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Synergetic role of digital leadership and artificial intelligence (AI) in HRM for sustainable performance: A dual-method approach using SEM and NCA

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ABSTRACT

This study aims to investigate the role of digital leadership in influencing artificial intelligence in human resource management (AIHRM) and sustainable performance, with a particular focus on the mediating roles of managerial and technological innovation in Bangladesh. To achieve the research goal, data were collected from 281 human resource-oriented employees using judgmental sampling. Structural equation modeling (SEM) was used to validate the path analysis, while necessary condition analysis (NCA) was employed to determine the minimum essential conditions for achieving sustainable performance, thereby complementing SEM's limitations. The results indicate that digital leadership has a significant positive impact on AIHRM, managerial innovation, and sustainable performance, while AIHRM plays a significant positive role in enhancing sustainability. Additionally, managerial innovation partially mediates between digital leadership and performance, and AIHRM and performance, whereas technological innovation shows an insignificant mediating effect between both digital leadership and performance, as well as AIHRM and performance. Notably, to maintain a minimum of 50 % sustainable performance, organizations require 13.3 % in digital leadership capabilities, whereas achieving 100 % sustainable performance necessitates approximately 80 % in digital leadership, 73.3 % in AIHRM, 71.6 % in managerial innovation, and 62.7 % in technological innovation capabilities. This study contributes by integrating human and dynamic resources to explain how digital leadership practices and the synergistic effect of AIHRM foster managerial and technological innovation, leading to sustainable outcomes in emerging economies.

1. Introduction

In the rapidly evolving post-COVID-19 era, digital leadership (DL) has emerged as a crucial organizational capability. DL enables organizations to navigate digital transformation (DT), harness artificial intelligence (AI), and promote technical and nontechnical innovations, especially within the human resource management (HRM) domain, to achieve sustainable performance (SP). Organizations worldwide are embracing AI-driven tools and digital platforms to remain competitive and resilient. Since the COVID-19 pandemic, the evolution of AI has increased the importance of DL, as leaders have been required to redesign work processes, ensure employee adaptability, and drive technology-enabled transformation in the workplace [1]. Furthermore, in the post-COVID-19 era, the development of generative AI technologies appears closely linked to institutional DT, as evidenced by the emergence of AI systems such as ChatGPT, Gemini AI, Bard, and Deepseek. To navigate the volatile digital landscape with an expert hand, there is no alternative to digital laureateship. Luck et al. [2] noted that

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DL possess various skills, such as being visionary, encouraging experimentation, thinking outside the box, being experts in strategy formulation, and being communicative and cooperative. Through this skill, DL can foster innovation, encourage learning, and promote the adoption of AIHRM that facilitates agility, transparency, and employee engagement [3]; however, the interaction between humans and technology is vital for addressing the dynamics of resource sustainability.

AI is at the forefront of shaping new trends and approaches across industries [4]. For example, Bley et al. [5] described a high surge (270 %) of AI in the last 4 years. It is projected that investment in AI will gradually rise by around 24.5 %, reaching 85.3 billion United States dollars (USD) from 2021 to 2025, and AI is being used to enhance service and productivity, minimize costs, and improve operations [6]. Moreover, AI could contribute 13 trillion USD in gross domestic product from now to 2020 [7]. Based on the Network Readiness Index report of 2024, Bangladesh scores higher than 43.56, indicating that its digital infrastructure and readiness are medium-to-low, which affects the rollout of AI implications for national firms and government services. Furthermore, Bangladesh scores 43.73 in the technology sub-index, with internet subscriptions ranking 5th, international internet bandwidth ranking 20th, and AI scientific publications ranking 14th. This result indicates that while internet adoption in Bangladesh is progressing, AI adoption at the organizational level is relatively low.

Moreover, the IMF Artificial Intelligence Preparedness Index (AIPI) shows that Bangladesh ranks 113th with a rating of 0.38, indicating limited technological innovation (TI), regulation, and data governance compared to developed countries [8]. The application of AI for talent acquisition is significant among human resource professionals [9]. Additionally, another study found AI applications in the banking sector, particularly in customer and HR workflows [10]. It shows that AI use is limited, but some organizations are experimenting with it where it has been practically demonstrated; most organizations are not trying to use AI for HRM systems. In fact, the implications of new technology in Bangladesh include several challenges (e.g., limited resources, infrastructure problems, lack of vision, and fear of new technology). Within this situation, the STST theory provides a lens for understanding how the interaction between technological structures and human systems drives or constrains sustainable performance. The findings have broader generalizability to other emerging economies in South Asia and beyond (e.g., India, Vietnam, and Indonesia) with similar levels of digital and HRM, given cultural and economic similarities.

This study model has been justified through the use of sociotechnical systems (STS) [11,12] and dynamic capabilities [13]. The collaboration acknowledges that alignment at the human, organizational, and contextual levels is just as important as technical infrastructure in developing successful IT systems. In line with recent research by Sarker et al. [14], the proposed project focuses on how technological systems and social structures will change together as Bangladesh goes digital. Here, DL transformational and visionary mindsets, the integration of dynamic technological resources (e.g., DL and AIHRM systems), and the development of innovative capabilities (e.g., sensing, seizing, and reconfiguring opportunities) can only lead to organizational sustainability. Managerial innovation involves implementing new managerial processes, practices, or structures that enhance an organization's adaptive capabilities and effectiveness [15,16]. DL, through their visionary, transformational leadership and strategic competencies, foster an environment conducive to MI by encouraging and empowering employees, knowledge sharing, and promoting participative decision-making [17,18]. Digital leaders' innovative managerial process (e.g., AI-based recruitment, digital training, and digital performance tracking) facilitates the efficient use of HR and digital resources, leading to enhanced SP [19,20]. Additionally, technological innovation (TI) reflects a firm's ability to develop, adopt, and implement new technologies to enhance operational efficiency and value creation [21]. In practice, AI in HRM encourages data-driven decision-making and process automation, but its full potential is realized only when it is complemented by TI, which promotes system integration, process optimization, and knowledge sharing [22,23]. Therefore, considering the theoretical background of STS and the dynamic capabilities view (DCV). The synergistic role of DL and AIHRM is key to influencing MI and TI for achieving SP.

In particular, organizations in emerging economies face challenges balancing the development of advanced technological infrastructure with addressing shortages of skilled talent [24]. Therefore, DL is increasingly recognized as a critical strategic asset that guides digital transformation by shaping its vision [17,25], fostering innovation [26,27], and driving AI adoption in HRM functions. Moreover, integrating DL as a strategic enabler propels AIHRM and serves as a dynamic capability, with DL strengthening each other to facilitate managerial innovation (MI) and technological innovation (TI), which are crucial pathways for achieving SP. As the COVID-19 pandemic accelerated the need for digital innovation in the workplace, it forced firms to rethink HR practices with AI and to depend on strong DL to navigate uncertainties. As a result, the integration of DL and AIHRM is growing in importance for the management of human-AI collaboration, the promotion of innovation, and the improvement of employee well-being-critical factors for ensuring long-term performance and resilience [28]. Furthermore, Chowdhury et al. [29] suggested using leadership strategies based on perspective and role, while Erhan et al. [26] recommended using DL as key independent constructs. Additionally, existing studies often overlook the mediating roles of MI and TI in achieving SP, particularly in developing country perspectives, where AIHRM can play a pivotal role [30,31]. Limited resources frequently constrain the implementation of MI and TI necessary for transforming HRM systems.

The existing literature primarily focuses on individual aspects, such as the role of DL in DT and innovation [18,27,32], innovative work behavior [26], SP [33], or the effect of AI-augmented HRM on sustainable organizational performance [34,35]. Moreover, several studies focus on AIHRM and its effects on sustainable performance [6,27] and on balancing AI automation with human-centered intelligence [36]. Additionally, the systematic literature found AI support for workplace outcomes (Pereira et al., 2023), AI effects on HRM activities [37,38], and that AI-driven insights enhance SP [39]. Furthermore, AI in green HRM practice positively influences sustainable work management [40], and sustainable HRM, well-being, and AI technology positively support employee engagement [41]. Moreover, AI adoption has a positive impact on organizational performance [42].

Furthermore, research on the integration of leadership AIHRM is minimal. AI technologies in the education sector can enhance data-informed, inclusive, and transformational models of leadership [43]. Ethical leadership is necessary to avert bias, discrimination, and data security issues when effectively applying AI in HRM [44]. AI-powered HRM underscores the importance of balancing efficiency and human-centeredness [45]. Maghsoudi et al. [46] noted, through a meta-analysis that DL and AIHRM for decision-making are emerging themes. Supporting this, Tinguely et al. [47] noted that in the digital era of AI, we need an inclusive leadership system that is more system-design-focused. The above literature clearly shows that there is empirical research on AIHRM and SP, while theoretically linking DL to AIHRM; however, given the necessity of DL and its integration with AIHRM for exploring SP, it remains unexplored. Therefore, considering the literature gap and opportunities to explore from DL→AIHRM→SP. This study sought to make a contribution to the research arena, where DL is considered a strategic resource, and to open new pathways for research addressing the AI era. MI plays a pivotal role in overseeing the strategic alignment of AI systems with organizational goals, while TI provides the tools necessary to adapt to fluctuating market demands and remain competitive [48,49]. Some studies focused solely on MI [15], while others analyzed TI [50,51]; however, little is known about how DL constructs interact to foster AIHMR, MI, and TI, and how this integrated model influences SP. Therefore, the objective of this study is to examine

the direct and indirect effects of DL on AIHRM and SP, including the mediating roles of MI and TI in achieving SP, using a dual SEM and NCA approach. To bridge the identified research gap, this study aims to address the following questions (RQs):

RQ1. What is the role of DL in influencing AIHRM to drive SP in emerging economies?

