions of AI as a growth enabler drive engagement with personalized training modules, upskilling opportunities, and career planning tools, significantly impacting talent development initiatives (Jerez-Jerez, 2025). However, fears of job displacement and skepticism about fairness can hinder adoption, underscoring the need for trust and transparency to optimize talent development (Abdullah & Fakieh, 2020). Additionally, AI-driven HR analytics facilitates workforce readiness by analyzing performance metrics, career trajectories, and market trends to identify skill gaps and create personalized learning pathways (Felemban, Sohail, & Ruikar, 2024). Predictive analytics also aligns training initiatives with strategic goals, fostering a culture of continuous learning (Bagis & Yulianeu, 2024). Despite these benefits, challenges such as data privacy concerns and equitable access to opportunities must be addressed for sustainable outcomes (Basri, 2023; Ghaleche, 2023). The mediating role of employee perceptions is pivotal, as positive views enhance engagement with AI systems, whereas negative perceptions undermine their effectiveness (Arora & Mittal, 2024; Jerez-Jerez, 2025). This dynamic relationship emphasizes the importance of fostering trust, transparency, and inclusivity in AI implementations, bridging the gap between technological capabilities and human factors, and creating a resilient talent pipeline aligned with future challenges. Empirical evidence validates this integration, offering a robust framework for organizations aiming to strategically enhance talent development through AI technologies (Riaz and Ghanghas, 2024). However, the Model of this paper is shown in Figure (1) as follows.

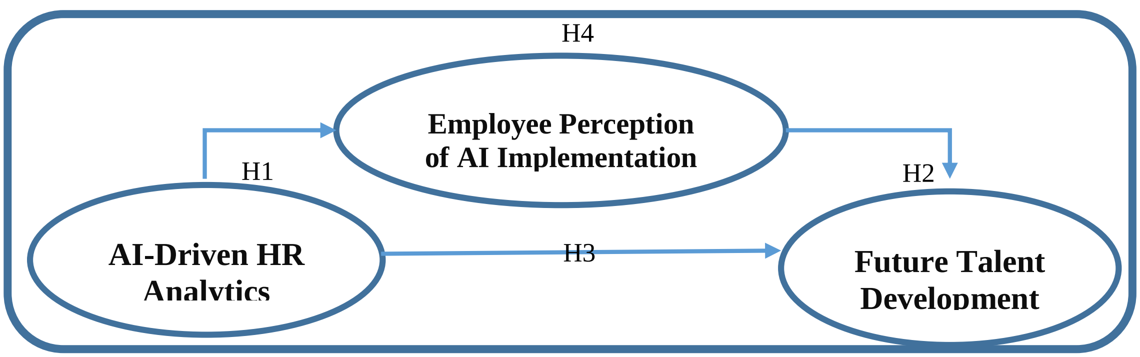

Figure 1: Research Model

METHODOLOGY

A survey-based research methodology is ideal for this study and provides an efficient way to test the ties between AI-enabled HR analytics, employee beliefs/attitudes toward AI implementation, and future talent management. Using surveys allows researchers to collect quantitative data in a standardized way and apply advanced statistical techniques to assess complex relationships.

Considering that Middle Eastern public universities are diverse institutionally and demographically, to capture widely different experience and perspectives, this is a useful approach. This random sampling has cemented the design of the study — by ensuring that there is very little selection bias and a representative dataset. This variation increases the potential for a rich picture of how AI technologies are impacting HR practices and talent development in an area with especially different cultural and institutional environments. Data were collected from a sample of public universities in the Middle East, which included 356 samples. The use of advanced analytical tools, including Smart PLS 4.0.3 for Structural Equation Modeling (SEM) and SPSS 29 for descriptive and regression analyses, reflects the methodological rigor of the study. SEM is particularly valuable for testing both direct and indirect effects, such as the mediating role of employee perceptions in the relationship between AI-driven HR analytics and future talent development. The structural equation modeling (PLS-SEM) utilized in the study provides empirical evidence for the positive mediating role of trust in AI, confirming its crucial relationship in determining attitudes towards the implementation of AI (Felemban et al., 2024). This analytical depth allows the study to provide evidence-based insights into the interconnectedness of technology adoption, employee attitudes, and organizational outcomes. Meanwhile, SPSS facilitates the summarization of demographic data and the identification of response patterns, offering a foundational understanding that complements the more sophisticated SEM analyses.

RESULTS

Descriptive Analysis Results

SPSS-29 was used to analyse the demographics of a sample (n=356) from public universities in Middle east. Gender, Male 283 (79.5), Female73 (20.5). The distributions align with the relative lack of gender parity in the overall workforce and senior administration roles in higher education across the region. As for the age profile, we see an overwhelming majority of mid-career professionals (61.8% i.e., 220 respondents) in the 30 – 45 years bracket providing that this study largely draw perspectives of those who are currently steering HR practices In our sample, 112 (31.5%) were aged over 46 years olds providing view points from more mature professionals and only 24 (6.7%) provided views from younger respondents under the age of30, in line with our thinking that HR decision making roles require considerable experience. The sample was also highly educated, with 274 (76.9%) of the respondents holding bachelor's degrees and 82 (23.1) holding advanced degrees where this workforce should demonstrate the academic excellence demanded in public universities. Professional experience was also a significant factor, as most (58.7%) had been working between 5 and 15 years while the remaining (31.2%) more than 15 years, representing an experienced group able to evaluate the effectiveness of AI-based HR tools.

