Journal of Organizational and End User Computing
Volume 36 • Issue 1

Analyzing the Impact on Talent Acquisition and Performance Management:

HR and Data Analysis

Li Wenting, Universiti Kebangsaan Malaysia, Malaysia

Wan Mohd Hirwani Wan Hussain, Universiti Kebangsaan Malaysia, Malaysia*

Jia Xinlin, Universiti Sains Malaysia, Malaysia

Meng Na, Universiti Kebangsaan Malaysia, Malaysia

https://orcid.org/0000-0003-2504-5371

Syed Shah Alam, Prince Sultan University, Saudi Arabia

ABSTRACT

The aim of this research is to explore the mediating and moderating effects of various HR functions and regulatory environments on the relationship between AI integration and data-driven decision making in HRM. The study was conducted in a corporate sector in Malaysia, focusing on businesses actively integrating AI into their HRM functions. A total of 376 individuals successfully submitted the questionnaire, representing an 83.5% response rate. The direct and indirect effects of Workforce Planning (WP), Learning and Development (LD), Employee Engagement and Retention (EER), Performance Management (PM), Talent Acquisition (TA), and Data-Driven Decision Making (DDM) were examined through the partial least squares structural equation modeling approach (PLS-SEM). The results demonstrate that AI-enriched HR functions, including workforce planning, learning and development, employee engagement & retention, performance management, and talent acquisition, play a critical role in driving DDM.

KEYWORDS

Data-Driven Decision Making, Performance Management, Talent Acquisition, Workforce Planning

INTRODUCTION

The rapid advancement of artificial-intelligence (AI) technology and its increasing prevalence in multiple sectors mark a significant milestone in the digital revolution (West & Allen, 2018; Wu et al., 2024). With its sophisticated capabilities in cognition, learning, and pattern recognition, AI has begun to instigate transformative shifts in traditional operational paradigms, thereby redefining the modus operandi of diverse sectors (Bozdag, 2023; Xu et al., 2024). The realm of human-resource management (HRM) has not remained unaffected by this technological disruption (Azizi et al., 2021).

DOI: 10.4018/JOEUC.342603

*Corresponding Author

In fact, the intersection of AI and HRM has emerged as a prominent area of interest in terms of both practical application and academic inquiry (Cayrat & Boxall, 2022). The unique attributes of AI, such as predictive analytics, machine learning, and natural language processing, offer unprecedented opportunities to enhance and optimize HRM practices. These AI-driven innovations hold the potential to revolutionize numerous facets of HRM such as workforce planning, learning and development, performance management, and talent acquisition, among others (Chowdhury et al., 2023; Liu et al., 2024). In the realm of workforce planning, for instance, AI can provide sophisticated predictive models to anticipate talent needs and aid in proactive planning. Similarly, within learning and development, AI-powered platforms can deliver personalized, adaptive learning experiences, thereby boosting the efficacy of training programs (Maghsudi et al., 2021). In performance management and talent acquisition, too, AI is poised to introduce improved accuracy and efficiency, thereby transforming conventional approaches (Johnson et al., 2021).

The existing literature, while rich in discussions on the technical dimensions and pragmatic applications of AI (Nurkin, 2023; Raska & Bitzinger, 2023; Yao et al., 2015), often overlooks the significant role of AI in data-driven decision-making, a recognized determinant of organizational success (Mikalef et al., 2019; Provost & Fawcett, 2013; Rialti et al., 2019). Current studies offer insight into AI's potential in refining decision-making processes (Akter et al., 2022; Babu et al., 2021; Cybulski & Scheepers, 2021) but primarily concentrate on its broad organizational impacts, bypassing a focused exploration of its effects within HRM practices. Consequently, the first objective of this study is to investigate the influence of AI integration into HRM on data-driven decision-making.

Moreover, while the existing body of work acknowledges the potential of AI to optimize HRM processes (Bozdag, 2023; Cayrat & Boxall, 2022; Chowdhury et al., 2023; Larson & DeChurch, 2020), it stops short of fully illuminating how AI catalyzes data-driven decision-making within HRM. Despite some recognition of the transformative potential in HRM (Chams & García-Blandón, 2019; Škudienė et al., 2020), the literature lacks empirical evidence that supports these claims. The complexities surrounding AI-driven HRM practices, such as fostering a data-driven decision-making culture and potential challenges therein, remain underexplored.

Further, there is a noticeable dearth of comprehensive discussions around the myriad forms of AI applications within HRM, including AI-based workforce planning and AI-powered learning and development, and their specific implications for data-driven decision-making (Jaiswal et al., 2022). The general implications of AI on strategic HR decision-making (Ghislieri et al., 2018), as well as the mediating and moderating effects of diverse AI-based HR functions and the role of regulatory environments in the AI-HR nexus, have not been adequately examined (Cascio & Montealegre, 2016; Kehoe et al., 2023). This forms the basis for the second objective of this study: exploring the mediating and moderating effects of various HR functions and regulatory environments on the relationship between AI integration and data-driven decision-making in HRM. Addressing the gaps identified, this research contributes new insights by presenting a comprehensive exploration of AI-based HR functions' role in data-driven decision-making.

In this research, we aim to provide a significant contribution to both theoretical understanding and practical application in the field of human-resource management through the lens of artificial intelligence. The study is designed to bridge the gap between advanced technology and strategic HR practices, offering a comprehensive analysis of how AI can revolutionize various aspects of HRM. From a theoretical perspective, our study is set to make substantial contributions by integrating multiple theoretical frameworks to understand AI's role in HRM. By employing strategic human-resource management (SHRM), we will provide insights into how AI can align HR strategies with broader organizational objectives, potentially reshaping the field of strategic HRM. Through the resource-based view (RBV), our study will conceptualize AI as a unique and valuable strategic asset, offering a new dimension to the theory by highlighting the role of technological resources in gaining competitive advantage. Information-processing theory (IPT) will be used to explore how AI facilitates the handling of complex and voluminous data, enhancing decision-making processes. Institutional theory will add another layer to our understanding by examining the influence of regulatory and legal frameworks on the integration of AI in HRM. This multidimensional approach will enrich the theoretical landscape by providing a holistic view of AI's integration in HRM.

On the practical front, our study stands to provide invaluable insights for organizations seeking to harness AI in their HR practices. By examining the relationship between AI-enhanced HR processes and data-driven decision-making, we will offer evidence-based recommendations for leveraging AI to optimize HR functions. By exploring AI applications in various HRM areas such as workforce planning, talent acquisition, and learning and development, our research will serve as a strategic guide for successful AI integration. This will empower organizations to make informed decisions, ultimately enhancing their HRM effectiveness through AI-driven insights. In essence, our study is positioned to make a meaningful contribution by providing a nuanced understanding of AI's role in HRM, both from a theoretical standpoint and in practical application. It aims to add to the discourse on AI's transformative potential in business, offering new perspectives and strategies for organizations to navigate the evolving landscape of HR technology.

ARTIFICIAL INTELLIGENCE IN HRM: AN OVERVIEW

Artificial intelligence has emerged as an influential catalyst in the digitization of human-resource management (Prentice et al., 2020). By integrating complex algorithms and predictive analytics into HR functions, AI offers unprecedented opportunities to transform traditional HRM (West & Allen, 2018). The breadth of AI's influence extends from streamlining recruitment processes to enhancing performance evaluations (Hunkenschroer & Luetge, 2022).

While Amoako et al. (2021) argue that AI's primary contribution to HRM lies in its ability to drive data-oriented decision-making, other studies (Johnson et al., 2021) emphasize its role in enhancing the efficiency of talent acquisition. This difference in perspective highlights the multifaceted impact of AI on HRM, forming a crucial context for our investigation. The capacity of AI technology to analyze extensive datasets and deduce actionable insights constitutes a significant shift toward evidence-based HR practices (Marler & Boudreau, 2017).

Opinions vary on the role of AI in workforce planning. Falletta and Combs (2021) emphasize how AI can use employee data to anticipate workforce trends and guide strategic decisions. Others suggest that, despite its potential, the role of AI in workforce planning remains largely unexplored and needs further examination. This study will delve into these differing viewpoints, offering a broader and more nuanced understanding of the topic.

Although some scholars assert that AI has substantially transformed performance management through unbiased assessments provided by automated HR systems (Chilunjika et al., 2022), others Euchner (2019) maintain that while AI's potential to refine performance management has been substantiated, the dynamics of its practical implementation remain somewhat murky and need further scholarly attention. This study will explore these differing perspectives to offer a more balanced understanding of AI's role in performance management.

The integration of AI in talent acquisition has garnered substantial interest. Gilliland et al. (2021) revealed how machine-learning algorithms can sift through large pools of applications, identify potential fits, and even predict job performance, thus enhancing the efficiency of talent acquisition. Yet the existing research has focused primarily on the advantages, leaving the challenges relatively unexplored.

Views vary when considering the role of the legal and regulatory environment in the adoption and use of artificial intelligence in HRM. While John-Mathews et al. (2022) and Martin (2019) argue that ethical and legal considerations could significantly influence AI adoption, others suggest that these concerns, though growing, have yet to be thoroughly researched in the context of their impact on AI's integration into HRM. This divergence of opinions underscores the need for more comprehensive research on the interplay between legal considerations and AI adoption, an issue this study aims to address.

In essence, although the literature acknowledges the transformative potential of AI in HRM and its propensity to enable data-driven decision-making, research has been fragmented and has revolved primarily around its merits. Thus, a comprehensive examination of AI's role in HRM, accounting for its impact on data-driven decision-making across various functions and considering the moderating role of legal and regulatory factors, is warranted. This research will attempt to bridge this gap in literature.

THEORETICAL FRAMEWORK

This study's theoretical scaffolding draws on the concepts of four primary theories: strategic human resource management (Stroh & Caligiuri, 1998), resource-based view (Wernerfelt, 1984), information-processing theory (Swanson, 1987), and institutional theory, all of which are situated within the overarching institutional environment.

SHRM, as proposed by Becker and Huselid (2006), posits a causal relationship between the alignment of organizational objectives and human-resource strategies, leading to a sustainable competitive advantage. This theory has received significant empirical support, demonstrating how strategic HRM initiatives positively impact organizational performance (Doz, 2020). In the era of rapid advancement in AI, the integration of this technology within HR functions becomes a strategic necessity (Rana & Sharma, 2019). Through the SHRM lens, this study scrutinizes how AI-enriched HR practices, including workforce planning, learning and development, and employee engagement, align with data-driven decision-making and performance management.