RQ2. What are the mediating roles of AIHRM, MI, and TI in the interlink between DL and SP?

RQ3. Can MI and TI play a mediating role in the interlinkage between AIHRM and SP?

This study is organized around empirical data collected from 281 employees of HRM departments in emerging economies. The proposed theoretical model was tested using analysis of moment structures (AMOS-SEM) and NCA to investigate the direct and indirect effects, as well as the required strength of DL, AIHRM, MI, and TI to ensure SP. This investigation is grounded in STS and DCV theories. The study is organized as follows. Section 2 presents the theoretical foundation and the development of the hypothesis. Sections 3 and 4 cover the research methods and analysis, and Section 5 provides the discussion and conclusion.

2. Theoretical foundation and hypotheses

2.1. Sociotechnical systems (STS) and dynamic capabilities view (DCV)

This era of Industry 4.0 is driven by advanced technologies and the collaboration between humans and AI; thus, it is imperative to understand how DL and AI-powered systems, combined, contribute to employee-centric, innovation-driven outcomes. This study conceptualizes how STS [11,12] lenses can be applied through the interaction of humans as digital leaders with technology (e.g., AIHRM, MI, TI) to achieve organizational sustainability. STS provides a lens for understanding how the interaction between technological structures and human systems drives or constrains sustainable performance [52]. STS theory postulates that organizational performance depends on the effective alignment between social subsystems (e.g., leadership, employee skills, HR practices) and technical subsystems [11,53]. In the context of AIHRM, STS theory explains why DL is critical in orchestrating human capabilities, managerial practices, and intelligent technologies into a coherent system rather than treating technology as an isolated driver of performance. However, STS theory alone provides a largely static explanation focused on alignment at a given point in time. To address how organizations continuously adapt and renew these aligned systems under digital disruption, this study incorporates the DCV which emphasizes an organization's ability to sense opportunities, seize them through appropriate investments, and reconfigure resources to sustain competitive advantage over time [54,55].

In line with recent studies by Sarker et al. [14], the endeavor focuses on how technological systems and social structures will change together as Bangladesh goes digital. Together, STS and DCV explain how organizations build, integrate, and reconfigure internal and external resources and capabilities to address technological structural changes. For instance, dynamic learning (DL) and artificial intelligence in human resource management (AIHRM) work together synergistically to achieve sustainable performance (SP). The roots of DCV and the resource-based view (RBV) emphasize valuable, rare, inimitable, and non-substitutable resources [56]; these resources can be used to gain a competitive advantage and enhance performance [57,58].

DCV extends RBV by focusing on adaptive and reconfiguration processes [54], underscoring how DL and AI application innovation dramatically transforms routines toward sustainability. Teece et al. [57] explained, "Dynamic capabilities represent an organization's ability to sense, seize, and reconfigure resources in response to rapidly evolving environments." In this view, DL is essential in the transformational role of addressing interactional capabilities, given its vision-sharing, intellectual stimulation, and digital capabilities [18,26] in sensing, seizing, and reconfiguring the use of emerging AI tools and techniques for HRM. Moreover, DL can leverage technological and managerial innovation to reconfigure data-driven, responsive, and adaptive HR practices [59,60].

However, the challenges rely on limited resources, such as digital capabilities, investment in technology, and achieving SP in developing economies. To transform conventional HRM systems into digital-first, AI-integrated platforms, enterprises must develop static and dynamic organizational capabilities. Additionally, the MI holds that DL enhances MI by fostering a risk-tolerant, vision-driven, and learning-oriented culture. In contrast, DL supports TI by promoting technological openness, facilitating digital experimentation, and integrating AI tools within HR and operational systems. Together, TL and DCV theory provide a lens for explaining the integration of DL, AIHRM, MI, and TI systems toward sustainable performance in emerging economies. Furthermore, IT integration can enhance organizations' ability to achieve more effective and sustainable business outcomes [61]. Finally, the integration of STS theory will not only appear as leadership capabilities in interacting with technology and DL but also express strategic foresight and behavioral capabilities that support the adoption of AIHRM, MI, and TI processes toward sustainable outcomes.

2.2. Relationship of DL, AIHRM, and SP

In the era of AI, the relationship between humans and AI is essential to ensuring a competitive position, as supported by STS and DCV theory. Digital leaders focus on embracing digital transformation and incorporating digital managerial and TI, including conceptualizing, promoting, and institutionalizing AI-driven tools within HR functions. AIHRM demonstrates the integration of AI technologies into HRM functions such as recruitment, training and development, skills upgrading, career planning, performance management, talent management, job evaluation, reward management, and turnover management [34]. DL supports the advancement of digital business processes, enhances operational efficiency through AI and technology, and strengthens organizational capabilities [62,63]. Moreover, leaders with strong digital acumen can overcome resistance to AI, advance digital skill enhancement for HR professionals, and integrate AI technology to align with company objectives and workforce requirements [64]. While DL are prone to cultivating a culture of innovation [26] and agility [35], enabling the deployment of AI to enhance HRM strategies and decisions [65]. In line with STS theory, effective integration of human and technological subsystems enhances performance when leadership facilitates alignment between digital tools and employee competencies.

Through the application of STS and DCV theory, AI-augmented HRM is supported by digital leaders who foster a culture of technology adoption, enabling AI-based decision-making and sustainability. In line with previous research, this study confirms that DL has a significant effect on AIHRM adoption [66]. From this perspective, Chowdhury et al. [29] noted that AIHRM influences power shaping SP across three categories: economic, social, and environmental. Research has shown that many organizations adopt AI to improve HRM systems, and that AI can streamline HR functions [67]. Actually, AIHRM plays a crucial role in developing organizational sustainability by improving resource efficiency, reducing human error, and enhancing employee well-being. Previous studies have shown that AIHRM improves organizations' societal performance by cultivating talent, advancing employees' well-being, ensuring equity and justice for communities, improving working conditions, and raising staff creativity and efficiency in the workplace [68,69]. Furthermore, it enhances economic performance through novel concepts, such as reducing lead times, minimizing costs, and delivering high-quality goods and services with environmental performance [70]. Therefore, AIHRM results in more efficient utilization of human resources, thereby directly supporting an organization's sustainability.

Grounded in DCV, DL possess dynamic capabilities for sensing, seizing, and reconfiguring technological opportunities and challenges

[55], and they also possess knowledge aligned with the organizational vision and mission, thereby encouraging proactive innovation behaviors [71]. Additionally, DL facilitates a working environment that supports experimentation, risk-taking, and continuous learning, which are essential for innovation in digital environments [72]. DL also enhances the organization's ability to adopt and integrate new digital tools by promoting cross-functional collaboration and agile decision-making [18,26]. DL enables such adaptive reconfiguration by fostering digital awareness, strategic agility [35], and innovation-oriented decision--making in the HRM system [6]. Leaders with digital capabilities play a critical role in aligning AIHRM practices with organizational sustainability goals, thereby contributing to the development of eco-efficient, socially responsible organizational systems [73]. To ensure SP, each company needs a robust leader, and organizations are more likely to boost their performance when implementing DL as a whole [74,75]. Moreover, many researchers found that DL has direct and indirect influence on SP [33,76,77]. DL bridges this alignment by guiding AIHRM adoption, enabling organizations to adapt, innovate, and enhance SP. Therefore, this study proposes the following hypotheses:

H1. *AIHRM mediates the relationship between DL and SP.*
H1a. *DL has a significant positive impact on AIHRM.*
H1b. *AIHRM has a positive impact on SP.*
H1c. *DL has a positive impact on SP.*

2.3. Relationship of DL, MI, and SP

DL plays a crucial role in helping organizations cope with the challenges of rapid technological change by fostering a vision-driven, innovation-centric culture [3]. Leaders who embrace digital mindsets are more likely to foster an organizational environment conducive to continuous learning, experimentation, and innovative problem-solving, collectively referred to as a MI [78]. "Managerial innovations are new organizational structures, administrative systems, management practices, processes, and techniques that could create value for the organization" [15,79]. Theoretically, a DL transformational mindset leverages managers' dynamic capabilities to adjust to a changing environment. Furthermore, organizations worldwide have recognized that DL is essential to innovation. Under such circumstances, DL facilitates MI, empowering staff to foster a strong organizational culture and boost job engagement [80]. In practice, it is observed that, due to the evolution of AI, DL is not confined to TI; it also emphasizes reorganizing structures, administrative systems, practices, and processes to enhance value. The characteristics of the digital leader enable effective MI and organizational change, leading to successful transformation within organizations [81]. Digital leaders typically inspire the integration of digital technologies and data-driven insights into strategic and operational decision-making, thereby enhancing MI capacity [72]. Moreover, big data analytics and knowledge management systems strengthen the positive relationship between AI capabilities and green innovation, underscoring the importance of integrating these technologies to promote environmentally responsible industrial practices [61]. Thereafter, it can be assumed that DL is the key necessity for the MI success.