Path Coefficients

Path coefficients are among the most important indicators used in ratifying relationships between independent and dependent variables, and indicate both the strength (magnitude) of such relationships and their direction. Path coefficients signify clearly how individual constructs relate to each other and represent valuable information of the structural model. The analysis also R^2 (R-Square) which is the determination coefficient that is used to measure how much variance of an endogenous (dependent) variable can be explained by exogenous (independent) variables. Baron and Kenny (1986) suggest that R^2values of 0.67 or more demonstrate a strong, positive relationship between independent and dependent variables with high explanatory power. The direct and indirect effects of independent variables on dependent outcomes can be better demonstrated with higher R^2 which suggests that the predictive capacity increases. In this structural model framework, these metrics are utilized to investigate the links between AI-based HR analytics and employees' views of deploying hm/AI implementation to future talent development. This measurement model reflecting those relationships is presented in Figure (1) bellow:

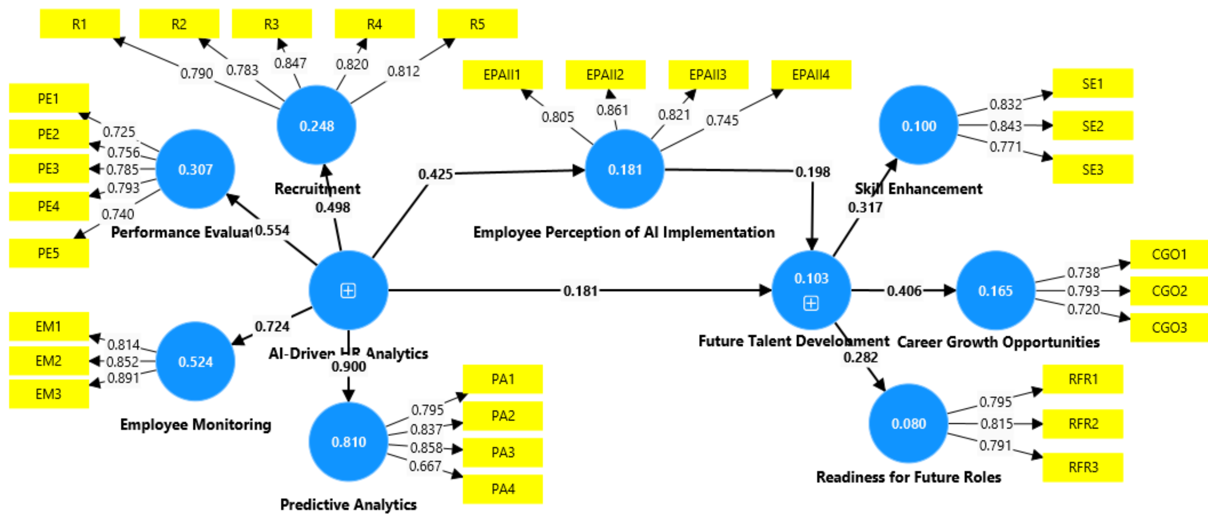

Figure 1: Finalized Measurement Model

The path coefficients for this paper are shown in the figure of Structural model on AI-driven HR analytics, perceptions among employees about AI implementation and shifting paradigm of talent development for the future, components Details of interactions with path coefficients, R^2 values and variable loadings. Based on Figure (1) above, the finalized measurement model serves as a detailed roadmap that illustrates the complex interrelationships among AI-driven HR analytics, employee perceptions of these practices, and future talent development. This study provides practical insights to fine-tune HRM policies in the context of public universities through the path coefficients and R^2 values.

AVE and Reliability

Tests of construct reliability and convergent validity in Structural Equation Modeling (SEM) must be performed to ensure the robustness of these measurement models. Common reliability assessments (Cronbach alpha, rho_c) assess the degree to which the internal consistency of the constructs. Values of reliability approaching unity indicate that the latent constructs represented by an observed variable have been consistently defined. Whereas convergent validity is evaluated with the Average Variance Extracted (AVE). AVE is the average variance extracted that indicates the share of variance that a construct explains in relation to measurement error. Commonly if the AVE is 0.50 or higher, then it has convergent validity since this value indicates that at least half of the variance in the indicator being measured is captured by its construct and therefore both of them are valid measures (Fornell and Larcker 1981). In combination, they provide a comprehensive assessment of the quality of measurement by the model. The data presented in the table (1) Reliability and Tests of AVE show the reliability measures (Cronbach's Alpha, rho_a, rho_c) and AVE values for all constructs related to the study.