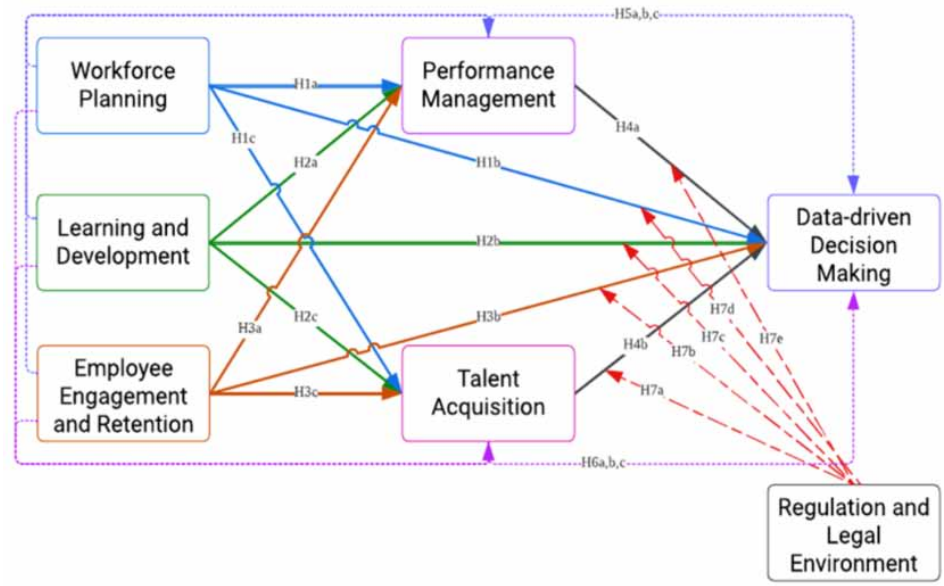
RBV, suggested by Barney (1991), emphasizes the strategic role of unique and nonreplicable resources in carving a competitive niche for organizations. Studies by Bhandari et al. (2022) and Donnellan and Rutledge (2019) validate the RBV framework by showing how IT resources can create sustained competitive advantages. Consequently, this study conceptualizes AI as a strategic asset that enhances the inherent value of HR practices for superior decision-making and performance outcomes.

IPT, as proposed by Swanson (1987), asserts that an organization's ability to process complex and voluminous data is central to its decision-making. O'Reilly (2017) further demonstrated the role of information processing in organizational adaptation and decision-making. Given AI's capacity to handle large datasets (Nurkin, 2023), this study employs IPT to elucidate the correlation between AI-infused HR practices and data-driven decision-making.

Finally, the influence of the institutional environment on HRM is acknowledged, particularly in terms of AI adoption. Institutional theory (DiMaggio & Powell, 1983) argues that organizational practices are often shaped by the regulatory, normative, and cognitive structures in their environment. Studies like that of Adebanjo et al. (2016) have confirmed this influence, demonstrating how external pressures shape organizational behavior and decisions. Therefore, the impact of regulatory and legal factors on AI adoption in HRM is examined through this theoretical lens.

Drawing on the advancements by Becker and Huselid (2006), our study reinterprets SHRM in the AI context, scrutinizing the causal relationship between AI-enriched HR strategies and organizational objectives. We explore how strategic alignment of AI in HRM can lead to sustainable competitive advantages, supported by empirical findings (Doz, 2020). Emphasizing the strategic necessity of AI integration in HR functions (Rana & Sharma, 2019), we examine its impact on workforce planning, learning and development, and employee engagement, aligned with data-driven decision-making and performance management. Expanding on Barney's (1991) RBV framework, we conceptualize AI as a unique and strategically valuable resource. Citing research by Bhandari et al. (2022) and Donnellan and Rutledge (2019), we argue that AI, as an IT resource, creates and sustains competitive advantages, recognizing AI as a strategic asset that enhances the efficacy of HR practices and drives superior decision-making and performance outcomes. In alignment with Swanson's (1987) IPT, and reinforced by insights from O'Reilly (2017), our study examines AI's role in processing large,

Figure 1. Theoretical Framework



complex datasets, a critical factor in organizational decision-making. We explore how AI's capacity for handling extensive data volumes (Nurkin, 2023) aligns with IPT principles and enhances data-driven decision-making within HR practices. Informed by DiMaggio and Powell (1983), we also examine how the institutional environment, encompassing regulatory, normative, and cognitive structures, influences AI adoption and implementation in HRM. Integrating findings from Adebanjo et al. (2016), we understand how external pressures and regulatory frameworks shape organizational behaviors and decisions regarding AI in HRM.

Our research methodically examines the intersections of these theories, elucidating their collective influence on AI integration in HRM. By merging SHRM and RBV, we gain insights into strategic alignment and competitive advantage through AI. IPT offers a perspective on AI's impact on data processing in decision-making, while institutional theory provides a macro view of the regulatory and legal influences on AI adoption. We argue that strategic alignment of AI-powered HRM practices can significantly improve decision-making processes through enhanced information processing and the strategic advantages AI brings. However, we also critically examine the complexities and regulatory pressures associated with AI adoption, potentially challenging organizations' capacity to leverage AI in HRM. This interplay of theories presents a comprehensive viewpoint for understanding the dynamics of AI integration into HRM for optimal, data-driven decision-making, ultimately highlighting the relevance and contribution of our study to both theoretical advancement and practical implications, as depicted in Fig. 1.

HYPOTHESIS DEVELOPMENT

AI-Based Workforce Planning

RBV suggests that companies can gain an edge over competitors by optimizing their internal resources (Barney, 1991). AI-based workforce planning, being one of such strategic resources, can significantly improve performance management within an organization. By analyzing patterns in performance data, AI can highlight areas that need improvement and even forecast future performance trends (Gabriel et al., 2022). Furthermore, AI aids in performance management by offering real-time feedback, along with personalized learning and development suggestions (Kaptein et al., 2015).

The relationship between AI-based workforce planning and data-driven decision-making aligns well with IPT. The theory posits that for an organization to make accurate and timely decisions, effective information processing is key (Galbraith, 1974). Through improved information-processing capability, AI-based workforce planning fosters data-driven decisions.

Using AI, HR professionals can use workforce data more proficiently in their decision-making processes. Predictive analytics and machine-learning algorithms enable HR managers to foresee future labor requirements, recognize trends and patterns, and make informed decisions about hiring, promotions, and retention (Alshehhi et al., 2021; Janiesch et al., 2021; Gilliland et al., 2021).

Human capital theory, which underlines the significance of skilled personnel for boosting organizational productivity and competitiveness (Marginson, 2019; Strober, 1990), supports the connection between AI-based workforce planning and talent acquisition. AI can refine talent-acquisition processes, predicting talent requirements, improving job-matching processes, and amplifying the candidate experience.

Empirical studies substantiate that artificial intelligence can greatly improve talent-acquisition processes. Through technologies such as machine learning, natural language processing, and predictive analytics, companies can make their hiring processes more efficient and increase the quality of candidates they recruit (Kersting, 2018). In addition, AI helps diminish bias in recruitment, contributing to more diverse and inclusive workplaces (Strods et al., 2021; Zhu et al., 2016). We hypothesize that:

H1a: There is a significant relationship between AI-based workforce planning and performance management.
H1b: There is a significant relationship between AI-based workforce planning and data-driven decision-making.
H1c: There is a significant relationship between AI-based workforce planning and talent acquisition.

Learning and Development

AI-enabled learning and development (LD) programs can significantly impact performance management by providing personalized training plans that accommodate pace and style. This not only enhances the learning experience, but also helps to improve overall performance (Anwar, 2018; Lee, 2019). Additionally, AI-facilitated real-time performance monitoring can help identify areas for improvement and guide the formulation of further training needs (Uddin et al., 2019). This aligns with RBV theory, emphasizing the potential of AI as a resource to augment internal capabilities, including performance management (Gerhart & Feng, 2021; Khanra et al., 2022).

By integrating AI into LD, organizations can harness the power of data to gain insight into employee skills, learning paths, and knowledge gaps. These data can then guide decisions related to training needs, fostering a culture of data-driven decision-making (Kumar et al., 2022; Provost & Fawcett, 2013). This idea directly aligns with IPT, which states that effective utilization of information can enhance the decision-making process within an organization (Reimsbach et al., 2018; Turkulainen, 2022).

AI can significantly improve the talent-acquisition process by identifying the skills gaps and learning potentials of candidates during LD programs (Kavitha et al., 2019). For example, AI-powered assessments during recruitment can help identify candidates who not only are fit for the current role, but also exhibit potential for future growth in the organization (O'Reilly, 2017). This observation resonates with the human-capital theory, which underscores the significance of acquiring talent that can bring value to an organization (Becker & Gerhart, 1996). Thus, we propose the following.

H2a: There is a significant relationship between AI-based HR learning and development and performance management.
H2b: There is a significant relationship between AI-based HR learning and development and data-driven decision-making.
H2c: There is a significant relationship between AI-based HR learning and development and talent acquisition.

Employee Engagement and Retention

AI's ability to analyze patterns in employee engagement and predict attrition risks has made it an important tool for performance management. Proactive engagement, based on AI insights, can lead to better performance and higher retention (Brettel et al., 2015; Maan et al., 2020). Furthermore, AI can generate personalized feedback for employees, enabling performance management to focus on individual areas of improvement (Chilunjika et al., 2022). This application of AI as a resource is consistent with RBV theory, which emphasizes the strategic use of firm resources to enhance internal capabilities and gain a competitive edge (Barney, 1991).

AI generates valuable data about employee engagement and reasons for attrition, providing insights that can enhance decision-making processes related to employee engagement and retention strategies (Gupta & Bhaskar, 2020). The effective use of such data aligns with IPT, which states that organizations can enhance their decision-making processes by effectively processing and utilizing information (Galbraith, 1974).

AI can aid talent acquisition by helping to identify factors related to employee engagement and retention in past hires, thereby informing recruitment strategies (Alam et al., 2021; Selwyn, 2016). Additionally, an organization with effective engagement and retention strategies can appeal more to potential hires. These observations resonate with human-capital theory, which highlights the importance of acquiring and retaining skilled and committed personnel for an organization's success (Becker & Chiswick, 1966). We hypothesize that:

H3a: There is a significant relationship between AI-based employee engagement and retention and performance management.
H3b: There is a significant relationship between AI-based employee engagement and retention and data-driven decision-making.
H3c: There is a significant relationship between AI-based employee engagement and retention talent acquisition.

Data-Driven Decision-Making

AI in performance management enables the collection and processing of large volumes of data related to employee performance. This data can be used to drive decision-making related to performance appraisals, identifying training needs, and succession planning, among other things (Anwar, 2018). Additionally, predictive analytics provided by AI can help managers anticipate future performance trends and take proactive steps to address them (Shah, 2023). This alignment of AI-enabled performance management with data-driven decision-making supports the tenets of information-processing theory, which highlights the importance of information-processing capabilities in organizational decision-making (Amoako et al., 2021).

AI in talent acquisition facilitates data-driven decision-making by providing insight into applicant tracking, candidate sourcing, and recruitment marketing. For instance, AI can analyze candidate data to identify patterns and trends that human recruiters might overlook, enabling more-informed hiring decisions (Jaiswal et al., 2022). AI can also predict hiring outcomes, thus reducing the uncertainty and risk associated with hiring decisions (Škudienė et al., 2020). The use of AI in talent acquisition aligns with human-capital theory and information-processing theory by demonstrating how effective information processing can enhance the acquisition of skilled personnel (Becker, 1966; Galbraith, 1973). Therefore, we posit:

H4a: There is a significant relationship between AI-based performance management and data-driven decision-making.
H4b: There is a significant relationship between AI-based talent acquisition and data-driven decision-making.

Mediation of Performance Management

Workforce planning involves anticipating future staffing needs and determining strategies to meet those needs. AI can improve this process by providing data-driven insights about workforce trends and patterns. Once implemented, these plans can be tracked and adjusted through AI-based performance-management tools that assess employee performance and productivity (Mira et al., 2019). The resulting data can then drive future workforce planning decisions, thus establishing AI-based performance management as a mediator between workforce planning and data-driven decision-making.

AI-driven LD programs can help identify areas of skills gaps and potential for growth, directly influencing the performance of employees. The data collected through AI-based performance-management tools post-training can provide valuable insights about the effectiveness of these programs, informing future LD decisions (Otoo, 2019; Uddin et al., 2019). This establishes AI-based performance management as a mediator between LD and data-driven decision-making, in line with the principles of information-processing theory (Galbraith, 1974).