Furthermore, in today's digitalized, knowledge-intensive work environments, MI is a pivotal force in driving organizational competitiveness and sustainability. Actually, MI incorporates the development and implementation of new managerial practices, processes, and structures that enhance organizational adaptability, responsiveness, and long-term value creation [79,82]. Information technology is a key factor in improving organizational operations and performance [82]. To address technological changes, new types of leaders emerged. Thereafter, MI played a crucial role in shaping organizational structural and administrative changes for enhancing sustainability. It is assumed that MI positively influences SP, suggesting that an organization's long-term ability to sustain success depends on MI, while it also addresses social and environmental concerns [83]. Moreover, firms that innovate their management practices often see higher levels of employee engagement and satisfaction, which are critical to sustainability and also increase operational efficiency [84,85]. These improvements directly contribute to an organization's long-term success. Especially in the context of emerging economies, where resource constraints and technological shifts pose unique challenges, organizations that embrace MI are more likely to sustain growth and performance [86]. Along with technological change, organizations are focusing on MI to ensure sustainability. Therefore, we have proposed the following hypothesis

H2: *MI mediates the relationship between DL and SP.*
H2a. *DL has a positive impact on MI.*
H2b. *MI has a positive impact on SP.*

2.4. Relationship of DL, TI, and SP

DL has emerged as a crucial factor in shaping how organizations navigate the dynamic nature of technological integration, especially in the HRM domain. TI refers to the process of developing new technologies or improving existing ones to create better products, services, or processes. Luck et al. [2] noted that DL possess various skills, such as being visionary, encouraging experimentation, thinking outside the box, and being experts in strategy formulation, as well as being communicative and cooperative. Through this skill, DL can foster innovation, encourage learning, and promote the adoption of AIHRM that facilitates agility, transparency, and employee engagement [3]. As technology and DL are interconnected, theological innovation is initiated and managed by DL. In the modern business landscape, TI has become a key enabler of organizational transformation, particularly in the adoption of AI tools in HRM [50]. TI plays a crucial role in enhancing organizational competitiveness, efficiency, and sustainability, especially in the context of AI-augmented HRM systems. The capacity to innovate technologically enables organizations not only to streamline operations but also to enhance decision-making through data-driven insights [87]. It further shows that strong organizational change capability and financial resilience amplify this relationship, emphasizing the need for firms to invest in AI skills and adaptive capacities to enhance sustainable business performance [61]. Therefore, it is presumed that DL supports MI and TI, as well as organizational sustainability.

Moreover, TI plays a crucial role in enhancing organizational competitiveness, efficiency, and sustainability, especially in the context of AIHRM systems. The capacity to innovate technologically enables organizations not only to streamline operations but also to enhance decision-making through data-driven insights [87]. However, implementing TIs is not without its challenges. Organizations in emerging economies often face barriers such as limited access to advanced technologies, a lack of skilled talent, and insufficient infrastructure [88]. TI is not only about adopting new tools but also about rethinking how organizations operate and create value. In the context of AI-oriented HRM, innovation involves reengineering processes to improve efficiency and contribute to long-term sustainability [89]. Organizations that embrace TI in HRM can achieve a competitive advantage by optimizing talent management, enhancing employee experience, and driving SP [90]. Thus, technological innovation is a vital component of the nexus between HRM and sustainable organizational performance in emerging nations [91]. Consequently, TI can be a key predictor of SP and can therefore serve as a channel through which DL translates into sustainable organizational practices and outcomes. Given the above, we propose the following hypotheses:

H3: *TI mediates the relationship between DL and SP.*
H3a. *DL has a positive impact on TI.*
H3b. *TI has a positive impact on SP.*

2.5. Relationship of AIHRM, MI, TI, and SP

In the era of AI, AI-augmented HRM transforms traditional HR functions through advanced data analytics, automation, and decision-making capabilities to achieve sustainable performance. AI-augmented

HRM refers to the use of AI in HRM processes such as recruitment, training and development, and performance appraisal [34]. To do so, DL leaders, who play an inevitable role in enhancing AIHRM and managerial and TI, can work toward achieving SP. AIHRM significantly improves decision-making and operational processes in HR departments [34]. In that case, align with DL wills and expectations, and after the AIHRM organization establishes MI and TI, it also needs to achieve organizational sustainability. AI tools can handle large datasets effectively, allowing HR professionals to make data-driven decisions and support access to information, thereby improving management's ability to respond to organizational needs [48]. In that case, to achieve the outcome, managerial innovations are more essential for addressing agile and dynamic markets [82]. As mentioned before, with the help of DL, AI-augmented HRM technologies are used in the organization, clearly enhancing efficiency in recruitment, training, and performance management by automating routine tasks, giving HR managers more time to focus on strategic initiatives [92]. AI technologies, combined with innovative practices (e.g., managerial and technological), enable organizations to improve productivity and adaptability [93].

Moreover, using AI in talent acquisition can result in more efficient and unbiased hiring processes, while AI-driven analytics can provide insights into employee behavior and engagement, helping organizations foster a more sustainable workforce [94]. Tambe et al. [48] highlighted the importance of applying AI to transform HRM, and Boon et al. [95] noted that HR practices can influence TI. Furthermore, AIHRM significantly contributes to the development and implementation of new technologies, enhancing organizational innovation capabilities, and also supports innovative projects and drives technological advancement [96]. At the same time, managerial innovation aligns with playing a key role in connecting AIHRM with SP, which indicates a smoothly integrated AIHRM for achieving SP. It also helps AI technologies align with the overall strategic objectives of sustainability [15]. Additionally, management plays a critical role in fostering a culture of innovation (managerial or technological) and in ensuring that technological advancements are effectively integrated into HR practices [97]. Together, they facilitate AI-driven decision-making across various HRM activities, including daily operations, relationship management, and transformational initiatives. The integration of DL, AIHRM, TI, and MI improves the efficiency, accuracy, and strategic value of HR processes, thereby enhancing sustainability. Therefore, we propose the following hypotheses:

***H4**: MI mediates the relationship between AIHRM and SP.*

***H4a.** AIHRM has a positive impact on MI.*

***H5**: TI mediates the relationship between AIHRM and SP.*

***H5a.** AIHRM has a positive impact on TI.*

Consistent with the above reasoning and relationship, H4 and H5 propose that managerial innovation and TI mediate the relationship between AIHRM and sustainable performance.

2.6. Model development

Industry 4.0 encourages seamless collaboration between machines and humans to transform organizational processes. An increasing number of academics are studying AI in HRM, but the mechanism by which DL leverages AI to achieve long-lasting results through two distinct innovation processes has not been thoroughly studied. Prior research [6,35,36,39,42] has discussed the connection between DL, AIHRM, and SP in different contexts but rarely integrates managerial and TI simultaneously as mediating dynamic capabilities. For example, Erhan et al. [26] recommended using DL as a key construct, while Bresciani et al. (2021) emphasized the importance of integrating AI into HRM to enhance firm agility and resilience. Other studies have stressed the need to integrate MI and TI to address technological turmoil [21,98]. Our proposed research is novel in illustrating how these innovations bridge the sociotechnical alignment (STS) and capability reconfiguration (DCV) perspectives, particularly within emerging economy contexts employing a dual SEM-NCA approach. Fig. 1 presents this study's research model.

3. Methods

3.1. Research design

To accomplish the research goals, this study reviews relevant previous literature and develops a structured questionnaire (see Appendix A3) for empirical testing. After data collection, this study used Microsoft Excel to organize and analyze the data and to prepare a raw file for SPSS 23. SPSS 23 was used for data cleaning, descriptive statistics, and reliability testing, ensuring accuracy in preliminary analysis. We conducted various analyses, including frequency distributions, means, standard deviations, correlations, variance inflation factors (VIFs), data reliability, and common method variance (CMV). Furthermore, AMOS 24 was employed for confirmatory factor analysis and SEM, including testing measurement and structural model fit and relevant hypotheses. Finally, Python version 3.13 was used to assess NCA, including effect size and bottleneck analysis. In practice, SEM methods show the net effect and the sufficiency of independent variables (e.g., DL and AIHRM) on outcomes (SP). NCA identifies conditions that must be present for an outcome to occur but are insufficient on their own [99]. This use of multiple software programs guaranteed a thorough analysis, balancing statistical rigor and causal depth, which supports the choice of tools.