Table 1: Reliability Testing and AVE

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Recruitment	0.870	0.874	0.906	0.658
AI-Driven HR Analytics	0.701	0.704	0.835	0.628
Career Growth Opportunities	0.704	0.701	0.795	0.564
Employee Monitoring	0.814	0.842	0.889	0.727

Employee Perception of AI Implementation	0.824	0.836	0.883	0.655
Future Talent Development	0.732	0.733	0.779	0.638
Performance Evaluation	0.817	0.819	0.873	0.578
Predictive Analytics	0.802	0.833	0.870	0.628
Readiness for Future Roles	0.722	0.729	0.842	0.640
Skill Enhancement	0.749	0.756	0.856	0.666

As seen in the above Table 2, most constructs Recruit (0.870), Employee Monitoring(0.814) are all well over this line and thus indicate high reliability for the scales of measurement used in our study. Even constructs recorded a marginally lower alpha but still falling within the acceptable limits, such as AI-Driven HR Analytics (0.701) and Career Growth Opportunities (0.704), indicates stability in measurement. All the constructs highly reliable, as displayed in composite reliability values (which are consistently higher than 0.79). For instance, constructs like Recruitment (0.906) and Employee Monitoring (0.889) have very high composite reliability indicating their strength as a construct. Furthermore, convergent validity, as measured by the Average Variance Extracted (AVE), likewise justifies the model. The AVE indicates the strength of a construct in relation to measurement error and is considered to show adequate convergent validity if above 0.50. Hence, all constructs (Table 2) reach that standard with the higher AVE values of Employee Monitoring (0.727) and Skill Enhancement (0.666), conf. However, the AVE for Career Growth Opportunity (0.564) and Performance Evaluation (0.578) are slightly lower than.5 but still exceed minimum criterion (Fornell and Larcker, 1981), confirming valid indicators for their constructs. The findings show the latent variables sufficiently reflect their indicators, resulting in constructs like Recruitment (0.658) and Predictive Analytics (0.628) with high levels of explanatory power. The implications from these findings are manifold. This means that constructs, like Employee Monitoring and Skill Enhancement with AVE values greater than 0.5, are confirmed as reliable and robust representations of the underlying thought process within the measurement model, particularly when analyzing the impact of AI-driven HR analytics. In contrast to the relatively modest AVE values of constructs such as Career Growth Opportunities that might serve by adding or sharpening indicators as an explanatory variable. These findings highlight the utility of indicators to reflect HR impacts on AI for Middle Eastern public universities. In particular, Employee Monitoring and Skill Development constitute the core dimensions, whereas Career Advancement Opportunities and Performance Rating represent areas of improvement. Hence the results of reliability and AVE are indicating that the constructed model is not only valid but also reliable for looking into structural relationships, making it a good candidate for further analysis in an SEM framework.

R^2 and adjusted R^2 are important tests in Structural Equation Modeling (SEM) to assess how well independent variables explain dependent variables. R^2 quantifies the proportion of variance in a dependent (endogenous) variable that is predictable from its predictors (exogenous variables). The more independent variables in the model affect the outcome variable, the higher R^2 is and thus a stronger fit of the model to the data. When more predictors are added into a model, the adjusted R^2 becomes vital since it compensates the complexity of each gauge stage that raises an R^2. This is the reason why adjusted R^2 is less optimistic about the model´s smoothing power. R^2 and adjusted R^2 * measure of goodness of fit. This study has used AI-driven HR analytics, employee perception, and other related variables as independent variables in explaining the outcome variable of future talent capability, career growth opportunities and readiness for future role* The R^2 and adjusted R^2 values illustrated in Table 3 for the constructs estimated in the measurement model. However, Table 2 shows R^2 and adjusted R^2values results

Table 2: R^2 and adjusted R^2values results

Variables	R-square	R-square adjusted
Recruitment	0.248	0.246
Career Growth Opportunities	0.165	0.163
Employee Monitoring	0.524	0.523
Employee Perception of AI Implementation	0.181	0.179
Future Talent Development	0.103	0.098
Performance Evaluation	0.307	0.305
Predictive Analytics	0.810	0.810
Readiness for Future Roles	0.080	0.077
Skill Enhancement	0.100	0.098

