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Examining the Role of AI-Augmented HRM for Sustainable Performance: Key Determinants for Digital Culture and Organizational Strategy

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Abstract: In the wave of digitalization, organizations are increasingly focused on whether to prioritize digital culture or organizational strategy for the use of artificial intelligence (AI); there are mixed opinions, particularly when AI-augmented HRM draws attention as a tool for achieving sustainable organizational performance (SOP) in developing countries. This study aims to explore the influence of digital culture and organizational strategy on AI-augmented HRM and SOP, focusing on the mediating role of AI-augmented HRM in these relationships. To investigate the hypothesized relationships, 219 sample data were gathered from employees associated with HRM-oriented activities in Bangladesh, and SPSS 23 and AMOS software were used to test the SEM model. The results proved that digital culture has an insignificant effect and organizational strategy has a significant effect on AI-augmented HRM, and AI-augmented HRM has a substantial effect on SOP and partially mediates the relationship between organizational strategy and SOP. Based on the results, we infer that the successful implementation of AI-augmented HRM can lead to organizational sustainability in developing countries, where organizational strategy plays a pivotal role rather than digital culture. This research incorporates the resource-based view (RBV) and dynamic capabilities theories, which are crucial for the groundbreaking development of the research model. The results suggest that managers and responsible authorities should prioritize organizational strategy over digital culture when implementing AI-augmented HRM systems to ensure sustainability in developing countries. However, in the long run, organizations also need to concentrate on generating digitally favorable environments.

Keywords: digital culture; organizational strategy; AI-augmented HRM; sustainable organizational performance

1. Introduction

In the era of digitalization and digital transformation, the emergence of generative and other AI has gained momentum for its utilization in academia, business, and social organizations. Additionally, in an era of technological turbulence and volatility, uncertainty, complexity, and ambiguity (VUCA) environments, organizations face intrinsic and extrinsic pressure to adopt new advanced technologies and integrate them in the strategic framework, for instance, using AI in supply chains, operations, marketing, and HRM, for organizational management. Additionally, after the COVID-19 pandemic, generative AI programs, like Open AI, Google Bard, and Gemini AI, emerged and gained drastic popularity and spread the culture of using AI in business operations and management. According to Bley et al. [1], the use of AI has increased by 270% in the last four years, while Jangbahadur et al. [2] forecast that investments in AI will sharply rise by 24.5% in 2021, increasing from USD 85.3 billion to more than USD 204 billion by 2025. It is also observed that AI has been applied in different aspects of activities like improving service and productivity, minimizing cost, enhancing operations, maintaining customer loyalty, and employee management [2]. In fact, the application of AI in HRM started in the last decade, and in this era, its utilization has proliferated by enhancing resources, performance, decision-making, and problem solving in organizations [3]. Now, the following question arises: *"Is the use of AI-augmented HRM and sustainable organizational performance dependent on digital culture or strategy?"* In general, "DC is aspiring to foster a learning technological environment, develop teamwork, and together nurture culture to adopt profound change due to the digital transformation" [4,5]. "Strategy entails redesigning the entire business model to take advantage of digital opportunities" [6]. Therefore, digital culture focuses on teamwork and learning technological environments to adapt to digital changes, while strategy focuses on grasping opportunities arising from these digital evaluations. In addition, the term "AI-augmented HRM" describes how AI technologies are incorporated into different HR tasks to improve their efficacy, precision, and efficiency [2]. In essence, AI-augmented HRM involves utilizing AI to support HRM-related activities, thereby eliminating unconscious bias.

AI plays a significant role in generating numerous opportunities. In today's digital world, human resource management (HRM) and information technology (IT) have converged to proliferate work efficiency, enhance service delivery, standardize processes, empower managers, and transform HR activities [7,8]. However, a variety of factors contribute to the integration of IT and HRM, resulting in AI-augmented HRM, such as technological evolution, social media, organizational culture, competitive pressure, the pursuit of competitive advantages, strategic choices for sustainability, and more. According to Thite [9], HR is regarded as a "key transformation player" in supporting technology adoption and lowering change-resistant feelings. In order to effectively use AI and intelligence-based technologies in organizations, there is ongoing debate in the literature on AI-augmented HRM concerning the characteristics of employees' behaviors that should be taken into consideration. We contend that, to attain favorable results, the impact of the social–technological context can be further strengthened. Examples of this include an adaptable organizational structure, appropriate training, managing fear and change, and increasing employees' skills. Therefore, in the current environment of increasing digitization, we expect the adoption of modern technical advancements to develop more digital and cognitive HRM competencies, thereby improving overall organizational performance. Through the introduction of e-recruitment, e-training, and e-competence management functions, the transformation of HR technologies has significantly influenced HRM processes [10]. In a previous study, it was found that AI-enabled HRM improved employee performance and employee engagement had a mediating effect [2]. In a study conducted in Singapore, it was found that leadership or organization environment have a positive effect on HRM [11] and work culture has an has an effect on HRM [12]. Scholars argue that using AI to enhance human capabilities rather than to replace them maximizes organizational benefits, as both AI and people are capable of achieving high levels of performance [13]. Through AI-augmented processes, we argue that AI-supported HRM generates favorable outcomes and contributes to organizational sustainability.