3.2. Ethical approval

In this research, ethical standards were maintained in accordance with the Helsinki Declarations. To obtain ethical approval before starting data collection, the researchers of this study submitted the questionnaire, sampling details, and all other ethical requirements to the "Research Cell of the University of Barishal, Bangladesh," the local authority responsible for the ethical clearance certificate. After assessing all ethical concerns and guidelines, the authority approved and provided the certificate (ref no: FSB-EC-57/2024) for the further survey process.

3.3. Measurement constructs

This study model comprised five constructs. First, to assess DL (four items) taken from Niu et al. [32], which constructs the DL capacity to drive digital transformation and stay competitive, directly related to the research purpose of achieving SP. For measuring AIHRM (eight items), taken from Mollah et al. [35], which was previously used by Prikshat et al. [34], Mehrabad and Brojeny [100], Cesta et al. [101], Gratton [102], Huang et al. [103], and Lawler and Elliot [104], including recruitment, selection, training, development, employee turnover, job evaluation, and performance management. AI-augmented HRM reflected the extent to which AI technologies are integrated into HR practices grounded in STS theory. Next, the MI (six items) was adopted from Vaccaro et al. [85] and Zhang et al. [51]. MI represented leaders' ability to introduce novel management practices rather than traditional systems to address technological and environmental changes. Then, to assess TI, five items were adopted from Prajogo and Sohal [105] and Singh and Smith [106]. It indicates the capture of the development or adoption of new technologies to improve performance. Finally, to assess SP (six items) taken from Kordab et al. [107]. SP covers ensuring higher-quality, lower-cost service and rapidly responding to environmental changes to ensure effectiveness and profitability. This study also employs AI tools used by employees and demographic information, such as the size and age of organizations, employees' service experience, and positions in the organizations (see Appendix A1).

3.4. Data collection process

We adopted study constructs from previous studies. The

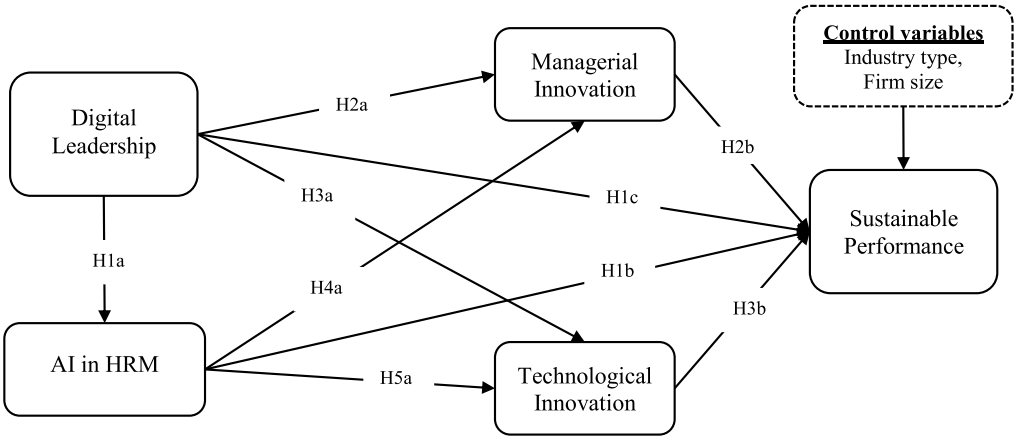

Fig. 1. Proposed research framework.

questionnaire scales (five-point) and items were presented in English and the native language for data collection purposes. In this research, ethical standards were maintained in accordance with the Helsinki Declarations. We collected ethical approval from the local academic authority and oral and written consent from each participant before starting the interview. Before final data collection, this study conducted a pilot study with 30 samples, which confirmed the data's validity. We gathered samples from various levels of employees and personnel in Bangladeshi organizations who are directly or indirectly involved in HRM activities. To collect the data, we used judgmental sampling, selecting respondents involved in HR-related activities in organizations (banks, insurance, private corporations, public organizations, and autonomous organizations) and with HR-related expertise. The study was aimed at HR professionals, managers, and executives with direct experience with AI-based HRM methods. Purposive sampling ensured that the data were relevant and the ideas were correct, as regular workers might not know enough about AIHRM or DL processes, which aligns with previous HRM and technology studies [108]. To ensure greater understanding, we included a brief note at the beginning of the survey questionnaire, instructing respondents on how to answer and advising that those without HR-related expertise or who are not inspired to participate should not. The respondents voluntarily participated in the study and provided their responses.

We conducted this survey via online platforms such as email, Facebook Messenger, and WhatsApp, and we met in person to solicit participation. These platforms were selected because of their widespread professional use for business and social communication in emerging economies. The multi-channel approach improved response diversity and inclusiveness and also enhanced response rates by reaching participants in real-time communication environments. The pilot study and final data collection period spanned four months, from May 1, 2024, to May 20, 2024. After conducting a May 1 pilot study, validity tests were conducted, and corrections were implemented based on its recommendations and findings. At the initial stage, 300 questions were distributed for the final data collection, which began on June 1, 2024, and concluded on July 30, 2024. Subsequently, an additional 150 questions were distributed in August 2024, and the final phase of data collection was completed within August 2024. Finally, a total of 305 responses were collected from the 450 questionnaires distributed; however, after data cleaning (e.g., incomplete responses were excluded) and listwise deletion of missing or improperly completed responses in SPSS during preliminary screening, 281 valid responses remained for the final analysis. This sample meets the minimum threshold for SEM-based analysis [108–110], which is supported by previous research. For example, Al Halbusi et al. (2025) used 218 samples from a two-wave data collection of 242 samples to examine the effect of search knowledge management on the circular economy [61]. The rigorous screening strengthened dataset quality, aligning with methodological standards in SEM-based HRM research [111]. The response rate was 67.78 %, which is considered acceptable compared to previous research findings in Bangladesh, such as Amin et al. [112] (52.5 %), Mahmud et al. [113] (47.2 %), and Amin and Oláh [114] (41.8 %).

3.5. Demographic profile

First, this study examined the different types of AI tools utilized in HR practices. The multi-response results showed that 45.79 % use Google AI, 42 % use OpenAI, 20 % use Microsoft Research, 16.4 % use Google Cloud, while others reported using Amazon Web Services (3.2 %), Human AI (3.2 %), OpenAI Gym (3.7 %), and other AI tools (16 %). Additionally, the results showed that approximately 14.9 % of responses came from small organizations, 13.5 % from medium-sized organizations, and 71.5 % from large organizations. Moreover, about 56.9 % of the organizations have been serving for >20 years, 14.9 % for <5 years, and 12.8 % for 5 to 10 years.

Additionally, regarding respondents' ages, the largest group (48.8 %) falls within the 30 to 39-year range, followed by 42.7 % aged 20 to 29. Regarding employee experience, the largest group (52.3 %) has 1 to 5 years of experience, followed by 28.5 % with 6 to 10 years, and 13.5 % with >15 years. Lastly, about 59.1 % of respondents hold mid-level HR management positions, 30.2 % hold general HR positions, and 8.9 % hold higher- or executive-level positions (see Appendix A1).

3.6. Common method variance test

To check for common method bias, this study first conducted the Kaiser–Meyer–Olkin (KMO) sampling adequacy test, which returned a value of 0.891, and Bartlett's test of sampling sphericity ($\chi^2 = 3856.013$, df = 300, $p < 0.05$). KMO tests are favored because they help identify CMV and determine whether the data are suitable for multivariate analysis. This test addresses CMV to ensure internal validity and to ensure that observed associations reflect actual constructs rather than measurement artifacts. These results indicate that DL, AIHRM, MI, TI, and SP are highly intercorrelated and are suitable for factor analysis. Additionally, common method variance (CMV) was assessed using Harman's single-factor test [115]. Harman's single-factor test yielded a value of 33.274 %, which is less than the 50 % threshold; this suggests that no single factor dominates the dataset and that there is no serious

concern about bias [116]. Furthermore, the principal components analysis of the variables revealed that six factors load on their respective columns in the "rotated component matrix," suggesting that the data are valid for further confirmatory analysis (see Appendix A2). Additionally, the study tested for multicollinearity using VIF (Table 1), with all values falling between 0 and 10, which are acceptable ranges [117]. Furthermore, a VIF range of 1 to 3 indicates no multicollinearity [118,119]; therefore, this model does not exhibit multicollinearity.

4. Results

4.1. Measurement and structural model

First, measurement validity was tested, and the results indicated that $\chi 2 = 463.210$, $\chi 2/df = 1.775$, GFI = 0.884, AGFI = 0.855, RMR = 0.036, RMSEA = 0.053, CFI = 0.945, TLI = 0.937, and IFI = 0.946 were within recommended ranges. According to the results, the GFI and AGFI are >0.8, indicating acceptable model fit [120,121]. Furthermore, if the value of RMSEA falls between 0.05 and 0.08, it indicates an acceptable model fit [122] (see Fig. 2); therefore, the proposed model meets the statistical fit requirements for the analysis and predictions. After testing the measurement model fit, convergent, and discriminant validity, we assessed the structural model fit using AMOS 24. The findings of the structural model fit revealed $\chi^2 = 463.967$, $\chi^2/df = 1.771$, GFI = 0.883, AGFI = 0.855, RMR = 0.036, RMSEA = 0.052, CFI = 0.945, TLI = 0.937, and IFI = 0.946. The structural model is deemed a good fit [120,121].