Table 2 shows relatively strong explanatory power across constructs in the model. Predictive Analytics is the most powerful construct, having an R^2value of 0.810, which means that it predictive owns 81% of its variance by its predictors. Hence, this shows its significant position in the AI based HR structure since predictable analytics produces efficient values directly to direct HR approach and strategy. Its robustness can be confirmed with the concordance of R^2 and adjusted R^2 for this construct. Likewise, Employee Monitoring is similarly impactful with an R^2 of 0.524 when proven variance from this construct and actionable AI competency integration into the HR practices are assessed. These constructs combined are the strongest drivers in the model, indicating their key impact on outcomes and allowing for consistent strategic implementation across these settings. On the other hand, a few constructs have mid-levels of explanatory power (R^2). Performance Evaluation (R^2 0.307) explains about 30% of its variance, which is a moderate level of dependence (partial dependants on ai powered hr analytics). It implies that there are other external variables driving this construct. Likewise, Recruitment (R^2 = 0.248, explaining ~25% of variance) demonstrates a small but significant relationship with AI-based analytics affecting recruitment as well. This result (R^2=0.181) provides further evidence that AI practices shape employee perception of the implementation of AI, but that a substantial portion of this variance is unexplained. Those moderate results point to the need for adding and/or refining variables in the present model. However, specific items (especially those related to talent development outcomes) show a comparatively low level of explanatory power. Again, constructs Fall back on Future Talent Development (R^2 = 0.103), Skill Enhancement (R^2 = 0.100), Readiness for Future Roles (R^2 = 0.080) would signal a weak relationship in that independent variables only account for a small proportion of the variance associated with these dependent variables. R^2 for these constructs, adjusted down slightly, challenges the full model to integrate more predictors or contextual features. Though Career Growth Opportunities (R^2 = 0.165) performs somewhat better, both account for a small portion of variance explained representing some gaps in linking AI-powered HR analytics to real talent outcomes. These findings went further to demonstrate the importance of tailoring approaches that better align AI-based HR processes with employee development outcomes.

Structural Model (Hypotheses Testing)

Structural Equation Modeling (SEM) is a powerful tool to test relationships between latent variables and allows us to understand direct and indirect effects. The structural model in this study provides key diagnostics of the hypotheses testing results by quantifying the extent to which AI-based HR analytics, employee perceptions regarding implementation of AI and its mediators impact future talent. This relationship is assessed through path coefficients, p-values and R^2 values enabling the model to capture for strength /or absence of connections with direction and significance. The above metrics point out the important drivers of talent development and employee engagement especially for AI adoption in Middle Eastern public universities. Such a tactic provides an opportunity to cover the studied phenomenon in full, addressing both theoretical and practical aspects. However, hypothesis testing is integral to statistical analysis, as it provides mechanisms for asserting if and how strongly one or more relationships exist between variables in your model. Hypotheses, a more specific prediction stemming from the theory, are then rigorously tested in turn to determine if the data support or contradicts such predictions. It means that relationships are inferred through their indicators [Original sample estimate (O), t-statistics (T) and P-value (P)]. First table of results, original sample estimates O with indications of positive or negative relationships are shown. t-statistics (criteria > 1,96 at α = 5%) signal statistical significance. Moreover, p-values less than 0.05 signify conventional cut-offs for strong associations. These indicators together prove the existence of links between variables or their importance, it also provides a deep explanation of such relationship which form the structural model.

The outcomes of hypothesis testing are visually summarized in Figure 2, which displays direct or indirect path coefficients between the constructs. This visualisation aligns with the detailed statistical analysis results showcased in Table (3), but provides easier and more concise overview of the relationships under study. Figure 2 is a composite of important path coefficients across all to pine identifying AI-driven HR analytics and employee perceptions are more closely related with one another than talent development. They underscore the significance of positive associations, statistical significance and explanatory power that allow a qualitative understanding of the overall structure and results of the model. This paper makes use of a legacy of statistical tests to ascertain if its hypotheses hold true, thus ensuring methodological rigor. The sign of the original sample estimate (O) indicates whether these relationships are positive or negative for each link examined. The statistical significance of these relationships is evaluated through t-statistics (T), where values greater than 1.96 imply the existence of a relationship. Moreover, p-values (P) are further confirmation, with those less than 0.05 indicating the relationships in the model that are statistically significant. Integrating these indicators strengthens and makes meaningful the relationships, provides a solid basis for measuring the influence of AI-enabled HRM practices and helps to build an insight into which factors shape future talent (development).