AI-enhanced engagement and retention strategies contribute to the overall performance of an organization. AI-based performance-management tools can assess the impact of these strategies by tracking metrics like productivity, job satisfaction, and attrition rates (Cybulski & Scheepers, 2021). The insights gathered from these assessments can inform future engagement and retention strategies, creating a mediation effect between engagement and retention and data-driven decision-making through AI-based performance management. We hypothesize that:

H5a: AI-based performance management mediates the relationship between workforce planning and data-driven decision-making.
H5b: AI-based performance management mediates the relationship between learning and development and data-driven decision-making.
H5c: AI-based performance management mediates the relationship between engagement and retention and data-driven decision-making.

Mediators of Talent Acquisition

Workforce planning is based on a strategic understanding of current and future staffing needs. AI can enhance this by providing predictive analytics for future labor requirements (Ahmed et al., 2022; Shah, 2023). Once these plans are formulated, AI-based talent acquisition tools can be deployed to hire the required talent, generating data about the hiring process and its effectiveness. These data can then inform future workforce planning, establishing AI-based talent acquisition as a mediator between workforce planning and data-driven decision-making.

AI-based LD programs can reveal crucial information about the skills gaps and training needs of current and potential employees. AI-driven talent acquisition can leverage this information to identify and recruit individuals who fit the defined skills requirements or show the potential for growth (Jaiswal et al., 2022). The data obtained from these processes can further inform future LD planning, thus establishing AI-based talent acquisition as a mediator.

Effective engagement and retention strategies can make a company more appealing to prospective employees. AI-driven talent acquisition can take advantage of this appeal to attract and recruit suitable candidates, generating data about the effectiveness of these strategies (Alwabel & Zeng, 2021). These data can then be fed into future engagement and retention planning, thus creating a mediation effect between engagement and retention and data-driven decision-making through AI-based talent acquisition. This aligns with information-processing theory, which highlights the importance of using information effectively in the decision-making process (Galbraith, 1974). We hypothesize that:

H6a: AI-based talent acquisition mediates the relationship between workforce planning and data-driven decision-making.
H6b: AI-based talent acquisition mediates the relationship between learning and development and data-driven decision-making.
H6c: AI-based talent acquisition mediates the relationship between engagement and retention and data-driven decision-making.

Moderation of Regulation and Legal Environment

Regulatory environments such as those dictated by the General Data Protection Regulation (GDPR) in the EU or the California Consumer Privacy Act (CCPA) in the United States can indeed affect how AI is utilized in workforce planning (Gammage & Novitz, 2019). According to studies by Babu et al. (2024) and Nuccio and Guerzoni (2019), these regulations directly influence the extent to which companies can utilize data-driven decision-making, which can moderate the impact of AI-based workforce planning.

Studies such as Verma et al. (2020) echo the fact that legal and regulatory requirements regarding data privacy and AI ethics guide how AI can be used within the learning and development sector. They noted that these factors could influence the relationship between AI and decision-making processes within an organization.

Performance-management systems that use AI are subject to legal requirements relating to data privacy, fair treatment, and feedback mechanisms (Kumar et al., 2022). This sentiment is shared by Gabriel et al. (2022), who suggest that legal considerations moderate the use of AI in performance management and, consequently, its impact on data-driven decision-making.

According to Kaliannan et al. (2023), talent-acquisition processes, particularly those utilizing AI, need to be carefully managed to adhere to regulations around fair hiring, nondiscrimination, and data privacy. These regulations influence how AI can be used, which, in turn, affects organizational decision-making processes. This supports the assumption that regulation and legal environment play a moderating role in the relationship between AI-based talent acquisition and data-driven decision-making. We hypothesize that:

H7a: Regulation and legal environment moderate the relationship between AI-based workforce planning and data-driven decision-making.
H7b: Regulation and legal environment moderate the relationship between AI-based HR learning and development and data-driven decision-making.
H7c: Regulation and legal environment moderate the relationship between AI-based performance management and data-driven decision-making.
H7d: Regulation and legal environment moderate the relationship between AI-based talent acquisition and data-driven decision-making.

METHODOLOGY

Research Design and Sampling

Our study is concerned primarily with the relationships among AI-based HR functions, data-driven decision-making, and the moderating role of the regulatory and legal environment within organizations. The context of this research is the corporate sector in Malaysia, focusing on businesses actively integrating AI into their HR functions.

Malaysia offers a diverse and technologically advanced business landscape, making it a suitable setting for our study. The cities of Kuala Lumpur, Wilayah Persekutuan Putrajaya and Selangor states were particularly chosen due to the high prevalence of companies operating with AI-enhanced HR functions, providing a comprehensive representation of AI utilization in HR across varying business scales and industries.

To ensure a representative and accurate dataset, we meticulously built the survey instrument. The questionnaire was designed with careful consideration to the clarity and precision of language, thereby avoiding potential misunderstandings. Additionally, attention was paid to the aesthetic presentation and the logical sequence of questions, which can significantly influence a participant's willingness and motivation to complete the survey (Yang et al., 2021).

In addition to the standard questions probing the application and effects of AI-based HR functions, the survey included preliminary screening questions to ensure the respondents' suitability. These questions aimed to determine whether participants held HR roles, participated in the implementation or overseeing of AI-based HR functions, and actively participated in data-driven decision-making within their organizations.

The study used an online snowball sampling approach, beginning data collection by contacting a small, select group of HR professionals in Selangor known to the researchers and confirmed to be involved in AI-based HR functions. Once these initial participants completed the survey, they were asked to share the survey link with other professionals in their network who also work with AI in HR functions.

Data was collected via several digital platforms, including LinkedIn, professional networking sites, and email, to ensure the survey reached a wide audience. This also enabled us to adhere to privacy regulations and avoided direct contact with respondents. Filtering questions were also included to ascertain the qualifications of the respondents.

We collected additional data on company size, industry, and extent of AI implementation in HR functions. This served to control for potential confounding variables and ensured that our results were applicable to the target population.

We extended invitations to 450 HR professionals in the targeted cities, out of which 376 agreed to participate. This represents a satisfactory response rate of 83.5%. We also highlighted the anonymous nature of the survey and the voluntary nature of participation to allay potential privacy concerns.

Measurement Instrument

The measurement elements of the scales in this study were designed to reflect and were adapted from prior studies, with slight modifications for the specific context of this research. Upon the completion of the initial questionnaire design, we solicited the feedback of eight respondents, asking them to review the questions and provide comments on the wording and clarity. Their valuable insight guided minor modifications to the items.

A five-point Likert scale, ranging from "strongly disagree" to "strongly agree," was implemented to measure all constructs in this study. All constructs were operationalized as reflective constructs, and their items were adapted from previous studies (given in Table 1) to fit the current context.

Participant demographic information was also collected for potential control variable purposes and additional analyses. Descriptive statistics for these demographic variables were performed using frequency analysis in IBM SPSS Version 26. Additionally, the partial least squares structural equation

Table 1. Measurement Items

Construct	Code	Items	Source
AI-Based Workforce Planning	WP1	AI technology effectively assists in forecasting future staffing needs in our organization.	Gabriel et al. (2022) and Gilliland et al. (2021)
	WP2	AI-driven analytics are integral to our strategic workforce planning processes.	
	WP3	Our organization utilizes AI to optimize workforce allocation and distribution.	
AI-Based HR Learning and Development	LD1	AI tools are effectively used for personalizing employee learning and development programs.	Arora et al. (2024)
	LD2	Our organization employs AI to identify skills gaps and recommend appropriate training.	
	LD3	AI-driven platforms enhance the effectiveness of our training and development initiatives.	
AI-Based Employee Engagement and Retention	EER1	AI-enabled systems in our organization help in tracking and improving employee engagement.	Alshehhi et al. (2021)
	EER2	AI tools provide insights that aid in developing strategies to retain top talent.	
	EER3	Our use of AI positively impacts employee satisfaction and loyalty.	
AI-Based Performance Management	PM1	AI technologies are utilized to set accurate performance goals and track progress.	Marler & Boudreau (2017)
	PM2	Our performance-management system, enhanced by AI, provides real-time, actionable feedback.	
	PM3	AI tools in our organization help in making unbiased and data-driven performance evaluations.	
AI-Based Talent Acquisition	TQ1	AI is instrumental in improving the efficiency and effectiveness of our recruitment processes.	Bamberger & Meshoulam (2000) and Faqihi & Miah (2023)
	TQ2	We use AI-driven analytics to identify the best candidates for job positions.	
	TQ3	AI technologies assist in reducing biases in our talent acquisition process.	
Regulation and Legal Environment	LE1	Our organization is well-informed about legal and regulatory requirements relevant to AI in HR.	Mirowska (2020)
	LE2	We consider the regulatory and legal implications when implementing AI in HR practices.	
	LE3	Regulatory and legal considerations are integral to our decision-making process regarding AI in HR.	
AI-Based Data-Driven Decision-Making	DDM1	AI helps in aggregating and analyzing data for strategic HR decision-making.	Rasmussen & Ulrich (2015)
	DDM2	We rely on AI-based insights to make informed HR management decisions.	
	DDM3	Our organization’s strategic HR decisions are significantly influenced by insights derived from AI-powered data analysis.	
	DDM4	The use of AI significantly improves the accuracy of our HR-related decisions.	

modeling approach (PLS-SEM) was employed to assess the validity and reliability of the measurement model and to analyze the structural model of this research.

HYPOTHESIS FORMULATION AND STRUCTURAL EQUATION MODELING

In this study, we adopt a structural equation modeling (SEM) approach, utilizing SmartPLS, to quantitatively assess the hypothesized relationships within our theoretical framework. The SEM methodology allows for the estimation of multiple and interrelated dependence relationships and is particularly suited for our complex model that integrates various constructs related to AI in HRM.

Below we present the hypotheses in a structured equation format. In these equations, β represents the path coefficients, indicating the strength and direction of the relationships between variables. ε denotes the error term, accounting for the variance in the dependent variables not explained by the model. The acronyms are DDM, data-driven decision-making; EER, employee engagement and retention; LD, learning and development; PM, performance management; RLE, regulation and legal environment; TA, talent acquisition; and WP, workforce planning.

Direct Effects

These relationships indicate a direct influence of one variable on another. The equations for direct-effect hypotheses (H1a–H4b) are as follows.

H1a, H1b, H1c (workforce planning on PM, DDM, and TA):

- $PM = \beta 1 * WP + \varepsilon 1$
- $DDM = \beta 2 * WP + \varepsilon 2$
- $TA = \beta 3 * WP + \varepsilon 3$

H2a, H2b, H2c (learning and development on PM, DDM, and TA):

- $PM = \beta 4 * LD + \varepsilon 4$
- $DDM = \beta 5 * LD + \varepsilon 5$
- $TA = \beta 6 * LD + \varepsilon 6$

H3a, H3b, H3c (employee engagement and retention on PM, DDM, and TA):

- $PM = \beta 7 * EER + \varepsilon 7$
- $DDM = \beta 8 * EER + \varepsilon 8$
- $TA = \beta 9 * EER + \varepsilon 9$

H4a, H4b (performance management and talent acquisition on DDM):

- $DDM = \beta 10 * PM + \varepsilon 10$
- $DDM = \beta 11 * TA + \varepsilon 11$

Mediation Effects

These relationships indicate that one variable influences another through a mediator variable. The equations for mediation-effect hypotheses (H5a–H6c) are as follows.