4.2. Reliability and validity test

Convergent validity was tested by calculating average variance extracted (AVE) and composite reliability (CR) values (Table 2). In calculating factor loadings and fitting the measurement model, MI4, MI4, T5, and SP6 were eliminated because their factor loadings were below 0.6 and did not contribute to the model fit (Fig. 2). The results of the convergent validity tests showed that CR >0.70, AVE >0.50, and Cronbach's alpha >0.70 [123,124]; therefore, we can infer that convergent validity is not problematic in this study. The results for the construct validity and reliability analysis are shown in Table 1 below. Construct and discriminant validity were calculated using Gaskination's StatWiki master validity tools. Additionally, we tested discriminant validity using Fornell and Larcker's [125] criterion. To evaluate discriminant validity, methods rely on the square roots of AVE values, which must be greater than the horizontal and vertical correlations [125]; however, Table 2 shows that all the constructions are significantly correlated with one another, and there is no discriminant validity issue in this model.

4.3. SEM path analysis

To assess the path-analysis results, this study has used 5000 bootstrap samples (J. F. Hair et al., 2009) to estimate 95 % confidence intervals. First, hypothesis H1a was supported, showing that DL has a substantial effect on AIHRM ($\beta = 0.464$, $p < 0.05$). Similarly, AIHRM has a substantial effect on SP ($\beta = 0.106$, $p < 0.05$), and DL has a substantial positive effect on SP ($\beta = 0.439$, $p < 0.05$); therefore, H1a, H1b, and H1c are accepted. Additionally, the indirect effect of DL —> AIHRM —> SP was significant, indicating that AIHRM partially mediates the link between DL and SP.

Second, the results showed that DL has a substantial positive impact on MI (β = 0.341, $p < .05$), and that MI subsequently has a significant positive effect on SP (β = 0.233, $p < 0.05$). Therefore, hypotheses H2a and H2b are accepted. Additionally, the indirect effect of DL —> MI —> SP is significant ($\beta = 0.079$, $p < 0.05$), indicating that MI significantly mediates the interlink between DL and SP. Third, the direct association between DL and TI is found statistically insignificant ($\beta = 0.112$, $p > 0.05$), as is the interlinkage between TI and SP ($\beta = –0.048$, $p > 0.05$). Moreover, the indirect effect of DL —>TI —> SP is also insignificant ($\beta = 0.079$, $p < 0.05$). Therefore, hypotheses H3a, H3b, and H3 are rejected.

Fourth, results discovered that AIHRM has a substantial impact on MI (H4a: $\beta = 0.317$, $p < 0.05$), while its effect on TI is not statistically significant (H5a: $\beta = 0.047$, $p > 0.05$). Along with the findings for H2b and H2c, the indirect relationship of AIHRM —> MI —> SP is significant (β = 0.074, $p < 0.05$), indicating that MI partially mediates the link between AIHRM and SP. In contrast, the indirect relationship AIHRM —> TI —> SP (β = –0.002, $p > 0.05$) is insignificant, suggesting that TI does not mediate between AIHRM and SP; therefore, hypotheses H5a and H5 are rejected. This study also considered firm size and firm type as contextual moderators (control variables). The results show that firm size has an insignificant positive effect ($\beta = 0.017$, $p < 0.05$), while industry types have an insignificant negative effect on SP ($\beta = –0.076$, $p < 0.05$). Fig. 3 and Table 2 summarize the direct and indirect effects of the hypothesized relationship in this study.

4.4. Necessary condition analysis (NCA)

An NCA was conducted to assess whether certain conditions are essential but not sufficient for achieving SP and AIHRM in emerging economies. As a supplementary approach to sufficiency-based methods such as SEM, NCA determines whether a predictor must be present at a minimum level for an event to occur [99]. Table 3 shows that the effect size of DL on SP is 0.234, demonstrating a medium-level strength of necessity, and that DL on AIHRM also shows a medium-level strength of necessity (effect size = 0.163), based on the threshold [99]. Moreover, the necessity of AIHRM, TI, and MI for SP is relatively lower, with effect sizes of 0.083, 0.079, and 0.186, respectively. These results explain that while these factors contribute to performance, DL emerges as a critical precondition for achieving both AIHRM and SP outcomes in emerging economies. Furthermore, the accuracy scores for all interlinks exceed 0.920, indicating a strong fit between the observed data and the theoretical necessity model. Meanwhile, condition inefficiency and outcome inefficiency scores are moderate for DL vs. SP (0.199 and 0.414) and MI vs. SP (0.286 and 0.479). This outcome reinforces that while necessary, these conditions are not always fully efficient, supporting the case for multifactor models in practice.

The bottleneck (Table 4) shows the minimum condition required to achieve a specific outcome. Such as attaining 100 % of SP, at least 80 % of DL necessary, and AIHRM adoption, at least 95 % of DL required.

Table 1
Construct validity and reliability analysis.

Constructs	CR	AVE	MSV	MaxR (H)	α	DL	AIHRM	MI	TI	SP	VIF
DL	0.803	0.506	0.539	0.810	0.802	**0.712**					1.245
AIHRM	0.923	0.600	0.273	0.927	0.927	.347**	**0.775**				1.370
MI	0.845	0.579	0.369	0.855	0.832	.421**	.468**	**0.761**			1.431
TI	0.836	0.563	0.017	0.864	0.834	.119*	.091	.021	**0.750**		1.024
SP	0.861	0.554	0.539	0.864	0.853	.618**	.432**	.540**	.018	**0.744**	-

Note(s): * = Correlation is significant at the 0.01 level (2-tailed). ** = Correlation is significant at the 0.05 level (2-tailed). Diagonal value (in bold) represents the square root of AVE. **α** = Cronbach's Alpha.

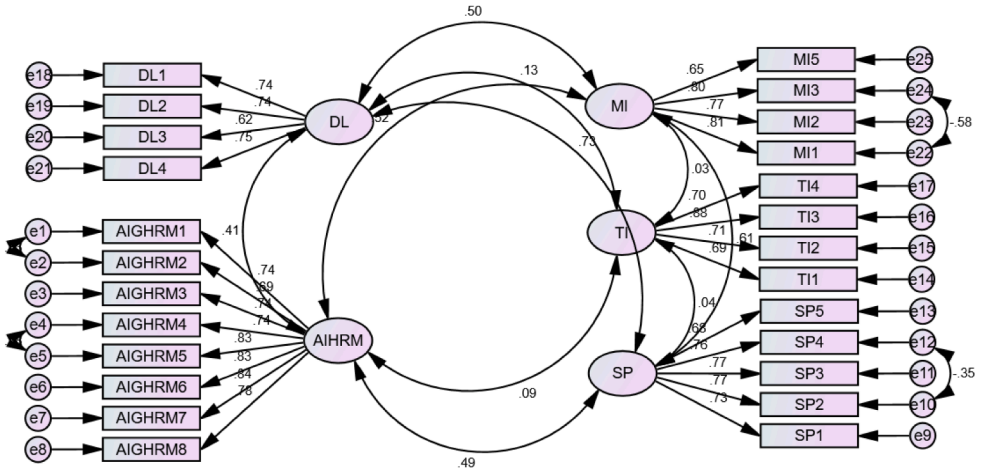

Fig. 2. Measurement model fit.

Table 2
Direct and indirect effect.

Hypothesis and relationships		*β*	Lower limit	Upper limit	*P*-Value	Comments
H1a	DL—>AIHRM	.464	.303	.623	.000	Accepted
H1b	AIHRM—>SP	.106	.035	.180	.005	Accepted
H1c	DL—>SP	.439	.326	.545	.000	Accepted
H1	DL—>AIHRM—> SP	.049	.017	.095	.003	Accepted
H2a	DL—>MI	.341	.214	.465	.000	Accepted
H2b	MI—>SP	.233	.116	.348	.001	Accepted
H2	DL—>MI—> SP	.079	.038	.137	.000	Accepted
H3a	DL—>TI	.112	−.038	.257	.150	Rejected
H3b	TI—>SP	−.048	−.124	.025	.198	Rejected
H3	DL—>TI—> SP	−.005	−.024	.002	.162	Rejected
H4a	AIHRM—>MI	.317	.234	.399	.000	Accepted
H5a	AIHRM—>TI	047	−.070	.164	.418	Rejected
H4	AIHRM—> MI—>SP	.074	.037	.120	.000	Accepted
H5	AIHRM—> TI—>SP	−.002	-0.016	.002	.274	Rejected

Note(s): DL= Digital leadership; AIHRM = Artificial intelligence in HRM; MI = Managerial innovation; TI = Technological innovation; SP = Sustainable performance.