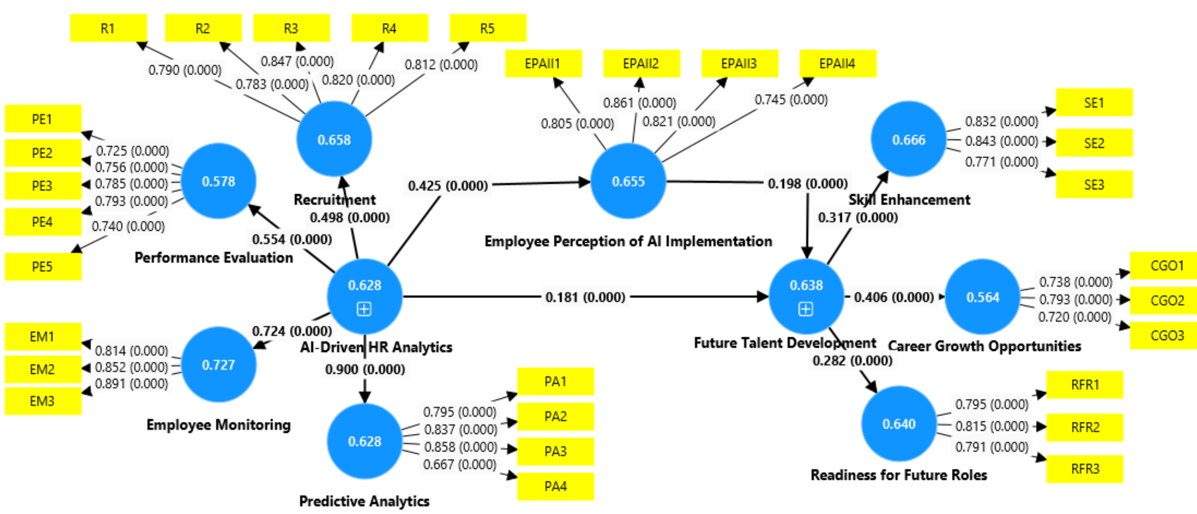

Figure 2: Hypothesis Testing Results

As all hypotheses support path coefficients and p-values that are statistically significant, the structural model illustrates the degree of strength and significance of the relationships between constructs. The strongest path (0.628, $p < 0.001$) is between AI-driven HR analytics and employee perception of the implementation of AI, which supports that a vital contributor in forming employee attitudes toward AI systems is indeed HR analytics Furthermore, employee perception of AI implementation is a significant predictor of future talent development (0.198, $p < 0.001$), highlighting that the key to enabling any developmental outcomes is securing employee buy-in and acceptance of AI. The direct effect of AI-driven HR analytics on future talent development is also important (0.181,

$p < 0.001$) meaning that systems powered by AI help in an implicit manner to improve talent development efforts. And a significant indirect path (of 0.198) demonstrates that not only strengthen but also amplify role of AI driven HR analytics in future talent development (the more employees perceive high levels of implementation of AI in their function, the higher is the effect of HR analytics on talent development) again confirming our model. The explanatory power of the predictors, shown as R^2 values, highlights the strength of the model in explaining 65% of variance in employee perception toward AI implementation ($R^2 = 0.655$) and similarly 64% of future talent development can be explained by constructs in our model ($R^2 = 0.638$). Predictive Analytics is a crucial driver ($R^2 = 0.900$) as part of the AI-driven HR analytics framework, while Readiness for Future Roles ($R^2 = 0.640$) and Skill Enhancement ($R^2 = 0.666$) have high explanatory power reflecting their strong relationship to AI-driven HR practices Career Growth Opportunities (R^2= 0.564) has the least amount of explanatory power, indicating that this will need a more focused intervention. For public universities in the Middle East, this study can provide guidelines on adopting AI systems strategically with transparency to foster positive perceptions of employees and invest in human capital development programs with a vision for skill improvement and foresight for future job roles. Some suggestions for future research include the need to identify more predictors of constructs with lower explained variance (e.g., intention to use AI-driven HR analytics), assess potential cultural and organizational boundary moderators, as well as conducting longitudinal studies aimed at determining whether AI-driven HR analytics manage to keep their negative impact over time. This approach and future research will maximize the transformative role of AI in the broader context of HR and talent management in public universities.

Path Coefficients for direct effect

One of the most important metrics provided by SEM, path coefficients convey how much each latent variable influence other variables, as well as the statistical significance and direction of those relationships. They provide researchers with the ability to test theoretical hypotheses based on direct and indirect effects of independent variables on dependent variables. Table 4: Path Coefficients for Results of the Path Coefficients highlights how these elements are linked in relation to AI-enabled HR analytics, which encompasses employee perceptions towards AI and its association with future talent development and relevant dimensions such as career advancement potential, skill development and preparation for a future role. For each of the relationships, key statistical indicators are reported in terms of the original sample O measure that indicates strength and direction (positive or negative) of the relationship between variables as well as amplitude (M) and stability (STDEV). The t-statistics indicate the significance of the relationship and if > 1.96, statistically significant at a 5% confidence level. Last, p-values validate that the relationships satisfy a significance level with traditional values of $p < 0.05$ denoting evidence of significance. Results as summarized in Table 4 support the condition of fulfilment of hypotheses as well as examination of structural model reliability.

Table 4: Results of the Path Coefficients

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI-Driven HR Analytics -> Employee Monitoring	0.724	0.724	0.025	29.083	0.000
AI-Driven HR Analytics -> Employee Perception of AI Implementation	0.425	0.428	0.043	9.919	0.000

AI-Driven HR Analytics -> Future Talent Development	0.181	0.181	0.052	3.502	0.000
AI-Driven HR Analytics -> Performance Evaluation	0.554	0.556	0.034	16.211	0.000
AI-Driven HR Analytics -> Predictive Analytics	0.900	0.901	0.007	126.649	0.000
AI-Driven HR Analytics -> Recruitment	0.498	0.501	0.037	13.467	0.000
Employee Perception of AI Implementation -> Future Talent Development	0.198	0.200	0.056	3.549	0.000
Future Talent Development -> Career Growth Opportunities	0.406	0.410	0.043	9.416	0.000
Future Talent Development -> Readiness for Future Roles	0.282	0.289	0.050	5.700	0.000
Future Talent Development -> Skill Enhancement	0.317	0.321	0.043	7.352	0.000