Though research on AI-HRM is still in its early stages, a rising volume of work claims that recent developments in automation technologies offer tremendous advantages for HRM [14,15]. Furthermore, organizations, both local and multinational enterprises (MNEs), have realized the benefits of AI-based tools and techniques to improve job performance, HR cost-effectiveness, employee retention, commitment, engagement [16], productivity [17], and other costs associated with HR [18]; other benefits include effective decision-making [19] and reduced HR-related and other operational costs [20]. Additionally, AI-based tools can help with recruitment, selection, evaluation, and interviewing the best candidates [20,21]. Additionally, they can assess the effectiveness of employee training [22] and identify new job profiles through Industry 4.0 advertisements [23]. A recent study found that AI-augmented HRM related to planning and development, recruiting and selection, training and development, compensation and benefit, and performance management has a positive effect on SOP, and employee engagement has a mediating effect; this underscores the significance of AI applications in HRM as a strategic approach for achieving sustainable competitive advantages [15]. However, the study did not address factors such as culture or strategy and their impact on SOP.

Furthermore, Wang [24] has shown that strategic orientation plays a crucial role in standard operating procedures. On the other hand, Budhwar et al. [3] mentioned that in the future, culture and strategies need to be adopted for AI-driven HRM functions, while Chowdhury et al. [25] suggested that organizational culture can be explored in a future study with AI systems. However, they have not addressed the role of AI-augmented HRM in mediating the relationship between strategy and SOP. Also, AI applications can be explored in different fields, such as marketing, supply chains, accounting, hospitality, and education, highlighting the need for empirical studies [15]. On the other hand, Muzaffar et al. [26] mentioned that DC and digitalization of HRM are interconnected, but theoretical analysis, empirical tests, and case studies should be conducted to examine the effect of digital culture on the digitalization of HRM. Similarly, Srisathan et al. [27] discovered a positive impact of organizational culture on SOP, but they did not address the role of AI-augmented HRM in mediating the relationship between DC and SOP. This study aims to address the previous research gap by empirically testing and determining the impact of digital culture and organizational strategy on AI-augmented HRM and SOP in the context of Bangladesh. While the findings are specific to this context, they may offer valuable insights for understanding similar trends in other developing countries. To bridge the gap in the literature, this study proposes a robust model that incorporates digital culture, organizational strategy, AI-augmented HRM, and SOP. This study aims to answer the following research questions:

RQ1. What factors—digital culture or organizational strategy—play a pivotal role in implementing AI-augmented HRM and SOP in developing countries?

RQ2. Can AI-augmented HRM act as a mediator between DC and SOP, as well as OS and SOP?

This research has applied the popular structural equation modeling (SEM) approach to analyze the research model with the RBV and dynamic capabilities view. Accordingly, research at the intersection of HRM and AI takes on a more interdisciplinary nature [28]. In the literature on AI-HRM, however, there is still insufficient knowledge on how AI and related technologies can provide solutions for efficient HRM and sub-functional areas, as well as how HRM functions enabled by AI connect to other operational tasks to improve outcomes for their organizations [29]. A review of automation technologies in HRM indicates that little is known about how employees, their productivity, and the overall performance of the organization are impacted by AI-enabled HRM operations [16]. DC and OS work together for inaugurating AI-augmented HRM in organizations for smooth HRM management based on the organization's culture and strategic needs. We have observed that due to high costs, a lack of leadership willingness, and the aversion of other organizations, most organizations' AI-augmented HRM strategies are in the early stages. Thereafter, it is essential to demonstrate how AI solutions with an HR focus enhance positive results while lowering negative effects through integration with digital culture and organizational strategy. On the other hand, while the literature currently available on AI-enabled HRM presents positive results, some authors believe that it is important to consider the drawbacks of these innovative tools for both employers and employees [30]. Therefore, it is crucial to prioritize organizational culture and strategic goals when implementing AI-augmented HRM to ensure organizational sustainability. Finally, this study has implications for understanding the importance of OS and DC for propelling AI-augmented HRM. Contextual factors, including linguistic, cultural, and competitor factors, can be used to inform decision-making about AI applications to minimize any biases, enhance efficiency, and sustain competitive advantages.