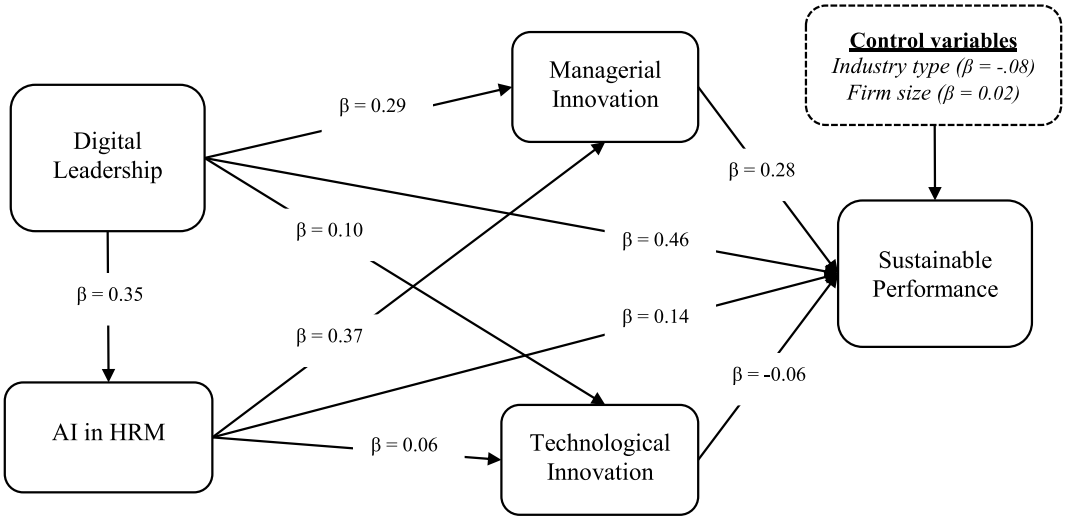

Fig. 3. The hypothesized model.

Similarly, to achieve 100 % of SP, the organization required at least 71.6 % MI and TI, and 62.7 % TI. These bottleneck percentages suggest that DL plays a foundational and constraining role in MI, TI, and performance. If DL is absent or weak, even a high level of AIHRM, MI, or TI would not be able to compensate and achieve the desired SP. Fig. 4 shows the NCA plot of the above relationships, analyzed in Python.

5. Discussions

This study explores the evolving role of DL in shaping AIHRM, MI, and TI innovation, which collectively contribute to SP in emerging economies. First, our findings confirm that DL has a positive impact on AIHRM, suggesting that its dynamic capabilities facilitate its adoption.

Table 3
NCA model effect summary.

Relations	Effects size	Accuracy	Condition Inefficiency	Outcome Inefficiency	Strength of Necessity
DL vs. SP	0.234	0.929	0.199	0.414	Medium
DL vs. AIHRM	0.163	0.982	0.041	0.660	Medium
AIHRM vs. SP	0.083	0.932	0.256	0.777	Small
MI vs. SP	0.186	0.943	0.286	0.479	Medium
TI vs. SP	0.079	0.946	0.377	0.745	Small

Table 4
Bottleneck table (%).

BI	DL vs. SP	DL vs. AIHRM	AIHRM vs. SP	MI vs. SP	TI vs. SP
0 %	NN	NN	NN	NN	NN
10 %	NN	NN	NN	NN	NN
20 %	NN	NN	NN	NN	NN
30 %	NN	NN	NN	NN	NN
40 %	NN	NN	NN	NN	NN
50 %	13.3	NN	NN	2.2	NN
60 %	26.7	10.0	NN	18.0	NN
70 %	40.0	40.0	NN	30.6	NN
80 %	53.3	66.7	6.7	43.2	14.7
90 %	66.7	96.7	41.3	59.0	38.7
100 %	80.0	95.0	73.3	71.6	62.7

DLs with strong digital skills and a transformative vision are more likely to simplify the complexities of advanced technologies, prioritize investment in them, and facilitate AI-oriented HR systems within organizations [76,126]. The integration of AIHRM systems holds immense potential to improve HR resource efficiency, promote diversity and inclusivity, and enhance employee well-being, thereby driving sustainable initiatives [127]. Additionally, AIHRM supports enhancing organizational sustainability, indicating that such tools facilitate the integration of AI techniques into existing business intelligence systems, enabling the assimilation, processing, and analysis of data to facilitate problem-solving and decision-making. These efforts lead to favorable HRM-specific operational, relational, and transformational outcomes connecting HR strategies with overarching business SP [34]. Furthermore, AIHRM entails integrating AI into HR practices to enhance efficiency, facilitate data-driven decision-making, and optimize talent management [128], which is crucial for SP in a digital environment, as it aligns with long-term economic, social, and environmental goals. In the present era of AI, organizations are continually seeking to improve strategic performance [129]. The NCA analysis also confirms that adopting AIHRM and achieving SP are contingent upon the presence of DL.

Second, as a critical mediator, DL positively influences MI, and MI, in turn, positively supports SP. Through digitally enabled leadership, organizations can restructure managerial processes and adopt innovative methods that enhance flexibility, responsiveness, and value creation, key components of SP [85,86]. Consistent with previous research, digital leaders often act as catalysts for innovation, promoting continuous learning and experimentation among teams [65]. As discussed, DL embodies dynamic capabilities to adapt to a rapidly changing technological environment by fostering a vision-driven and innovation-centric culture [3]. Moreover, the DL mindset cultivates an organizational environment conducive to continuous learning, experimentation, and innovative problem-solving, collectively referred to as MI [78].

Third, this study's results showed that DL has an insignificant impact on TI, thereby rejecting the hypothesized relationship. Similarly, TI does not mediate the interlink between DL and SP, nor between AIHRM and SP, highlighting the limited role of TI in enhancing SP within the context of Bangladesh. This outcome can be attributed to several challenges faced by firms, including inadequate technological infrastructure, a shortage of skilled workers, and insufficient managerial expertise to adopt and implement TIs. Additionally, organizations struggle to identify key drivers and strategically align their initiatives with industry demands [130]. There are some limitations to these incidents, notably limited research and development (R&D) facilities, venture capital, and industry-academic collaboration, which were previously highlighted by Crescenzi & Rodríguez-Pose [131]. Furthermore, many Bangladeshi firms remain at the early stages of technological adoption, focusing primarily on basic automation rather than strategic innovation research in university libraries [132]. Socioeconomic barriers and insufficient policy interventions further hinder the implementation of digitalization efforts [133]. Similarly, the NCA model also indicates that the necessity of TI for organizational sustainability is minimal (Effect size = 0.079), with a 62.7 % bottleneck required to achieve 100 SP.

Overall, the technological innovation progress in Bangladesh is unfavorable, with low levels of acceptance and application. To overcome these challenges, e-governance, and to ensure digital identity, Bangladesh Computer Council leads national e-gov programs to improve the country's ICT infrastructure, such as BanglaGovNet, Info-Sarker Phases II and III, Connected Bangladesh, and others, contributing to human resource development [134]. Additionally, the Bangladesh Association of Software and Information Services started local Hi-Tech Parks, a foreign university tech-transfer office for a joint PhD program, and the Commonwealth-SheTrades initiative with the UK for academic-scale spinouts [135]; however, the effects of this initiative may be delayed due to infrastructural constraints and limited R&D investment. In contrast, focusing on transforming Bangladesh into a smart goal lacks sufficient knowledge, investment, and research.

Fourth, the mediation analysis reveals that MI plays a significant mediating role in explaining DL and AIHRM in terms of sustainable outcomes. This finding supports the view that MI, which drives innovation in managerial processes such as adaptive decision-making, agile team structures, and technology-driven problem-solving, is essential for leveraging DL and breakthroughs in AI [1]. Additionally, findings reveal that the paths involving TI are statistically non-significant which identifies that Bangladesh as an emerging economies, here TI often functions as a lagging capability, constrained by infrastructural limitations, skill shortages, and institutional rigidity [136,137] Therefore, the performance impact of TI may not materialize immediately, even when digital leadership and AI systems are present. On the other hand, MI represents a proximal mechanism through which DL translates into sustainable performance. Changes in managerial practices, decision-making processes, coordination, and HR governance can be implemented more rapidly and yield immediate organizational benefits [79]. Furthermore, based on DCV perspective it seems that DL first enables MI, which then lays the organizational foundation for subsequent TI. To check it we have also gone through sequential logical testing of DL—>MI —> TI —> SP ($\beta = 0.001$, $p > 0.05$) is insignificant. It infers that TI in Bangladesh falls lagging capability for ensuring sustainable organizational performance right now. In future, this may create new logical ways to find the ensuring position of TI development.

Additionally, AI-enhanced HRM enhances MI by offering insights that facilitate innovative management techniques, including data-driven decision-making, adaptive leadership styles, and improved employee engagement tactics [138]. Interetingly, the NCA further supports this viewpoint by showing that achieving SP requires a medium level of MI. These findings demonstrate that AIHRM enhances recruitment, training, and performance management by automating tedious, routine tasks, freeing HR managers to focus on strategic initiatives [139]. Therefore, integrating DL and AIHRM makes MI a key factor in improving organizational HR operations and sustainability.