The values in Table 4 indicate the power and significance of the relationships between constructs in the structural model. One construct that has become a particularly important antecedent of several outcomes is AI-driven HR analytics. It is especially high impact on Predictive Analytics, path coefficient = 0.900; t-statistic = 126.649; p-value = 0.000 —providing a central tenet for informed HR decision making and strategies. Likewise, the relationship between Employee Monitoring (0.724, p = 0.000) and Performance Evaluation (0.554, p = 0.000), indicates it plays a significant role in the seamless functioning of HR services as well as evaluating employee performance. The path coefficients are strong with highly significant p-values, confirming that AI-driven HR analytics serves as the basis of the model. Likewise, HR analytics not only serve as a mediating effect between AI implementation and Employee perception of such implementations; the relationship between AI driven HR analytics and Employee Perception on AI Implementation (0.425, p = 0.000) is also significant with respect to that of purely measuring AI performance through simulations or data mining methods. This emphasizes the importance of deploying AI in a way that helps employees feel positively about implementation positively and have faith in the deployed AI technologies. The route of AI-powered HR analytics leads to Future Talent Development (0.181, p = 0.000) also proves that direct impacts are surely low by AI technologies but still they exist directly towards talent development. Yet, it is reinforced through Employee Perception which serves as a mediating variable (Path: Emp. Perception of AI Implementation to Future Talent Development = 0.198; p = 0.000). Model for relationships with Future Talent Development and its dimensions [Career Growth Opportunities (0.406, p=0.000), Skill Enhancement (0.317, p=0.000) and Readiness towards Future Roles(0.282, p=0.000)] further substantiate the model as a strong capture of the resources responsible for talent development outcomes in organizations between October 2023 Of these dimensions, Career Growth Opportunities appears to be the most strongly correlated and highlights how talent development allows for upward mobility and career advancement. Skill Enhancement and Preparation for Next Role, marginally weaker than above two theses but substantial in significance as well, hint that HR analytics with AI makes employees ready for future roles and enhances their skills. As shown in Table 4, high t-statistics on all relations confirm the stability and reliability of the relationships. Abstracting relationships such as that between AI-powered HR analytics and Recruitment for instance, (0.498, t = 13.467, p = 0.000), reinforces that idea of using AI to improve hiring processes and detecting top talent among applicants In the same vein, if there are significant t-statistics for other paths e.g. Future Talent Development to Skill Enhancement (t = 7.352), and Career Growth Opportunities (t = 9.416) et cetera, these paths further confirm that this linkage is indeed a valid one. The implications of these findings are substantial for Middle Eastern public universities and other organizations interested in AI-driven HR analytics. Emphasising predictive analysis, performance assessment, and other kinds of employee surveillance will lead to greater efficiency in the managerial apparatus but may provide a workforce that is neither more committed nor better-skilled. Additionally, the role of employee perceptions in mediation indicates that when AI technologies are applied, transparency and communication to practitioners is crucial. It is on the part of universities to make sure employees do understand the positive aspects both in utility and practicality they will see when AI driven HR analytics are implemented, as properly applying this technology goes a long way in solidifying public perceptions that further amplify these advancements influence and effects over talent development.

Mediation Effect

The perception of employees about the implementation of AI mediates the relationship between ai-driven HR analytics and leveraging talent for the future. To test the hypothesis, direct effects, indirect effects and mediating role of Employee Perception of AI Implementation is evaluated. Table (5) below give a summary of these effects, both direct and mediated, with an overall overview of the relationships between constructs.

Table 5: Result of Mediation Effect

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Indirect Effect					
AI-Driven HR Analytics -> Career Growth Opportunities	0.108	0.110	0.025	4.331	0.000
AI-Driven HR Analytics -> Future Talent Development	0.084	0.086	0.025	3.326	0.001
AI-Driven HR Analytics -> Readiness for Future Roles	0.075	0.078	0.023	3.271	0.001
AI-Driven HR Analytics -> Skill Enhancement	0.084	0.087	0.025	3.321	0.001
Employee Perception of AI Implementation -> Career Growth Opportunities	0.081	0.083	0.026	3.072	0.002
Employee Perception of AI Implementation -> Readiness for Future Roles	0.056	0.058	0.020	2.835	0.005
Employee Perception of AI Implementation -> Skill Enhancement	0.063	0.064	0.020	3.087	0.002
Mediation Effect					
AI-Driven HR Analytics -> Employee Perception of AI	0.084	0.086	0.025	3.326	0.001