2. Literature Review and Hypothesis

2.1. Digital Culture

The concept of culture is discussed in Radcliffe-Brown [31] from an anthropological perspective, where it is stated that a group of people or society's practices and beliefs are considered the fundamentals of the social structure. Generally, culture is associated with the sharing of values and beliefs [32]. As digitalization progresses, DC emerges, which is associated with the digital revolution. This perspective views computers as thinking machines that drive the universal use of computer science and digital information in the arts and humanities, leading to the digital convergence of media [33]. In contrast to OS, DC emphasizes the utilization of technology to cultivate values, beliefs, and habits. Also, DC aims to cultivate a technologically advanced learning environment, enhance collaboration, and collectively promote a culture conducive to significant transformation as a result of digital transformation [4,5]. Here, DC focuses on adopting AI in HRM to keep pace with the advancements and stay competitive in the market.

2.2. Organizational Strategy

In the digital age, strategies are mostly focused on the intersections of information systems and the strategic management of the top management for investment in IT, because the implementation of IT firms' strategies are needed for the governance of the organizations [34]. Strategy may be "described as a statement of the vital missions of an organization, the goals that must be attained, and the principal ways in which the resources available are to be used" [35]. According to the digital perspective, strategy entails redesigning the entire business model to take advantage of digital opportunities [6]. In fact, strategy focuses on the adaptation of the organization based on organizational shifts, technological changes, and the business environment [36]. This study's strategy focuses on the adoption of AI in HRM for sustainable organizational performance.

2.3. AI-Augmented HRM

AI is a wide class of advanced technologies used for computer and internet-based systems to perform work that, in general, needs human awareness, including decision-making [3,37]. AI has completely changed the talent acquisition process by delivering predicted insights and automating repetitive processes. AI systems are capable of effectively screening resumes, matching job prospects with requirements, and even forecasting a candidate's likelihood of succeeding in that position. Upadhyay and Khandelwal [38] asserted that by more precisely matching applicants to job opportunities, AI techniques improve the overall quality of recruits while additionally cutting down on the amount of time and bias associated with the recruiting process. AI-augmented analytics technologies evaluate personnel data to estimate turnover risks and determine employee engagement levels. According to Gamage [39], AI systems are capable of evaluating elements like workload, job satisfaction, and chances for personal growth, giving HR managers the ability to act proactively to increase employee retention. When AI is used for employee selection, sorting resumes, decision-making, employee training, career planning, job design, workforce planning, job evaluation, and turnover forecasting, this is referred to as AI-augmented HRM. Also "AI-augmented Human Resource Management" refers to the incorporation of AI technologies into various HR tasks to enhance their efficacy, precision, and efficiency, despite the lack of a specific definition for AI-enabled HRM [2]. This cutting-edge method supports and enhances HR tasks like hiring, employee engagement, performance management, and learning and development by utilizing machine learning, natural language processing (NLP), predictive analytics, and other AI capabilities. In this perspective, Binns [40] highlighted that in order to guarantee equitable and moral AI applications in HRM, businesses need to put strong data protection mechanisms in place and actively seek to minimize biases. Finally, AI-augmented HRM in organizational management provides better management of HRM systems with the help of AI, which positively supports SOP in an unpredictable and digitally volatile environment.

2.4. Theoretical Background

In the era of evolving AI technology, organizations face challenges in adjusting to the volatility, uncertainty, complexity, and ambiguity (VUCA) environment [41] and in integrating, building, and reconfiguring their internal and external competencies to adapt to dynamic environments. This research focuses on whether DC should take priority in fostering AI-augmented HRM and organizational sustainability. This research has been conducted based on two theoretical perspectives: one is a resource-based view (RBV), including digital culture, organizational strategy, and sustainable organizational performance, and the other is a dynamic capabilities view (DCV), which is specifically related to AI-augmented HRM.

Firstly, DC and OS serve as competitive resources for the organizations for enhancing other resources, like improving performance, effectiveness, and sustainability. As we know, the RBV developed by Barney enhances value, which is rare and inimitable [42]. In a previous study, it was found that culture enhances value [43], culture as a strategic resource [44] is supportive for enhancing competitive advantages [45], and culture enhances organizational performance [46]. Further, manufacturing strategy works as a resource [47], where firm strategies are developed for achieving competitive advantages [48,49], and this study focused on SOP, which is a resource for the organization. Thus, DC and OS have emerged as valuable organizational tools for effectively leveraging resources for organizational suitability.