H5a, H5b, H5c (WP, LD, and EER through PM on DDM):

- $DDM = \beta 12 * PM + \beta 13 * WP + \varepsilon 12$
- $DDM = \beta 14 * PM + \beta 15 * LD + \varepsilon 13$
- $DDM = \beta 16 * PM + \beta 17 * EER + \varepsilon 14$

H6a, H6b, H6c (WP, LD, and EER through TA on DDM):

- $DDM = \beta 18 * TA + \beta 19 * WP + \varepsilon 15$
- $DDM = \beta 20 * TA + \beta 21 * LD + \varepsilon 16$
- $DDM = \beta 22 * TA + \beta 23 * EER + \varepsilon 17$

Moderation Effects

These relationships suggest that the effect of one variable on another is influenced by a third variable. The equations for moderation-effect hypotheses (H7a–H7d) are as follows.

H7a, H7b, H7c, H7d (RLE moderates the relationship between WP, LD, PM, TA, and DDM):

- $DDM = \beta 24 * WP + \beta 25 * RLE + \beta 26 * (WP * RLE) + \varepsilon 18$
- $DDM = \beta 27 * LD + \beta 28 * RLE + \beta 29 * (LD * RLE) + \varepsilon 19$
- $DDM = \beta 30 * PM + \beta 31 * RLE + \beta 32 * (PM * RLE) + \varepsilon 20$
- $DDM = \beta 33 * TA + \beta 34 * RLE + \beta 35 * (TA * RLE) + \varepsilon 21$

This formulation provides a clear and systematic representation of the hypothesized relationships, facilitating a nuanced understanding of the interplay between AI integration in HRM practices and its organizational outcomes. The SEM approach, underpinned by these equations, allows for a comprehensive analysis of the direct, indirect, and moderating effects within our proposed model.

DATA ANALYSIS AND RESULTS

Of the targeted 450 respondents, a total of 376 individuals successfully submitted the questionnaire, representing an 83.5% response rate. The demographic breakdown of respondents in this study, presented in Table 1, shows a wide variety in age, education, professional experience, and positions within their respective organizations.

The majority of the respondents were in the age bracket of 26–35 years, accounting for 87.4% of the total sample. The next largest age group was those aged 36–45 years, contributing 9.7% to the overall sample. The least represented age group was those aged 16–25 years, with a minor 2.9% contribution to total responses.

Regarding the educational qualifications of the respondents, a majority (69.3%) held master's degrees. Those with a bachelor degree and diploma each constituted 30.2% of the total responses, while respondents with a doctorate were the least represented, at just 0.5%.

The respondents' experience within their firms was also diverse. The largest proportion of respondents (67.1%) had 3–5 years of experience, followed by those with 6–10 years of experience at 28.7%. Respondents with less than 3 years of experience and those with 11–20 years of experience in their firms contributed minor portions at 3.1% and 1.1%, respectively.

In terms of position, the majority of respondents (27.9%) held a managerial role, followed by deputy managers at 25% and senior managers at 21.3%. The remaining roles, including assistant managers, deputy heads of department, executives, executive assistants, and heads of departments, were relatively less represented, with frequencies ranging from 1.9% to 7.1%.

The demographic profile of our study in Malaysia, encompassing 376 respondents (refer to Table 2), reflects a diverse cross-section of the business landscape, crucial for analyzing AI's impact in HRM. Small organizations (1–50 employees) form the largest group, with 29.7% representation,

Table 2. Demographics of Respondents

	Frequency	Percent
Age		
16–25	11	2.9
26–35	328	87.4
36–45	37	9.8
Total	376	100
Education		
Bachelor’sDegree	12	27.1
Diploma degree	12	3.1
Doctorate	2	0.5
Master’s	260	69.3
Total	376	100
Experience in the Firm		
From 11 years to 20 years	4	1
From 3 years to 5 years	252	67.1
From 6 years to 10 years	108	28.6
Less than 3 years	12	3.3
Total	376	100
Position		
Assistant Manager	25	6.7
Deputy Head of Department	27	7.1
Deputy Manager	94	25
Executive	7	1.9
Executive Assistant	14	3.6
Head of Department	24	6.4
Manager	105	27.9
Senior Manager	80	21.4
Total	376	100
Organization Size		
Small (1–50 Employees)	112	29.7
Medium (51–200 Employees)	94	25
Large (201–500 Employees)	75	19.9
Very Large (501+ Employees)	95	25.4
Total	376	100

continued on following page

Table 2. Continued

	Frequency	Percent
Industry of Organization		
Technology/IT	75	19.9
Health Care	56	14.9
Education	37	9.8
Finance/Banking	56	14.9
Manufacturing	44	11.7
Retail	33	8.8
Government/Public Sector	50	13.4
Other	25	6.6
Total	376	100

indicating the prominence of startups and small businesses. Medium-size entities (51–200 employees) constitute 25%, and large organizations (201–500 employees) make up 19.9%, highlighting a significant middle-market presence. Very large organizations (501+ employees) account for 25.4%, showcasing input from major economic players.

In terms of industry distribution, technology/IT (19.9%), health care, and finance/banking (each 14.9%) are notably represented, underscoring their vital roles in Malaysia. The education and manufacturing sectors demonstrate moderate engagement, while the retail and government/public sectors contribute to the diversity of the sample. The “other” category (6.6%) encapsulates varied industries, adding to the study’s comprehensive scope. This demographic distribution ensures a holistic understanding of AI in HRM, providing insights into its role across different organizational contexts within Malaysia’s dynamic economy.

COMMON-METHOD BIAS

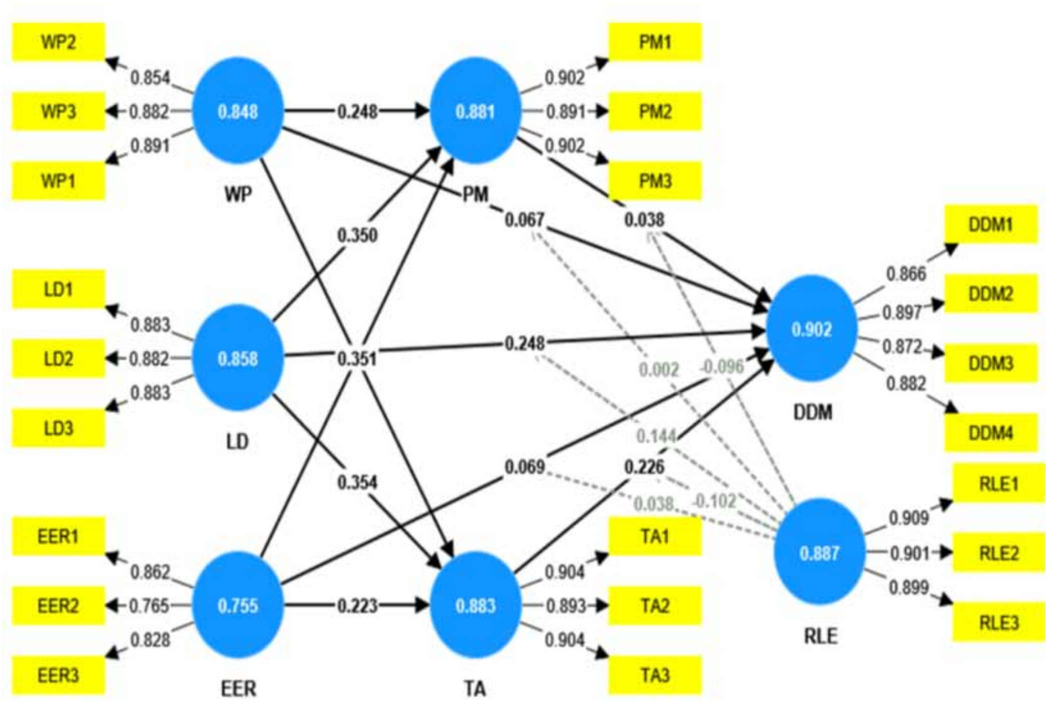
This study employed a combination of procedural and statistical strategies to detect and mitigate any potential common-method bias (MacKenzie & Podsakoff, 2012). To begin with, all measurement scales utilized in this study were adopted from previous studies, helping to reduce the likelihood of ambiguous terms or items in the questionnaire, minimizing the chance of misunderstanding on the part of the respondent.

Next, we implemented a clear initial criterion for the sample frame during the online survey data-collection phase to ensure that all participants met the criteria for the study. Our use of online snowball sampling has ensured the confidentiality of the responses, adding to the accuracy of the data provided.

For additional data validation, this study requested personal information, such as email addresses from participants. We also included filtering questions in the online survey to control the sample’s representativeness (Tehseen et al., 2017). These measures, combined, helped to minimize the potential for common-method bias during the survey-question design phase (MacKenzie and Podsakoff, 2012).

On the statistical front, we conducted a Harman’s single-factor test to check for common-method variance (CMV) in the data. The test revealed that a single factor accounted for less than 50% of the variance (Podsakoff et al., 2012), indicating that CMV was not a major concern in this dataset.

Figure 2. Measurement Model Evaluation



Additionally, we used the correlations matrix procedure to assess the impact of CMV on the correlations among the latent variables. The correlation coefficients among all the constructs were found to be less than 0.9. These results confirm that common-method bias is not a significant issue in this study.

MEASUREMENT MODEL EVALUATION

The evaluation of the measurement model was carried out by reviewing Cronbach's alpha (CA), factor loadings, composite reliability (CR), and average variance extracted (AVE) for all constructs. The outer load for the study indicators ranged from 0.568 to 0.956. Although Hair & Sarstedt (2019) advocate for an outer loading of at least 0.708 for measurement scales, it was decided to retain indicators with a value of more than 0.50 due to the importance of content validity. Internal consistency was determined by assessing Cronbach's alpha and composite reliability values for all variables (Table 3 and Fig. 2). The results demonstrated that all variables had Cronbach's alpha and composite reliability values exceeding 0.765 and 0.909, respectively, well above the recommended threshold of 0.7 as stated by Hair et al. (2019). Furthermore, an examination of the AVE values of all constructs showed that they ranged from 0.553 to 0.873, exceeding the acceptable cutoff value of 0.5. These findings affirm the consistency, reliability, and convergent validity of the constructs.

Additionally, the latent variable covariance for the constructs in this study was assessed. Table 4 demonstrates robust covariance between the latent exogenous and endogenous constructs. The covariance values also depict the degree of relationship between exogenous latent variables, providing valuable insight for further analysis.