Implementation -> Future Talent Development					

Based on the above table, overall structure of the results illustrates how employee perceptions serve to mediate major indirect impacts of AI-enabled HR analytics on different dimensions of talent development. In relation to career growth prospects, the indirect effect coefficient of 0.108 ($p < 0.001$), suggests that AI-driven HR analytics translate into employees' perception of career advancement via employee attitudes, while a very high T-statistic (4.331) further confirms the strength of this relationship. In the same vein, the indirect effect driving future talent development (0.084, $p = 0.001$) that points to trust in AI systems and a mediation effect on readiness for future roles (0.075, $p = 0.001$) showing how AI analytics improve employees' readiness for new roles. Skill improvement also has a significant direct effect on AI (0.084, $p = 0.001$), illustrating that employee perception plays an important mediating role in the impact of AI and skill improvement. The direct mediation effects of employee perceptions are also clear with significant coefficients for career growth opportunities (0.081, $p = 0.002$), readiness for future roles (0.056, $p = 0.005$), and skill enhancement (0.063, $p = 0.002$) where again they indicate the significance of employee attitudes as a mediator for these outcomes. Last but not least, the indirect effect from (1) AI-powered HR analytics to employee perceptions to future talent development (0.084, $p = 0.001$), further carried out in detail between groups of high and low a judgments, answers to how significantly amplified role does employee perceptions play on the AI impact over talent outcomes for high or low judgement teams respectively. All these findings together indicate that AI adoption, employee attitudes and organizational success are all inter-linked one way or the other. The strong coefficients and low p-values for each path indicate that these relationships are robust, suggesting organizations should ensure positive employee perceptions of AI systems. The AI-powered HR analytics should focus on transparency, trust and engagement with the AI tools used to ensure that their advantages are optimized for talent development across career development, skills development and preparation for future roles.

DISCUSSION

This study provides the most significant evidence for the First, Second through Third Effects of AI-Driven HR Analytics, Employee Perception of AI Implementation and Future Talent Development in Middle Eastern public universities. The findings reaffirm both direct and mediated relationships, highlighting the importance of technology capabilities and human factors in establishing talent development outcomes. A discussion critically contextualizes these findings in the literature and explores the implications. The results illustrate that there is a statistically significant and positive relationship between AI-Driven HR Analytics and Employee Perception of AI Implementation (Path Coefficient = 0.425, $p < 0.001$). This is consistent with the works of Riaz and Ghanghas (2024) and Bagis & Yulianeu (2024), who emphasize that HR systems powered by AI can improve perceived equality and openness about the HR procedure. This translates into improved efficiency due to removed biases in recruitment, performance evaluation as well as decision-making processes. Yet, there will still be obstacles to building trust in AI systems (Abdullah and Fakieh,2020), as data privacy issues, such as the resistance of changing system and regularization processes need to all be solved. Therefore, transparency and explain ability in AI systems along with proactive communication strategies are necessary for a positive employee experience. The coefficient of Employee Perception of AI Implementation on Future Talent Development = 0.198 ($p < 0.001$). This highlights how important employee mindset is for the success of talent development solutions using AI. According to Jerez-Jerez (2025), positive perceptions promote engagement with personalized training programs and career planning tools. AI helps employees feel as if their skills and attendance are more valuable to the organization (as opposed to automatically replaced), which in turn encourages them to take part in upskilling, creating a stronger talent pipeline. On the contrary, if the individuals have skepticism or their fear of losing jobs, it will stop these potential outcomes (Ghaleche 2023; Singh and Tarkar 2022). The firings highlight the importance of trust and employee participation in designing and implementing AI systems.

The Employee Perception of AI Implementation considerably affects the future talent development path coefficient 0.198 ($p < 0.001$) That highlights the significance of employee mindsets and their attitudes when it comes to making or breaking talent development initiatives in any organization with AI. Engagement with personalized training programs and career planning tools are driven by positive perceptions (Jerez-Jerez 2025). Human employees who think of AI as supplement to their work instead of a replacement are more likely to engage in upskilling programs and build the organization talent pool. On the other hand, scepticism or fear regarding the displacement of jobs could limit such benefits (Ghaleche, 2023; Singh & Tarkar, 2022). These results highlight the importance of building trust and involving employees when designing and implementing AI systems in organizations. In line with this potential, AI-Driven HR Analytics has a path coefficient of 0.181 ($p <0.001$), emphasising the direct impact these tools can have on Future Talent Development and workforce planning talent strategies as well. For instance, Felemban et al. (2024) found that predictive analytics allows organizations to assess existing skill gaps and tailor required training programs according to future workforce requirements. Nevertheless, the low to moderate level of explanatory power indicates that other factors such as organizational culture and leadership support are likely important in channelling AI-enabled HR analytics towards talent outcomes. A strong focus on these areas could make AI–driven systems for a future-ready workforce even more effective.