In Bangladesh, the government's "Digital Bangladesh" agenda and recommendations for integrating ICT into policy to develop, upgrade, and use a comprehensive national database for human resources for health [140] focus on how institutional mandates drive HR digitalization, but regulatory and implementation hurdles remain. Additionally,

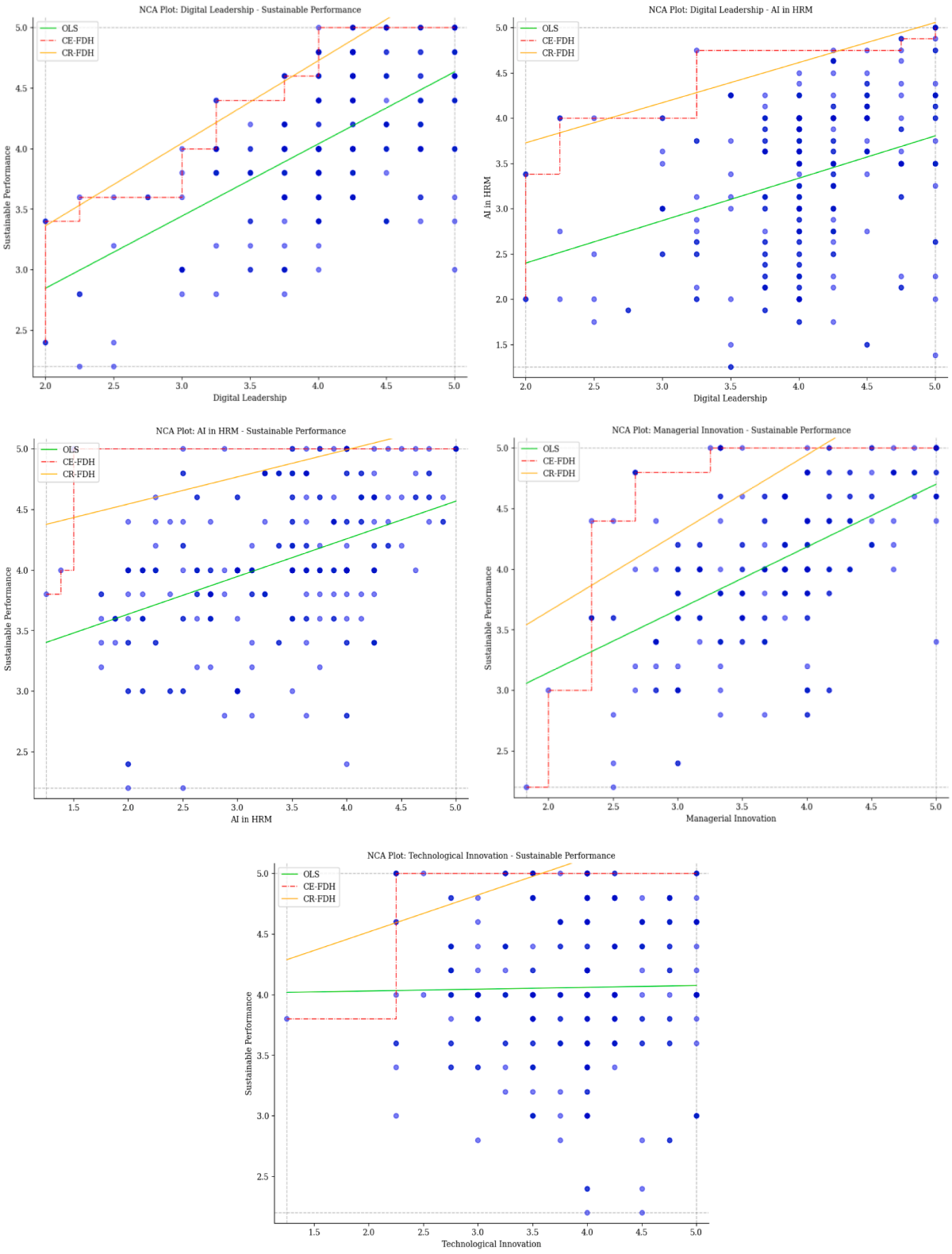

Fig. 4. Data plotting of NCA analysis.

Bangladesh's aspiration for a digital economy remains far off, constrained by infrastructure and access limitations [141]; therefore, the nation depends on DL for innovation and organizational sustainability. Furthermore, the culture of entrepreneurship is predominantly risk-averse, and family-business dynamics [142] indicate that deep-rooted cultural norms and institutional constraints constrain sustainable entrepreneurship in Bangladesh. Here, high and low power distance culture in group collectivism is evidenced in Bangladesh SMEs [143]; while Sultana [144] mentioned performance appraisal practice in Bangladesh is strongly influenced by cultural factors (e.g., collectivism, hierarchical relations), implying that AIHRM practices may unfold differently than in Western contexts.

TI in Bangladesh evolves through governmental support and university-industry collaboration, e.g., the information communication technology ministry and the university grant commission exclusively support IT infrastructure development, training and development, improved R&D, and research through numerous projects, encouraging more public–private partnership (PPPs) for overcoming resource and knowledge limitations and enhancing sustainability. Moreover, the policy should be implemented to foster a positive organizational culture for innovation [145] and knowledge management, as well as IT absorptive capabilities, for corporate sustainability [146]. Finally, this research framework emphasizes the need for a comprehensive approach to integrating DL into organizational subsystems to facilitate AIHRM adoption and address both managerial and TI. To achieve the expected success, firms need to adopt AIHRM and MI for effective management and organizational SP in developing economies. These insights are vital for organizations in emerging economies seeking to leverage AI and DL in HRM to achieve sustainable competitive advantage.

5.1. Theoretical and practical implications

This study's results have theoretical (STS and DCV) and practical implications for organizational leaders, HR professionals, and policymakers, particularly in emerging economies experiencing a growing infusion of digital technologies into workplace practices. The results suggest that DL plays a crucial role in enhancing AIHRM and innovation, as well as accelerating organizational sustainability. Therefore, organizations must focus on deploying DL to apply digital skills and dynamic capabilities, ensuring constant, smooth interaction with AIHRM and TI to ensure SP. The NCA analysis results confirm that, for ensuring the smooth implementation of AIHRM and SP, DL is a necessary precondition for the application of STS.

This theoretical contribution aligns with and expands upon the emerging discourse that technology must be human-centered to yield long-term sustainable benefits [128,147]. This study makes a unique theoretical contribution to STS and DCV by bridging the managerial, technological, strategic, and human domains of HRM transformation for SP. This contribution is particularly relevant in developing, labor-intensive contexts like Bangladesh, where AI adoption is likely to evoke employee anxiety and resistance, reflected as turnover intention [20], while investment in technology adoption is limited. The findings reveal that TI is not yet at a satisfactory level. NCA analysis further confirms that TI exerts only a weak influence on ensuring SP. This dual approach (SEM and NCA) contributes grounded STS and DCV theories to the growing body of digital transformation literature and sets a foundation, establishing that STS supports DCV in the context of emerging economies. Though the ICT ministry is investing in ICT development, the funds are insufficient. In that case, the government must increase its budget for education and technology development.

The findings advance the literature by demonstrating how the dynamic capabilities of DL enhance organizational success through its strategic vision, adaptability, and technological competence, and by helping organizations sense, seize, and reconfigure opportunities in dynamic market environments [54,60]. Moreover, this study contributes to the literature by demonstrating that DL substantially influences AIHRM, serving as a strategic antecedent that guides the successful implementation of AI in organizational management. Furthermore, by integrating MI and TI as dual mediators, our study addresses the "how" and "why" behind the connection between DL or AIHRM and SP. MI reflects the organization's strategic decision-making capability [15] through its organizational structure and management processes, while TI embodies the organization's digital adoption and collaboration capabilities that support organizational success [50]. Additionally, MI can transform managerial procedures by introducing AI-assisted decision--making and data-driven and innovation-oriented HR policies. Together, these practices enhance efficiency and responsiveness, ultimately improving SP. The application of STS and DCV to ensure organizational sustainable performance in emerging economies is an innovative contribution.

AI systems are being increasingly integrated into core HR functions, such as recruitment, performance appraisal, and talent development [6, 34]; thus, organizational leaders and policymakers must ensure the ethical and inclusive deployment of AI, supported by a clear governance model that protects employee data, ensures fairness, and promotes accountability [148]. Additionally, to enhance social studies, the government should adopt AI governance frameworks, ensure transparency, promote algorithmic fairness, and establish data privacy standards. HR leaders in public and private organizations need to establish AI ethics committees, conduct regular algorithm audits, and implement mechanisms for employee consent to ensure fair and responsible AI use. This study also recommends that HR managers create employee-centered AI systems that focus on efficiency, as well as motivation, fairness, and personal growth. Leaders must also embed sustainability values into their strategic vision, ensuring that AI adoption contributes to long-term environmental, social, and economic goals [127].