As displayed in Table 4, all heterotrait–monotrait (HTMT) ratios are below the 0.85 threshold, signifying sufficient discriminant validity among the constructs. For instance, the HTMT ratio between

Table 3. Result of Measurement Model

Variables	IEMS	OL	VIF	CA	CR	AVE
DDM	DDM1	0.866	2.520	0.902	0.902	0.773
	DDM2	0.897	2.989			
	DDM3	0.872	2.490			
	DDM4	0.882	2.689			
EER	EER1	0.862	1.685	0.755	0.766	0.672
	EER2	0.765	1.414			
	EER3	0.828	1.556			
LD	LD1	0.883	2.238	0.858	0.859	0.779
	LD2	0.882	2.082			
	LD3	0.883	2.162			
PM	PM1	0.902	2.561	0.881	0.881	0.807
	PM2	0.891	2.274			
	PM3	0.902	2.557			
RLE	RLE1	0.909	2.660	0.887	0.887	0.816
	RLE2	0.901	2.558			
	RLE3	0.899	2.447			
TA	TA1	0.904	2.535	0.883	0.884	0.811
	TA2	0.893	2.353			
	TA3	0.904	2.605			
WP	WP2	0.854	1.937	0.848	0.853	0.767
	WP3	0.882	2.100			
	WP1	0.891	2.168			

Note. VIF, variance inflation factor.

data-driven decision-making and employee engagement and retention is 0.712. Similarly, the ratios for DDM with other constructs such as learning and development, performance management, regulation and legal environment, talent acquisition, and workforce planning are below the 0.85 threshold, implying distinct constructs. This pattern holds across all variables, suggesting that each construct measures a distinct concept, thereby affirming discriminant validity. Therefore, the results confirm that the measurement model is robust and suitable for testing the structural model in this research.

HYPOTHESIS TESTING RESULTS AND DISCUSSION

Table 5 presents the R2, Q2, and root mean square error (RMSE) values for the DDM, PM, and TA constructs. The R2 values or the coefficient of determination measures the goodness-of-fit of our model. It explains the proportion of the variance in the dependent variable that is predictable from the independent variables. The R2 values for DDM, PM, and TA are 0.912, 0.790, and 0.798, respectively, indicating that the model explains a substantial amount of the variance in these constructs. The adjusted R2 values take into account the number of predictors in the model and provide a more accurate measure of the goodness-of-fit. For DDM, PM, and TA, the adjusted R2 values are 0.909,

Table 4. Heterotrait–Monotrait Ratio Matrix

	DDM	EER	LD	PM	RLE	TA	WP	RLE x EER	RLE x TA	RLE x WP	RLE x LD
EER	0.712										
LD	0.455	0.703									
PM	0.791	0.795	0.691								
RLE	0.798	0.830	0.711	0.792							
TA	0.789	0.825	0.745	0.677	0.892						
WP	0.665	0.696	0.821	0.526	0.703	0.674					
RLE x EER	0.664	0.684	0.606	0.650	0.734	0.596	0.634				
RLE x TA	0.731	0.694	0.678	0.721	0.761	0.658	0.662	0.892			
RLE x WP	0.695	0.696	0.651	0.689	0.735	0.623	0.683	0.896	0.725		
RLE x LD	0.700	0.676	0.684	0.714	0.756	0.647	0.663	0.892	0.736	0.712	
RLE x PM	0.736	0.697	0.688	0.717	0.769	0.663	0.674	0.669	0.507	0.712	0.843

0.788, and 0.796, which are quite close to their respective R2 values, indicating a good fit with a minimal overfitting problem (Fig. 3).

The Q2 or predictive relevance value is obtained through the blindfolding procedure and should be greater than zero for the model to have predictive relevance. The Q2 values for DDM, PM, and

Figure 3. Hypothesis Testing Results

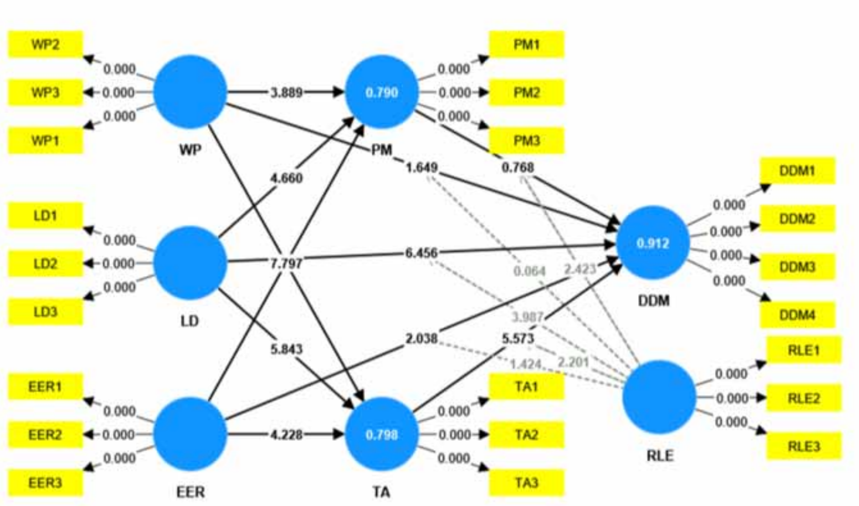


Table 5. R2, Q2, and RMSE

	R2	R2 Adjusted	Q2 Predicted	RMSE	MAE
DDM	0.912	0.909	0.883	0.345	0.258
PM	0.790	0.788	0.782	0.470	0.351
TA	0.798	0.796	0.793	0.458	0.356

TA are all well above 0 (0.883, 0.782, 0.793, respectively), indicating that our model has significant predictive power. Finally, the RMSE and mean absolute error (MAE) are metrics that measure the average magnitude of the errors in a set of predictions. The lower these values, the better the model's predictions. For DDM, PM, and TA, the RMSE values are 0.345, 0.470, and 0.458, while the MAE values are 0.258, 0.351, and 0.356. The relatively low values indicate good predictive accuracy of our model.

In the present investigation, we examined the direct and indirect relationships between several variables in the context of human-resources management: workforce planning, learning and development, employee engagement and retention, regulation and legal environment, performance management, talent acquisition, and data-driven decision-making. The hypothesis testing and model assessment were conducted using the path coefficient's significance, and the effect size (f2) of the variables, as reported in Table 6. The variance inflation factor for all variables ranged between 1.168 and 4.923, remaining below the suggested threshold of 5 (Sarstedt et al., 2014). Therefore, the issue of multicollinearity does not seem to be problematic in our model. Moreover, we applied a bootstrapping procedure to measure the path coefficient, standard error, and t-statistics. The critical value for the one-tail test was set at 1.645 at a 5% significance level.

The supported hypothesis H1a, with a beta of 0.248, a t-statistic of 3.889, and a p-value of 0.000, indicates a significant and positive relationship between AI-based workforce planning and performance management. This aligns with the resource-based view, as discussed by Barney (1991), emphasizing the strategic benefits derived from optimizing internal resources. The role of AI in enhancing performance management is further corroborated by literature, with Gabriel et al. (2022) and Kaptein et al. (2015) highlighting AI's capabilities in analyzing performance data and providing real-time feedback. Hypothesis H1b does not find empirical support, as indicated by a beta of 0.067, a t-statistic of 1.649, and a p-value of 0.099, suggesting a weak or nonsignificant relationship between AI-based workforce planning and data-driven decision-making. Despite the theoretical support from information-processing theory (Galbraith, 1974), which underscores the importance of efficient information processing in decision-making, our findings suggest a more complex scenario. Our study finds robust support for hypothesis H1c, with a beta of 0.375, a t-statistic of 7.797, and a p-value of 0.000, demonstrating a strong positive relationship between AI-based workforce planning and talent acquisition. This is consistent with human-capital theory, which highlights the significance of skilled personnel in enhancing organizational productivity and competitiveness (Marginson, 2019; Strober, 1990). The literature supports this connection, with studies by Kersting (2018), Alshehhi et al. (2021), and Gilliland et al. (2021) emphasizing AI's transformative role in talent-acquisition processes. This is further reinforced by research indicating AI's contribution to reducing biases in recruitment (Strods et al., 2021; Zhu et al., 2016), thereby promoting more diverse and inclusive workplaces.

The strong support for Hypothesis H2a, indicated by a beta coefficient of 0.350, a t-statistic of 4.660, and a p-value of 0.000, reflects a significant positive relationship between AI-enabled LD and performance management. This aligns with the findings of Anwar (2018) and Lee (2019), who emphasized that AI-facilitated personalized training plans enhance the learning experience and contribute to overall performance enhancement. Furthermore, the integration of AI in LD aligns with RBV, as AI is seen as a strategic resource augmenting internal capabilities, including performance management (Gerhart & Feng, 2021; Khanra et al., 2022). Additionally, Hypothesis H2b is strongly supported ($\beta = 0.248$, $t = 6.456$, $p = 0.000$), suggesting that AI-integrated LD positively impacts data-driven decision-making. This finding corroborates with Kumar et al. (2022) and Provost & Fawcett (2013), who highlighted AI's capability to harness employee skills data for insightful decision-making, fostering a culture where decisions are based on data insights. This is in line with IPT, emphasizing the effectiveness of information utilization in enhancing organizational decision-making processes (Reimsbach et al., 2018; Turkulainen, 2022).

The strong support for Hypothesis H3a, with a beta coefficient of 0.351, a t-statistic of 4.554, and a p-value of 0.000, indicates a substantial positive relationship between EER and PM. This aligns with

Table 6. Results of the Structural Model Analysis

Hypothesis	Path	Original Sample	Sample Mean	Standard Deviation	t-Statistics (|O/STDEV|)	p-values	f2	Support
H1a	WP -> PM	0.248	0.245	0.064	3.889	0.000	0.078	Supported
H1b	WP -> DDM	0.067	0.066	0.041	1.649	0.099	0.010	Not Supported
H1c	WP -> TA	0.375	0.374	0.048	7.797	0.000	0.184	Supported
H2a	LD -> PM	0.350	0.347	0.075	4.660	0.000	0.136	Supported
H2b	LD -> DDM	0.248	0.249	0.038	6.456	0.000	0.127	Supported
H2c	LD -> TA	0.354	0.351	0.061	5.843	0.000	0.144	Supported
H3a	EER -> PM	0.351	0.357	0.077	4.554	0.000	0.180	Supported
H3b	EER -> DDM	0.069	0.070	0.034	2.038	0.042	0.012	Supported
H3c	EER -> TA	0.223	0.227	0.053	4.228	0.000	0.076	Supported
H4a	PM -> DDM	0.038	0.033	0.050	0.768	0.442	0.002	Not Supported
H4b	TA -> DDM	0.226	0.229	0.041	5.573	0.000	0.103	Supported
	Mediation Effect							
H5a	WP -> PM -> DDM	0.009	0.008	0.013	0.732	0.464		Not Supported
H5b	LD -> PM -> DDM	0.013	0.011	0.018	0.752	0.452		Not Supported
H5c	EER -> PM -> DDM	0.013	0.012	0.018	0.736	0.462		Not Supported
H6a	WP -> TA -> DDM	0.085	0.086	0.019	4.527	0.000		Supported
H6b	LD -> TA -> DDM	0.080	0.080	0.020	4.028	0.000		Supported
H6c	EER -> TA -> DDM	0.050	0.052	0.016	3.233	0.001		Supported
	Moderation Effect							
H7a	RLE x WP -> DDM	0.002	-0.002	0.037	0.064	0.949	0.006	Not Supported
H7b	RLE x LD -> DDM	0.144	0.143	0.036	3.987	0.000	0.000	Supported
H7c	RLE x PM -> DDM	-0.096	-0.087	0.040	2.423	0.015	0.019	Supported
H7d	RLE x TA -> DDM	-0.102	-0.110	0.047	2.201	0.028	0.049	Supported

studies by Brettel et al. (2015) and Maan et al. (2020), which emphasize AI's potential in analyzing employee-engagement patterns and predicting attrition risks, thereby enhancing performance-management strategies. This observation resonates with RBV theory, highlighting the strategic use of AI as a resource to augment internal capabilities (Barney, 1991).