One of the major contributions of this paper is that it reiterates and confirms Employee Perception of AI Implementation as mediator in the relationship between AI-Driven HR Analytics and Future Talent Development. The indirect path with path coefficient 0.084, $p = 0.001$) highlights the role of employee attitudes as mediators between the technical features of HR analytics enabled by AIdriven machine analytical capabilities and actual outcomes. Positive perception enhances the functionality of AI systems by providing a foundation of trust, active participation and partnership towards development aspirations. The finding aligns with Arora and Mittal (2024), who state that trust in AI systems positively influences participation in a talent development program using AI. However, Basri (2023) and Ghaleche (2023) sounded a warning about the impact of ethical considerations or lack of transparency on such a mediating effect in the long-term. These results relate with earlier studies that stresses upon a blended approach of technological and humanistic perspective in HR processes. For instance, Li et al. and Jerez-Jerez (2025) stress on AI adoption, which heavily relies on employee perceptions and behaviour. Yet while this study contributes to the literature examining AI by conceptualizing and modeling how employee perceptions mediate between formal design and the functioning of AI, a subtlety that makes a difference between designs which function effectively or ineffectively, determinations of another order than the levels on their own. This calls for organizations to look towards this kind of analysis, but not without addressing aspects like the resistance to change and data privacy concerns so as to gain from AI-driven HR analytics.

A key contribution of this study is its confirmation of the mediating role of Employee Perception of AI Implementation in the relationship between AI-Driven HR Analytics and Future Talent Development. The indirect effect, with a path coefficient of 0.084 ($p = 0.001$), underscores the importance of employee attitudes in translating the technical capabilities of AI-driven HR analytics into actionable outcomes. Positive perceptions amplify the effectiveness of AI systems by fostering trust, engagement, and alignment with developmental goals. This finding aligns with the work of Arora and Mittal (2024), who emphasize that trust in AI systems enhances participation in AI-enabled talent development programs. However, as Basri (2023) and Ghaleche (2023) caution, ethical concerns and issues of transparency must be addressed to sustain this mediating effect. These findings resonate with prior research emphasizing the interplay between technological and human factors in HR processes. For instance, Li et al. (2019) and Jerez-Jerez (2025) similarly highlight the critical role of employee attitudes in the successful adoption of AI systems. However, this study expands the discourse by explicitly modeling the mediating role of employee perceptions, offering a more nuanced understanding of how these perceptions influence the efficacy of AI implementations. The evidence underscores the need for organizations to address potential barriers, such as resistance to change and data privacy concerns, while leveraging the benefits of AI-driven HR analytics. For Middle Eastern public universities, these findings have significant practical implications. Strategic investments in AI-driven HR systems must be complemented by initiatives to build employee trust and engagement. Transparency, proactive communication, and targeted training programs can help demystify AI technologies and align them with employee development goals. Institutions that address these challenges effectively can harness the full potential of AI to develop a resilient and future-ready workforce, contributing to national visions such as Saudi Arabia's Vision 2030. This study provides a robust framework for understanding the interplay between AI-driven HR analytics, employee perceptions, and talent development, offering actionable insights for policy makers and institutional leaders seeking to navigate the complexities of AI adoption in HR practices.

CONCLUSION

This paper aims to investigate AI-Driven HR Analytics, Employee Perception of AI Implementation & Future Talent Development in Middle Eastern public universities. The investigation yielded statistically sound inferences on these interrelated variables using a survey-based approach scenario and sophisticated statistical tools such as Structural Equation Modeling (SEM). The results show that AI-driven HR analytics arguably have an impactful effect on employee perceptions and talent development outcomes, which is largely mediated by employee perceptions. One major limitation in this paper is the use of self-reported data that may contain social desirability or central tendency bias. The cross-sectional nature of study also limits the assessment of causation and long-term effects. Although the study is contextually relevant, it restricts findings to public universities in the Middle East that other regions or sectors with different cultural and institutional contexts are less likely to benefit from. Further studies overcoming these limitations with longitudinal designs, broader organizational sectors and additional mediators or moderators (such as organizational culture and employee engagement) could be conducted in the future. This paper provides several important implications for public universities, policymakers and organisations in the Middle East region. AI HR analytics and strategies that address employee perceptions need to be connected if public universities are indeed to cultivate the trust, transparency, and engagement needed for this data-driven approach to work. Policymakers can utilize these results to ensure that AI initiatives align not only with national goals (e.g., Saudi Vision 2030), but also the critical importance of public universities in developing future talent. As organizations look to implement ethical AI, they should move away from treating technology as a replacement for people and instead approach it as an enhancement or supplement. This paper suggests that to reap the full benefits of HR analytics driven by AI, holistic approaches should be developed which involve routine training programmes, clear communication and well-established data privacy measures. Engaging employees in the design and deployment of AI systems can improve trust and acceptance, helping to ensure that AI capabilities are aligned with achieving organizational goals. Regularly assessing and fine-tuning these practices will ensure that AI-powered HR stays relevant and effective over time. The importance of this study to society is providing universities in the Middle East with ontological foundations for preparing university graduates as future-ready and employable workforce a source for socio-economic progress. From a scientific perspective, it contributes to the understanding of employees' perceptions as mediators in the relationship between AI-driven HR analytics and talent development, thereby providing a foundation for future research. For practitioners, the results offer practical implications for creating inclusive and effective AI-powered HR technology strategies that promote organizational preparedness and innovation.

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