Overall, in emerging economies, organizations are increasingly recognizing the value of using DL and AIHRM as a strategic asset to optimize HR operations and achieve SP goals. In particular, DL helps leaders combine technological adaptability, strategic vision, and innovation, all of which are essential to implementing AIHRM systems. To facilitate easier transitions to AIHRM, DL cultivates a culture of learning agility, openness to digital experimentation, and alignment between human and AI capabilities. DL fosters a culture of learning agility, openness to digital innovation, and collaboration between human and AI capabilities to make the shift to AIHRM easier. To improve the use of DL capabilities, an organization can start training in digital leadership, integrate HR analytics, and align AIHRM with other systems for better results and long-term success. Finally, organizations should leverage the collaboration between DL and AIHRM to develop a resilient, innovative workforce that can thrive in uncertain, dynamic environments. Managers are encouraged to view DT not merely as a technological upgrade but as a strategic shift in culture, leadership, and human capability development.

5.2. Limitations and future research scope

This study represents a successful empirical investigation into the integrated role of DL and AIHRM in shaping SP, with MI and TI as mediators, in emerging economies; however, we must acknowledge some limitations. First, this study attempts to empirically analyze cross-sectional data from a 281-sample dataset due to resource and time constraints, and the cross-sectional approach is practical for the exploratory stage. Future research should aim to include bigger sample sizes, and longitudinal studies would strengthen causal inference and external validity. Furthermore, longitudinal studies could capture the temporal evolution of DL and AIHRM effects on SP, particularly as digital ecosystems mature, allowing observation of dynamic adjustments over time. Second, this study was conducted based on STS and RBV. DCV theory is sometimes criticized for limited contextual sensitivity and prescriptive ambiguity [149]. For example, DCV fails to adequately elucidate the precise contextual settings under which dynamic skills, such as MI or AIHRM, produce optimal performance benefits. Future research could integrate institutional theory to explain how external environments, cultures, or economies influence these linkages. Moreover, it could be tested using the ability, motivation, and opportunity (AMO) framework and AI and human psychology theories.

Third, this study considers DL as an independent construct, with AIHRM, MI, and TI as mediators, and SP as the predictor. As per finding DL—>MI —> TI —> SP is insignificant but from a DCV perspective, this may open temporal sequencing logic. Such as DL first enables MI, which then lays the organizational foundation for subsequent MI. However, to find the temporal sequencing logic need time-based explanation and longitudinal research. Additionally, as DCV emphasizes capability

development as an evolutionary process, and clarifies that the non-significant TI paths reflect a theoretical boundary condition rather than a measurement limitation or purely contextual effect. Future studies could incorporate additional relevant constructs, such as innovation mindset, organizational culture, and work-life balance, as mediators. Such studies can consider pressure groups, technological dynamism, and ethical considerations as potential moderators. Finally, Bangladesh is an emerging economy that has considered as a study field, where complete digitalization has not yet been achieved, and the availability of expert digital leaders and the application of AIHRM are in their preliminary stages. Therefore, the generalizability of findings may still be limited; however, conducting a similar study in developed countries and a cross-cultural study may yield more established results.

6. Conclusions

As industries gradually transition toward Industry 5.0, effective collaboration between humans and machines is key to maximum output for the organizations. Currently, to achieve organizational goals, DL and AIHRM can provide analytical support to identify high-potential employees, assess skill gaps, and personalize career development plans [48], thereby enhancing overall efficiency. DL makes a substantial contribution to enhancing organizational performance, while AIHRM has also been shown to improve organizational performance through AIHRM and MI. Furthermore, DL, AIHRM, MI, and TI were found to play necessary roles in achieving SP in emerging economies, as demonstrated through NCA. This study presents a robust and integrative model that highlights the pivotal role of DL and AI in reshaping HRM practices to achieve SP, particularly in the rapidly evolving digital landscapes of emerging economies. Ultimately, DL is instrumental in fostering a collaborative culture where AI tools are viewed as augmenting rather than replacing human capabilities. Such human–machine integration is vital for advancing long-term organizational sustainability.

Ethical clarance

In this research, ethical standards were maintained following Helsinki declarations. To attain the ethical approval, before starting the data collection, the researchers of this study applied attaching the questionnaire, sampling details, and all other ethical requirements to the "Research Cell of the University of Barishal, Bangladesh" the local authority for the ethical clearance certificate. After assessing all ethical concerns and guidelines, the authority approved and provided the certificate (ref no: FSB-EC-57/2024), for the further survey process.

Declaration on using generative AI

The authors used generative AI tools (ChatGPT) only for language editing and grammatical corrections. All intellectual content, analysis, and interpretations were produced solely by the authors. After using this AI tool/service, the author(s) reviewed and edited the content as needed, taking full responsibility for the publication's content.

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CRediT authorship contribution statement

Md. Alamgir Mollah: Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Data curation, Conceptualization. **Mohammad Bin Amin:** Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Md. Mahafujur Rahman:** Visualization, Validation, Resources, Investigation, Data curation. **K.M. Anwarul Islam:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources. **Nitai Chandra Debnath:** Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Gouranga Chandra Debnath:** Writing – review & editing, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Judit Oláh:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.teler.2026.100303.

Appendices

Table A.1, Table A.2, Table A.3.

Table A.1
Demographic information.

Entity	Category	Frequency	Percentage
Organization size	Small (Fewer than 49 employees)	42	14.9
	Medium (50 to 99 employees)	38	13.5
	Large (>100 employees)	201	71.5
Organization age (Years)	<5	42	14.9
	5 to10	36	12.8
	11 to15	22	7.8
	16 to 20	21	7.5
	>20	160	56.9
Respondents age (Years)	Below 20	2	0.7
	20 ~ 29	120	42.7

(continued on next page)

Table A.1 (*continued*)

Entity	Category	Frequency	Percentage
	30 ~ 39	137	48.8
	40 ~ 49	17	6.0
	50 ~59	4	1.4
	>60	1	0.4
Employees experiences (Years)	<1	38	13.5
	1 to 5	147	52.3
	6 to10	80	28.5
	11 to 15	16	5.7
	>15	38	13.5
Employees' position	General HR staff	85	30.2
	Middle-level HR management	166	59.1
	High-level HR management	13	4.6
	CEO/Owner	12	4.3
	Others	5	1.8
Total		281	100 %

Table A.2
Factor analysis.

	Component				
	1	2	3	4	5
DL1					.795
DL2					.740
DL3					.675
DL4					.677
AIGHRM1	.770				
AIGHRM2	.736				
AIGHRM3	.777				
AIGHRM4	.777				
AIGHRM5	.809				
AIGHRM6	.820				
AIGHRM7	.805				
AIGHRM8	.755				
TI1			.777		
TI2			.807		
TI3			.873		
TI4			.791		
MI1				.700	
MI2				.844	
MI3				.710	
MI5				.680	
SP1		.735			
SP2		.704			
SP3		.773			
SP4		.618			
SP5		.709			

Table A.3
Questionnaire of the researh.

Digital Leadership	Source(s)
1. Leaders are technically capable.	Niu et al. [32]
2. Capable to assist digital governance.	
3. Digitalization is an important factor for staying competitive	
4. Cable of evaluating the level of digital capabilities for digital transformation.	
Artificial Intelligence in HRM	
1. Applied AI system for the selection process.	Mehrabad and Brojeny [100]
2. AI used for searching candidate data from résumés.	Prikshat et al. [34]
3. We use AI in training programs to improve decision-making in crisis situations.	Cesta et al. [101]
4. Take AI's support for re-skilling and upskilling.	Gratton [102]
5. Use AI for career planning and performance and management.	Prikshat et al [34].
6. We use AI to help plan jobs and manage our workforce.	Huang et al. [103]
7. We use AI as a smart tool to evaluate different jobs.	Lawler and Elliot [104]
8. We use AI to predict which employees might leave the company.	Fan et al. [150]; Li et al. [151]
Managerial Innovation	
1. Organizational rules and procedures within our frequently renewed.	Vaccaro et al. [85]; Zhang et al. [51]
2. Employees' tasks and functions are frequently checked.	
3. Frequently implements new management structures.	

(*continued on next page*)

Table A.3 (*continued*)

Digital Leadership	Source(s)
4. Compensation policy has been changed in the last three years.	
5. Organizational intra-and inter-departmental communication frequently changed.	
6. Continuously changing elements of the administrative structure	
Technological Innovation	
1. We use the newest technology to create new products, services, or processes.	Prajogo and Sohal [105]; Singh and Smith [106]
2. We develop new products, services, or processes quickly and can compete with others.	
3. We use modern and updated technology in our work.	
4. We quickly start using the latest technologies in our processes.	
5. Our company often changes its methods, tools, and technology to keep up.	
Sustainable Performance	
1. We are providing high-quality services.	Kordab et al. [107]
2. We are cable of low-cost production and service operation.	
3. We are capable of performing effective delivery service.	
4. We adapt rapidly with unexpected changes.	
5. We can contest properly in the existing market.	
6. It seems our organization are profitable in the industry.	

Data availability

Data will be made available on request.

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