Moreover, Hypothesis H3b is supported, albeit weakly, suggesting that EER influences data-driven decision-making. With a beta of 0.069 and a p-value of 0.042, the findings imply that AI-generated data about employee engagement can provide critical insights to enhance decision-making processes related to engagement and retention strategies. This effective use of data aligns with IPT, which advocates for the utilization of information to improve decision-making within organizations (Galbraith, 1974). The support for Hypothesis H3c ($\beta = 0.223$, $p = 0.000$) indicates that EER strategies, informed by AI, positively impact talent acquisition. This is consistent with human-capital theory (Becker, 1966), emphasizing the significance of acquiring and retaining skilled personnel for organizational success. AI aids in identifying factors related to employee engagement and retention, thereby informing effective recruitment strategies (Alam et al., 2021; Selwyn, 2016).

Contrastingly, Hypothesis H4a, which explores the impact of PM on data-driven decision-making, is not supported ($\beta = 0.038$, $p = 0.442$). Despite AI's capacity for processing large volumes of performance data, the findings suggest a nonsignificant direct impact of PM on decision-making processes, indicating potential complexities in data utilization for decision-making. Hypothesis H4b is strongly supported ($\beta = 0.226$, $p = 0.000$), demonstrating that AI in talent acquisition significantly influences data-driven decision-making. This aligns with the role of AI in analyzing candidate data and predicting hiring outcomes, enhancing the effectiveness and efficiency of hiring decisions (Jaiswal et al., 2022; Škudienė et al., 2020).

Hypotheses H5a, H5b, and H5c, assessing the mediation effect of AI-based performance management between WP, LD, EER, and DDM, were not supported (p-values > 0.05). These findings suggest that while AI enhances various aspects of HRM, its role as a mediator in these specific pathways might be less direct or influenced by other factors not captured in this study. This contradicts the expectations based on literature, where AI-based performance-management tools were theorized to act as effective mediators. For instance, Mira et al. (2019) and Otoo (2019) suggested that AI-driven insights from performance management can inform and refine workforce planning and LD strategies, and Cybulski & Scheepers (2021) pointed toward AI's role in enhancing engagement and retention strategies.

Conversely, Hypotheses H6a, H6b, and H6c, which evaluated the mediation effect of AI-based talent acquisition between WP, LD, EER, and DDM, were supported, indicating that AI in talent acquisition plays a significant role in translating workforce planning, learning and development, and engagement and retention strategies into data-driven decisions. This is in line with the literature, where AI's predictive analytics in workforce planning (Ahmed et al., 2022; Shah, 2023), its role in identifying skills gaps and training needs in LD (Jaiswal et al., 2022), and its effectiveness in enhancing engagement and retention strategies (Alwabel & Zeng, 2021) were noted. These findings align with information-processing theory (Galbraith, 1974), emphasizing the effectiveness of using information in decision-making processes.

For Hypothesis H7a, examining the moderation effect of RLE on the relationship between WP and DDM, the findings indicate a nonsignificant moderation effect. With a beta coefficient of 0.002, a t-statistic of 0.064, and a p-value of 0.949, the results suggest that RLE does not significantly impact the use of AI in workforce planning for enhancing DDM. This outcome, though contrary to literature suggesting significant impacts of regulations like GDPR and CCPA on data-driven decision-making in workforce planning (Gammage & Novitz, 2019; Babu et al., 2024), may imply the presence of other mediating factors or a varied impact of RLE across different contexts. Conversely, H7b, assessing RLE's moderation effect between LD and DDM, shows a significant influence, as evidenced by a beta of 0.144, a t-statistic of 3.987, and a p-value of 0.000. This finding aligns with the literature, which notes that legal and regulatory requirements significantly guide AI usage in LD, thereby affecting decision-making processes within organizations (Verma et al., 2020). Similarly, Hypothesis H7c indicates a significant moderation effect of RLE on the relationship between PM and DDM. With a beta of -0.096, a t-statistic of 2.423, and a p-value of 0.015, it suggests that legal considerations around data privacy and fairness significantly moderate the use of AI in performance management (Kumar et al., 2022; Gabriel et al., 2022). Hypothesis H7d also reveals a notable moderation effect of RLE in the relationship between TA and DDM. The beta of -0.102, t-statistic of 2.201, and p-value of 0.028 support the notion that regulatory frameworks significantly influence the application of AI in talent acquisition, which in turn affects decision-making processes (Kaliannan et al., 2023).

Our comprehensive analysis of the hypotheses reveals the multifaceted impact of AI on various HRM practices, offering nuanced insights into the strategic integration of technology in the field. The significant findings across most hypotheses underscore the pivotal role of AI in enhancing performance management, talent acquisition, and data-driven decision-making processes. While AI's influence in linking workforce planning to data-driven decision-making was less pronounced, its substantial role as a mediator in other HRM domains highlights its transformative potential. Furthermore, the study elucidates the criticality of the regulation and legal environment in moderating the efficacy of AI applications in HRM. These results not only affirm the theoretical propositions underpinning our research but also provide empirical evidence of the dynamic interplay between AI, HRM practices, and the regulatory landscape. The insights garnered from this study contribute significantly to the understanding of AI's role in HRM, offering valuable implications for practitioners and policymakers in the ever-evolving landscape of HR technology.

IMPLICATIONS

Theoretical Implications

Our study on the integration of AI in HRM practices not only delves into the intricate dynamics of workforce planning, learning and development, employee engagement and retention, performance management, talent acquisition, the regulatory and legal environment, and data-driven decision-making, but also intricately explores the application of four primary theoretical frameworks—strategic human resource management, resource-based view, information-processing theory, and institutional theory. The empirical findings from this study yield significant theoretical implications, enriching and expanding the conventional understanding of these established theories within the context of contemporary HR technologies.

Drawing upon SHRM, our research empirically underscores the strategic importance of aligning AI-enhanced HR practices with organizational objectives, as proposed by Becker & Huselid (2006) and Stroh & Caligiuri (1998). The study demonstrates that the integration of AI in workforce planning, learning and development, and employee engagement transcends a mere technological upgrade, representing a strategic imperative that contributes to sustainable competitive advantages. This revelation extends the applicability of SHRM into the technological advancement era, highlighting a paradigm shift in strategic HR management.

Aligned with RBV, as suggested by Barney (1991), our study positions AI as a unique and strategic asset within organizations. The profound impact of AI across various HR functions supports the RBV framework, affirming the role of distinctive IT resources in fostering competitive advantages. This insight broadens the RBV scope, emphasizing the criticality of advanced technological resources, such as AI, in augmenting HR practices and decision-making processes.

From the IPT perspective (Swanson, 1987), our findings emphasize AI's capability in efficient data processing, aligning with the theory's focus on enhancing decision-making through effective information management. The study illustrates that AI-infused HR practices significantly contribute to data-driven decision-making, thereby applying IPT in the context of modern HR technology and expanding its theoretical realm.

Furthermore, the study reinforces institutional theory (DiMaggio & Powell, 1983) by showcasing how regulatory and legal environments shape the adoption and application of AI in HRM practices. The discernible influence of external pressures on organizational decisions regarding AI implementation provides empirical backing to the theory, underlining the pivotal role of institutional factors in sculpting organizational practices within the AI and HRM domain.

Our study also contributes to the literature by challenging the direct relationship between workforce planning and DDM, as previously suggested. These challenges established norms, prompting a reevaluation of the relationship between these HRM elements. Additionally, our findings on the mediating role of TA in HR practices and the significant impact on HR decision-making processes offer new insights into the behavioral aspects of HRM.

In conclusion, our study validates and extends these theoretical frameworks within the AI in HRM context. By unraveling the intricate interplay between AI technology and strategic HR management, this research makes a substantial contribution to the academic literature, deepening the understanding of AI's role in HRM and paving the way for future scholarly investigations in this dynamic field.

Practical Implications

The practical implications of our study extend to both human-resource professionals and organizational leaders in various industries. Drawing on the findings of our research, we highlight the following implications. First, the findings emphasize the critical role of strategic human resource management elements such as workforce planning, learning and development, employee engagement and retention, performance management, and talent acquisition in driving data-driven decision-making. Our study shows that a harmonious alignment of these variables can effectively foster DDM, which is increasingly seen as an imperative for organizational success. This suggests that HR leaders and executives can significantly improve their decision-making processes by strategically managing and aligning these HR factors.

Second, our research reveals that the direct relationship between the mentioned HR factors and DDM is not as pronounced as previously thought. Rather, the connection is significantly mediated by TA. This implies that, to fully harness the potential of HR practices in making data-driven decisions, organizations should focus not only on individual HR elements but also on how these elements are effectively acquired and managed.

Third, our findings shed light on the paramount importance of minimizing uncertainty in WP, LD, EER, and PM practices. Uncertainty in these areas can lead to difficulty in TA, hence affecting the DDM process. Therefore, it is imperative for HR professionals and managers to proactively address uncertainties, not only for effective TA but also for seamless DDM.

Additionally, our study underscores the significance of ensuring that information within an organization is effectively processed, as suggested by IPT. Effective information processing can be achieved by reducing uncertainties and maximizing the utility of TA in enhancing the quality of DDM.

Last, the findings suggest that perceived scarcity, especially in TA, can amplify anxiety levels within an organization, which may then hamper effective DDM. Hence, ensuring the availability of adequate resources, in terms of both quantity and quality, is critical for fostering data-driven culture within organizations. By implementing these strategies, organizations can not only enhance their decision-making processes but also build a more resilient and agile organization that can navigate through the uncertain and dynamic business environment.

CONCLUSION AND FUTURE RESEARCH

Our research offers a crucial supplement to the existing scholarship by presenting and scrutinizing a model that delineates the direct and indirect effects of workforce planning, learning and development, employee engagement and retention, and performance management on talent acquisition and data-driven decision-making. Results validate a robust correlation between the HR elements outlined above and TA and further reveal the integral mediating role TA plays in these relationships. This study of TA's mediating role illuminates the mechanisms by which HR elements can indirectly shape DDM. Furthermore, this research expands our comprehension of these HR dynamics in the context of organizational decision-making, particularly in data-intensive environments, underscoring the importance of strategic deployment of HR processes to boost TA efficiency and, subsequently, DDM.

Despite the significant theoretical and practical contributions, our study does harbor certain limitations. First, the study's data were sourced from organizations at a specific point in time utilizing a cross-sectional approach. Although such a design offers insightful perspectives into the dynamics among HR practices, a longitudinal or time-lagged design could uncover more nuanced developments and patterns over time in these relationships, thereby offering a more comprehensive understanding. Future researchers are, therefore, urged to consider adopting such designs to augment the richness and applicability of their findings.

Second, the heavy reliance on self-reported data in our study may introduce response bias, which could compromise the precision of our findings. To counter this limitation, we encourage future research to employ more-objective data-collection methodologies or incorporate third-party evaluations to mitigate potential biases.

Third, our study probes only a select few strategic HR practices as precursors to effective TA and DDM. There may be other organizational elements such as leadership style, organizational culture, and technology infrastructure that can significantly shape TA and DDM. Thus, future research endeavors should incorporate these elements for a more holistic understanding.

Last, our findings' generalizability may be circumscribed to specific organizations or industries, as certain contextual factors might moderate the relationships we explored. Consequently, we advocate for future research to reproduce our study across varied contexts—different industries, organizational sizes, and geographical locations. A mixed-method approach, combining both quantitative and qualitative data, could further deepen the richness of insights gathered. In summation, our research serves as a catalyst for deeper exploration into the relationships between strategic HR practices, TA, and DDM, emphasizing the necessity for future scholarly endeavors to broaden and deepen our understanding in this pivotal field.

AUTHOR NOTE

The authors thank Universiti Kebangsaan Malaysia and Prince Sultan University for their support. This study adhered to the principles of the declaration of Helsinki and followed strict ethical standards. Participation was anonymous and confidential. There was no funding for this research. Informed consent was obtained by phone from all authors. All authors have read and agreed to the published version of the manuscript. The authors declare no competing interest. The data presented in this study are available on request from the corresponding author.

FUNDING

This work was supported by a research grant LRGS/2020/UKM-UKM/01/5/1 & GSB-2024-009 Research under the Ministry of Higher Education, Malaysia and UKM-GSB.

REFERENCES

Adebanjo, D., Teh, P. L., & Ahmed, P. K. (2016). The impact of external pressure and sustainable management practices on manufacturing performance and environmental outcomes. *International Journal of Operations & Production Management*, *36*(9), 995–1013. doi:10.1108/IJOPM-11-2014-0543

Ahmed, S., Chowdhury, B., Khalil, I., Haque, R., & Bin Senathirajah, A. R. (2022). Analyzing key factors affecting sales performance amongst Malaysian SMEs: A structural path modeling approach. International Journal of eBusiness and eGovernment Studies, 14(3), 560–577. https://doi.org/10.34109/ijebeg

Akter, S., Michael, K., Uddin, M. R., McCarthy, G., & Rahman, M. (2022). Transforming business using digital innovations: The application of AI, blockchain, cloud and data analytics. *Annals of Operations Research*, *308*(1-2), 7–39. doi:10.1007/s10479-020-03620-w

Alam, I., Kartar Singh, J. S., & Islam, M. U. (2021). Does supportive supervisor complements the effect of ethical leadership on employee engagement? *Cogent Business & Management*, *8*(1), 1978371. Advance online publication. doi:10.1080/23311975.2021.1978371

Alshehhi, K., Bin Zawbaa, S., Abonamah, A. A., & Usman Tariq, M. (2021). Employee retention prediction in corporate organizations using machine learning methods. *Academy of Entrepreneurship Journal*, *27*(2).

Alwabel, A. S. A., & Zeng, X. J. (2021). Data-driven modeling of technology acceptance: A machine learning perspective. *Expert Systems with Applications*, *185*, 115584. doi:10.1016/j.eswa.2021.115584

Amoako, G., Omari, P., Kumi, D. K., Agbemabiase, G. C., & Asamoah, G. (2021). Conceptual framework—Artificial intelligence and better entrepreneurial decision-making: The influence of customer preference, industry benchmark, and employee involvement in an emerging market. *Journal of Risk and Financial Management*, *14*(12), 604. doi:10.3390/jrfm14120604

Anwar, M. (2018). Business model innovation and SMEs performance—Does competitive advantage mediate? *International Journal of Innovation Management*, *22*(7), 1850057. doi:10.1142/S1363919618500573

Arora, M., Prakash, A., Mittal, A., & Singh, S. (2024). HR analytics: What's holding users back? Global Knowledge. *Memory and Communication*, *73*(3), 432–452. doi:10.1108/GKMC-03-2022-0067

Azizi, M. R., Atlasi, R., Ziapour, A., Abbas, J., & Naemi, R. (2021). Innovative human resource management strategies during the COVID-19 pandemic: A systematic narrative review approach. *Heliyon*, *7*(6), e07233. doi:10.1016/j.heliyon.2021.e07233 PMID:34124399

Babu, M. M., Rahman, M., Alam, A., & Dey, B. L. (2024). Exploring big data-driven innovation in the manufacturing sector: Evidence from UK firms. *Annals of Operations Research*, *333*(2-3), 689–716. doi:10.1007/s10479-021-04077-1 PMID:33897083

Bamberger, P., & Meshoulam, H. (2000). Human Resource Strategy: Formulation, Implementation and Impact. Sage publication.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. doi:10.1177/014920639101700108

Becker, B., & Gerhart, B. (1996). The impact of human resource management on organizational performance: Progress and prospects. *Academy of Management Journal*, *39*(4), 779–801. doi:10.2307/256712

Becker, B. E., & Huselid, M. A. (2006). Strategic human resources management: Where do we go from here? *Journal of Management*, *32*(6), 898–925. doi:10.1177/0149206306293668

Becker, G. S., & Chiswick, B. R. (1966). Education and the distribution of earnings. *The American Economic Review*, *56*, 358–369.

Bhandari, K. R., Ranta, M., & Salo, J. (2022). The resource-based view, stakeholder capitalism, ESG, and sustainable competitive advantage: The firm's embeddedness into ecology, society, and governance. *Business Strategy and the Environment*, *31*(4), 1525–1537. doi:10.1002/bse.2967

Bozdag, A. A. (2023). AIsmosis and the pas de deux of human–AI interaction: Exploring the communicative dance between society and artificial intelligence. *Online Journal of Communication and Media Technologies*, *13*(4), e202340. doi:10.30935/ojcmt/13414

Brettel, M., Chomik, C., & Flatten, T. C. (2015). How organizational culture influences innovativeness, proactiveness, and risk-taking: Fostering entrepreneurial orientation in SMEs. *Journal of Small Business Management*, *53*(4), 868–885. doi:10.1111/jsbm.12108

Cascio, W. F., & Montealegre, R. (2016). How technology is changing work and organizations. *Annual Review of Organizational Psychology and Organizational Behavior*, *3*(1), 349–375. doi:10.1146/annurev-orgpsych-041015-062352

Cayrat, C., & Boxall, P. (2022). Exploring the phenomenon of HR analytics: A study of challenges, risks and impacts in 40 large companies. *Journal of Organizational Effectiveness: People and Performance*, *9*(4), 572–590. doi:10.1108/JOEPP-08-2021-0238

Chams, N., & García-Blandón, J. (2019). On the importance of sustainable human resource management for the adoption of sustainable development goals. *Resources, Conservation and Recycling*, *141*, 109–122. doi:10.1016/j.resconrec.2018.10.006

Chilunjika, A., Intauno, K., & Chilunjika, S. R. (2022). Artificial intelligence and public sector human resource management in South Africa: Opportunities, challenges and prospects. *SA Journal of Human Resource Management*, *20*, 12. doi:10.4102/sajhrm.v20i0.1972

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review*, *33*(1), 100899. doi:10.1016/j.hrmr.2022.100899

Cybulski, J. L., & Scheepers, R. (2021). Data science in organizations: Conceptualizing its breakthroughs and blind spots. *Journal of Information Technology*, *36*(2), 154–175. doi:10.1177/0268396220988539

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, *48*(2), 147–160. doi:10.2307/2095101

Donnellan, J., & Rutledge, W. L. (2019). A case for resource-based view and competitive advantage in banking. *MDE. Managerial and Decision Economics*, *40*(6), 728–737. doi:10.1002/mde.3041

Doz, Y. (2020). Fostering strategic agility: How individual executives and human resource practices contribute. *Human Resource Management Review*, *30*(1), 100693. doi:10.1016/j.hrmr.2019.100693

Euchner, J. (2019). Little ai, Big AI—Good AI, Bad AI. *Research Technology Management*, *62*(3), 10–12. doi:10.1080/08956308.2019.1587280

Falletta, S. V., & Combs, W. L. (2021). The HR analytics cycle: A seven-step process for building evidence-based and ethical HR analytics capabilities. *Journal of Work-Applied Management*, *13*(1), 51–68. doi:10.1108/JWAM-03-2020-0020

Faqihi, A., & Miah, S. S. (2023). Artificial IntelligenceDriven Talent Management System: Exploring the Risks and Options for Constructing a Theoretical Foundation. *Journal of Risk and Financial Management*, *16*(31), 31. Advance online publication. doi:10.3390/jrfm16010031

Gabriel, S., Bentler, D., Grote, E.-M., Junker, C., Meyer zu Wendischhoff, D., Bansmann, M., Latos, B., Hobscheidt, D., Kühn, A., & Dumitrescu, R. (2022). Requirements analysis for an intelligent workforce planning system: A socio-technical approach to design AI-based systems. *Procedia CIRP*, *109*, 431–436. doi:10.1016/j.procir.2022.05.274

Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, *4*(3), 28–36. doi:10.1287/inte.4.3.28

Gammage, C., & Novitz, T. (2019). *Sustainable trade, investment and finance: Toward responsible and coherent regulatory frameworks*. Edward Elgar Publishing., doi:10.4337/9781788971041

Gerhart, B., & Feng, J. (2021). The resource-based view of the firm, human resources, and human capital: Progress and prospects. *Journal of Management*, *47*(7), 1796–1819. doi:10.1177/0149206320978799

Ghislieri, C., Molino, M., & Cortese, C. G. (2018). Work and organizational psychology looks at the Fourth Industrial Revolution: How to support workers and organizations? *Frontiers in Psychology*, *9*, 401270. doi:10.3389/fpsyg.2018.02365 PMID:30546335

Gilliland, M., Tashman, L., & Sglavo, U. (2021). *Business forecasting: The emerging role of artificial intelligence and machine learning*. Wiley., doi:10.1002/9781119782605

Gupta, K. P., & Bhaskar, P. (2020). Inhibiting and motivating factors influencing teachers' adoption of AI-based teaching and learning solutions: Prioritization using analytic hierarchy process. *Journal of Information Technology Education*, *19*, 693–723. doi:10.28945/4640

Hair, J. F. Jr, & Sarstedt, M. (2019). Factors versus composites: Guidelines for choosing the right structural equation modeling method. *Project Management Journal*, *50*(6), 619–624. doi:10.1177/8756972819882132

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics*, *178*(4), 977–1007. doi:10.1007/s10551-022-05049-6

Jaiswal, A., Arun, C. J., & Varma, A. (2022). Rebooting employees: Upskilling for artificial intelligence in multinational corporations. *International Journal of Human Resource Management*, *33*(6), 1179–1208. doi:10.1080/09585192.2021.1891114

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, *31*(3), 685–695. doi:10.1007/s12525-021-00475-2

John-Mathews, J. M., Cardon, D., & Balagué, C. (2022). From reality to world. A critical perspective on AI fairness. *Journal of Business Ethics*, *178*(4), 945–959. doi:10.1007/s10551-022-05055-8

Johnson, R. D., Stone, D. L., & Lukaszewski, K. M. (2021). The benefits of eHRM and AI for talent acquisition. *Journal of Tourism Futures*, *7*(1), 40–52. doi:10.1108/JTF-02-2020-0013

Kaliannan, M., Darmalinggam, D., Dorasamy, M., & Abraham, M. (2023). Inclusive talent development as a key talent management approach: A systematic literature review. *Human Resource Management Review*, *33*(1), 100926. doi:10.1016/j.hrmr.2022.100926

Kaptein, M., Markopoulos, P., De Ruyter, B., & Aarts, E. (2015). Personalizing persuasive technologies: Explicit and implicit personalization using persuasion profiles. *International Journal of Human-Computer Studies*, *77*, 38–51. doi:10.1016/j.ijhcs.2015.01.004

Kavitha, K., Latha, R., Hassan, S. N., & Thirukumaran, K. (2019). Impact of skill development training on mushroom cultivation in Kanyakumari District of Tamil Nadu. *Journal of Krishi Vigyan*, *7*(2), 144–148. doi:10.5958/2349-4433.2019.00050.3

Kehoe, R. R., Collings, D. G., & Cascio, W. F. (2023). Simply the best? Star performers and high-potential employees: Critical reflections and a path forward for research and practice. *Personnel Psychology*, *76*(2), 585–615. doi:10.1111/peps.12558

Kersting, K. (2018). Machine learning and artificial intelligence: Two fellow travelers on the quest for intelligent behavior in machines. *Frontiers in Big Data*, *1*, 6. doi:10.3389/fdata.2018.00006 PMID:33693322

Khanra, S., Kaur, P., Joseph, R. P., Malik, A., & Dhir, A. (2022). A resource-based view of green innovation as a strategic firm resource: Present status and future directions. *Business Strategy and the Environment*, *31*(4), 1395–1413. doi:10.1002/bse.2961

Kumar, S. A., Ananda Kumar, T. D., Beeraka, N. M., Pujar, G. V., Singh, M., Narayana Akshatha, H. S., & Bhagyalalitha, M. (2022). Machine learning and deep learning in data-driven decision making of drug discovery and challenges in high-quality data acquisition in the pharmaceutical industry. *Future Medicinal Chemistry*, *14*(4), 245–270. doi:10.4155/fmc-2021-0243 PMID:34939433

Larson, L., & DeChurch, L. A. (2020). Leading teams in the digital age: Four perspectives on technology and what they mean for leading teams. *The Leadership Quarterly*, *31*(1), 101377. doi:10.1016/j.leaqua.2019.101377 PMID:32863679

Lee, H. W. (2019). Performance-based human resource management and federal employee's motivation: Moderating roles of goal-clarifying intervention, appraisal fairness, and feedback satisfaction. *Review of Public Personnel Administration*, *39*(3), 323–348. doi:10.1177/0734371X17721300

Liu, B., Li, M., Ji, Z., Li, H., & Luo, J. (2024). Intelligent productivity transformation: Corporate market demand forecasting with the aid of an AI virtual assistant. *Journal of Organizational and End User Computing*, *36*(1), 1–27. doi:10.4018/JOEUC.340038

Maan, A. T., Abid, G., Butt, T. H., Ashfaq, F., & Ahmed, S. (2020). Perceived organizational support and job satisfaction: A moderated mediation model of proactive personality and psychological empowerment. *Future Business Journal*, *6*(1), 21. doi:10.1186/s43093-020-00027-8

MacKenzie, S. B., & Podsakoff, P. M. (2012). Common method bias in marketing: Causes, mechanisms, and procedural remedies. *Journal of Retailing*, *88*(4), 542–555. doi:10.1016/j.jretai.2012.08.001

Maghsudi, S., Lan, A., Xu, J., & Van der Schaar, M. (2021). Personalized education in the artificial intelligence era: What to expect next. *IEEE Signal Processing Magazine*, *38*(3), 37–50. doi:10.1109/MSP.2021.3055032

Marginson, S. (2019). Limitations of human capital theory. *Studies in Higher Education*, *44*(2), 287–301. doi:10.1080/03075079.2017.1359823

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. *International Journal of Human Resource Management*, *28*(1), 3–26. doi:10.1080/09585192.2016.1244699

Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics*, *160*(4), 835–850. doi:10.1007/s10551-018-3921-3

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*, *30*(2), 272–298. doi:10.1111/1467-8551.12343

Mira, M. S., Choong, Y. V., & Thim, C. K. (2019). The effect of HRM practices and employees' job satisfaction on employee performance. *Management Science Letters*, *9*(6), 771–786. doi:10.5267/j.msl.2019.3.011

Mirowska, A. (2020). AI evaluation in selection: Effects on application and pursuit intentions. *Journal of Personnel Psychology*, *19*(3), 142–149. doi:10.1027/1866-5888/a000258

Nuccio, M., & Guerzoni, M. (2019). Big data: Hell or heaven? Digital platforms and market power in the data-driven economy. *Competition & Change*, *23*(3), 312–328. doi:10.1177/1024529418816525

Nurkin, T. (2023). AI and technological convergence. In M. Raska & R. A. Bitzinger (Eds.), *The AI wave in defence innovation* (pp. 37–58). Routledge., doi:10.4324/9781003218326-3

O'Reilly, C. A. III. (2017). Individuals and information overload in organizations: Is more necessarily better? *Academy of Management Journal*, *23*(4), 684–696. doi:10.2307/255556

Otoo, F. N. K. (2019). Human resource management (HRM) practices and organizational performance: The mediating role of employee competencies. *Employee Relations*, *41*(5), 949–970. doi:10.1108/ER-02-2018-0053

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, *63*(1), 539–569. doi:10.1146/annurev-psych-120710-100452 PMID:21838546

Prentice, C., Dominique Lopes, S., & Wang, X. (2020). Emotional intelligence or artificial intelligence—An employee perspective. *Journal of Hospitality Marketing & Management*, *29*(4), 377–403. doi:10.1080/19368623.2019.1647124

Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big Data*, *1*(1), 51–59. doi:10.1089/big.2013.1508 PMID:27447038

Rana, G., & Sharma, R. (2019). Emerging human resource management practices in Industry 4.0. *Strategic HR Review*, *18*(4), 176–181. doi:10.1108/SHR-01-2019-0003

Raska, M., & Bitzinger, R. A. (Eds.). (2023). *The AI wave in defence innovation*. Routledge., doi:10.4324/9781003218326

Rasmussen, T., & Ulrich, D. (2015). Learning from practice: How HR analytics avoids being a management fad. *Organizational Dynamics*, *542*(3), 1–7. doi:10.1016/j.orgdyn.2015.05.008

Reimsbach, D., Hahn, R., & Gürtürk, A. (2018). Integrated reporting and assurance of sustainability information: An experimental study on professional investors' information processing. *European Accounting Review*, *27*(3), 559–581. doi:10.1080/09638180.2016.1273787

Rialti, R., Zollo, L., Ferraris, A., & Alon, I. (2019). Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model. *Technological Forecasting and Social Change*, *149*, 119781. doi:10.1016/j.techfore.2019.119781

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2014). PLS-SEM: Looking back and moving forward. *Long Range Planning*, *47*(3), 132–137. doi:10.1016/j.lrp.2014.02.008

Selwyn, N. (2016). Digital downsides: Exploring university students' negative engagements with digital technology. *Teaching in Higher Education*, *21*(8), 1006–1021. doi:10.1080/13562517.2016.1213229

Shah, M. (2023, February 25). AI in predictive analytics: Driving business insights and actionable intelligence. Medium. https://shahmm.medium.com/ai-in-predictive-analytics-driving-business-insights-and-actionable-intelligence-2aa88d23409b

Škudienė, V., Vezeliene, G., & Stangej, O. (2020). Transforming human resource management: Innovative e-HRM value creation for multinational companies. In V. Škudienė, J. Li-Ying, & F. Bernhard (Eds.), *Innovation management* (pp. 140–166). Edward Elgar Publishing., doi:10.4337/9781789909814.00021

Strober, M. H. (1990). Human capital theory: Implications for HR managers. *Industrial Relations*, *29*(2), 214–239. doi:10.1111/j.1468-232X.1990.tb00752.x

Strods, C., Berka, A., & Linney, S. (2021). Effective global mobility and international recruitment during a pandemic. In D. Burgos, A. Tlili, & A. Tabacco (Eds.), Radical solutions for education in a crisis context. Lecture notes in educational technology (pp. 53–67). Springer. doi:10.1007/978-981-15-7869-4_4

Stroh, L. K., & Caligiuri, P. M. (1998). Strategic human resources: A new source for competitive advantage in the global arena. *International Journal of Human Resource Management*, *9*(1), 1–17. doi:10.1080/095851998341161

Swanson, H. L. (1987). Information processing theory and learning disabilities: An overview. *Journal of Learning Disabilities*, *20*(1), 3–7. doi:10.1177/002221948702000102 PMID:3805889

Tehseen, S., Ramayah, T., & Sajilan, S. (2017). Testing and controlling for common method variance: A review of available methods. *Journal of Management Sciences*, *4*(2), 142–168. doi:10.20547/jms.2014.1704202

Turkulainen, V. (2022). Contingency theory and the information processing view. In W. Tate, L. Ellram, & L. Bals (Eds.), *Handbook of theories for purchasing, supply chain and management research* (pp. 248–266). Edward Elgar Publishing., doi:10.4337/9781839104503.00020

Uddin, M. A., Mahmood, M., & Fan, L. (2019). Why individual employee engagement matters for team performance? Mediating effects of employee commitment and organizational citizenship behaviour. *Team Performance Management*, *25*(1/2), 47–68. doi:10.1108/TPM-12-2017-0078

Verma, S., Singh, V., & Bhattacharyya, S. S. (2020). Do big data-driven HR practices improve HR service quality and innovation competency of SMEs. *The International Journal of Organizational Analysis*, *29*(4), 950–973. doi:10.1108/IJOA-04-2020-2128

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, *5*(2), 171–180. doi:10.1002/smj.4250050207

West, D. M., & Allen, J. R. (2018, April 24). How artificial intelligence is transforming the world. Brookings. https://www.brookings.edu/articles/how-artificial-intelligence-is-transforming-the-world/

Wu, Z., She, Q., & Zhou, C. (2024). Intelligent customer service system optimization based on artificial intelligence. *Journal of Organizational and End User Computing*, *36*(1), 1–27. doi:10.4018/JOEUC.340386

Xu, A., Li, Y., & Donta, P. K. (2024). Marketing decision model and consumer behavior prediction with deep learning. *Journal of Organizational and End User Computing*, *36*(1), 1–25. doi:10.4018/JOEUC.336547

Yang, Y., Tang, Y., Zhang, Y., & Yang, R. (2021). Exploring the relationship between visual aesthetics and social commerce through visual information adoption unimodel. *Frontiers in Psychology*, *12*, 700180. doi:10.3389/fpsyg.2021.700180 PMID:34552529

Yao, X., Jin, H., & Zhang, J. (2015). Towards a wisdom manufacturing vision. *International Journal of Computer Integrated Manufacturing*, *28*(12), 1291–1312. doi:10.1080/0951192X.2014.972462

Zhu, C., Zhu, H., Xiong, H., Ding, P., & Xie, F. (2016). Recruitment market trend analysis with sequential latent variable models. In *KDD '16: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 383–392). ACM. doi:10.1145/2939672.2939689

Li Wenting is currently pursuing Ph.D. at Graduate School of Business. She is currently trying to publish articles into international journals in the area of Technology Management.

Wan Mohd Hirwani Wan Hussain is an Associate Professor at the Graduate School of Business, Universiti Kebangsaan Malaysia. He is authors for more than 50 articles published into reputed international journals and conference proceedings. He is currently supervising more than 10 Ph.D. students. His area of research in Technology Management.

Jia Xinlin is pursuing Ph.D. at the School of Management, Universiti Sains Malaysia. He is doing his Ph.D. in the area of Management.

Meng Na is pursuing her Ph.D. at the Graduate School of Business, Universiti Kebangsaan Malaysia. Her ORCID:0000-0003-2504-5371.

Syed Shah Alam is an Associate Professor at the Department of Marketing, College of Business Administration, Prince Sultan University, Riyadh, Saudi Arabia. He is authored for more than 100 articles published into top ranking journals. His primary research interests focus on technology driven marketing, consumer behavior, technology innovation adoption and green marketing. He has been listed in the Stanford University list of Top 2% Scientist in the world as being the most cited scientist in a large range of disciplines.