Secondly, the theory of dynamic capabilities is defined as "the potential of the organization to reconfigure, integrate, and coordinate internal and external skills to deal with rapid turbulence in commercial environments" [50,51]. In fact, AI-augmented HRM propels dynamic capabilities by supporting AI-based data analytics and rapid decision-making, which helps organizations adjust to changes, increase competitiveness, and improve organizational sustainability. Along with this, AI-augmented HRM enhances dynamic capabilities, permitting organizations to create and transform organizational HRM-related capabilities, which ultimately provides unique competitive advantages for the organizations. In addition, AI applications in HRM support the transformation of the management of people's work environments [52], while the integration of AI in HRM ensures competitive advantages by integrating organizational core competencies, leading to efficient process management, efficient decision-making, and increases in employee satisfaction [53]. In sum, DC, OS, and AI-augmented HRM collectively enhance SOP. So forth, integrating the RBV and DCV can work for SOP in developing countries.

2.5. Effect of Digital Culture on AI-Augmented HRM and Sustainable Organizational Performance

The 21st century is the age of the digitalization of communication, in which technology is identified with society and the new media network from the social morphology is used to revolutionize the cultural process [54]. Digital culture and AI are playing pivotal roles to change HRM and SOP. Leveraging AI for HRM requires a strong understanding of digital culture, which is defined as the widespread integration of digital technology into corporate practices, attitudes, and behaviors. DC culture is closely related to technology, data, and amiable novelty, agility, and creativity in the digital environment of the organizations [55]. Based on a previous study, DC encourages personnel to actively welcome new technologies, promotes experimentation [55,56], supports the rapidly changing digital environment for collaborative knowledge sharing, and emphasizes learning and continuous improvements [57] for organizational sustainability. Organizational operations and culture have been profoundly changed by the rapid growth of digital technology. Organizations with a strong digital culture are more likely to adopt and implement AI technologies in HRM processes such as employee engagement, performance management, and recruiting [58]. There is a lack of research related to DC and AIHRM. As per theoretical assumptions, Muzaffar et al. [26] explain that culture is associated with HRM, and the review by Prikshat et al. [15] mentions that AI integration in HRM is receiving much traction and surging up, which encourages empirical tests of DC and AI-augmented HRM.

Moreover, augmented by AI, HRM improves talent management and hiring substantially, which are the keys to organizational competitiveness and sustainability. In order to find candidates that are the greatest match for organizational jobs, AI algorithms can evaluate vast amounts of applicant data; this improves hiring quality and shortens the hiring process [59]. AI-augmented HRM solutions may offer individualized employee experiences, increase productivity, and improve decision-making [60]. DC encourages data-driven decision-making and ongoing innovation in HR procedures, which enables the application of AI in talent management [36]. Today's performance management is becoming more objective and effective due to AI technology. The real-time analysis of employee performance data by AI-augmented technologies can reveal productivity trends and opportunities for development. The efficacy of AI-augmented performance management systems is further increased by a digital culture that emphasizes openness and ongoing feedback, which improves worker performance and organizational outcomes [61]. AI-powered HRM solutions can help increase worker retention and engagement. Huang and Rust [62] assert that AI can provide personalized learning and development opportunities tailored to the needs and career goals of each employee. This is made possible by digital culture, which creates an atmosphere that values innovation and ongoing learning and increases satisfaction with work and retention [63].

Lastly, incorporating AI-driven HRM practices with digital culture enhances company performance in several ways. First and foremost, AI-augmented HRM increases operational effectiveness, which reduces costs and maximizes resource use [58]. Improved employee engagement and retention lead to a more driven and efficient staff, which in turn promotes long-term organizational success [62]. Finally, by advancing diversity, equity, and inclusion—all essential elements of a sustainable business strategy—AI-augmented HRM may promote organizational sustainability goals [60]. Utilizing AI-augmented HRM to improve long-term organizational performance requires a strong digital culture. Therefore, recruitment, performance management, employee engagement, and overall operational efficiency may all be enhanced by firms by creating an environment that encourages the adoption and efficient use of AI technology in HRM. Organizations that adopt a strong digital culture will be better positioned to achieve long-term success as digital technology and AI continue to advance. Therefore, this study proposes the following hypothesis:

H1a. *Digital culture has a positive influence on AI-augmented HRM.*

H1b. *Digital culture has a positive influence on SOP.*

2.6. Effect of Organizational Strategy on AI-Driven HRM and Sustainable Organizational Performance

In the era of IR4, the importance of AI has gained momentum in HRM due to the structured and unstructured data analysis capabilities of AI. However, organizational strategy plays a major role in the deployment and use of AI-augmented HRM in organizations. The framework for the use and integration of AI technology in HRM is provided by organizational strategy. Aligning AI-augmented HRM practices with the organization's objectives, core values, and operational procedures is ensured by a well-defined strategy [64]. Strategic planning is essential for determining the domains in which AI may provide the most benefits, establishing precise goals, and guaranteeing that the required infrastructure and resources are available [60]. AI-augmented HRM adoption requires strategic alignment to be effective. Businesses may successfully incorporate AI into HRM procedures by having a well-defined strategy, which guarantees that the activities are aligned with larger business goals. According to Westerman et al. [61], this alignment aids in establishing a culture that encourages technological change, gaining executive support, and prioritizing AI initiatives.

Moreover, strategically using AI-augmented HRM improves talent acquisition and management for sustainability. AI can connect people to appropriate positions, forecast work performance, and find the best applicants by analyzing enormous volumes of data [59]. Also, businesses may increase the effectiveness of hiring, lessen prejudice, and improve the general caliber of hires by strategically focusing on utilizing AI for talent management [62]. Therefore, the application of AI in staff development and performance management is also influenced by organizational strategy. In addition, real-time feedback, skill gap identification, and the customization of learning and development programs may all be achieved through the strategic application of AI-driven solutions. This promotes a culture of continuous improvement by enhancing both individual and team performance and coordinating employee development with company objectives [58]. When combined with a strong organizational plan, AI-augmented HRM greatly increases employee engagement and organizational sustainable performance [2]. Strategic AI integration into HRM fosters innovation, increases efficiency, and improves decision-making, all of which contributes to long-term corporate performance. According to Westerman et al. [61], AI-driven HRM may improve resource utilization, lower operating costs, and streamline procedures—all of which are essential for sustainability. In summary, organizational strategy is a key factor in determining how AI-augmented HRM is adopted and how it affects long-term organizational success, and AIHRM leads to organizational sustainability. Drawing from the aforementioned discussions, this study posits the following hypothesis:

H2a. *Organizational strategy has a positive influence on AI-augmented HRM.*

H2b. *Organizational strategy has a positive influence on SOP.*

2.7. AI-Augmented HRM and Sustainable Organizational Performance

HRM and organizational sustainability are interconnected. AI-augmented performance management systems may provide objective evaluations and individualized development plans, encouraging a culture of continuous growth and professional growth. By determining skill gaps and suggesting pertinent training modules, AI personalizes learning and development programs. AI-augmented learning systems, according to Sharma and Balyan [65], may adjust to the particular requirements of each individual, providing specialized training opportunities that support continuous learning and skill development. According to Chowdhury et al. [25], AI-enabled HRM efficiently drives organizations toward economic, environmental, and socially related SOPs. AI technologies enable real-time feedback and continuous performance monitoring, resulting in assessments that are more objective, and data-driven. Machine learning, deep learning, and predictive analytics are just a few of the AI technologies that will continue to grow and be integrated into HRM in the future. As these technologies grow, HR professionals will have access to increasingly advanced tools to improve strategic planning and decision-making. Research indicates that AI-enabled HRM improves organizations' social performance by fostering talent development, promoting employee well-being, ensuring equity and justice within communities, enhancing working conditions, increasing supplier commitment, and boosting employee efficiency and creativity in the workplace [3,66,67]. In a study, Jangbahadur et al. [2] found that AI-enabled HRM was positively associated with SOP. Similarly, another study proved that AI-enabled HRM enhances organizational economic performance through the implementation of new innovative ideas, minimizing lead time, lowering production costs, and fostering the production of goods and services [17].

The use of AI in HRM has significantly improved how businesses manage their workforces. AI-augmented HRM may make traditional HR procedures more effective and efficient by automating repetitive operations, offering actionable insights, and improving employee experiences. Therefore, based on the above discussion, the following hypothesis is posited:

H3. *AI-augmented HRM has a positive effect on SOP.*

2.8. Mediation Effect of AI-Augmented HRM

HRM and AI together have the power to completely change an organization's operation system related to employee recruitment and retirement. In addition to increasing productivity, AI-augmented HRM procedures are influenced by organizational culture as well as strategy for the promotion of sustainable organizational development. A strong DC is essential for attaining sustainable performance through the effective use of AI-augmented HRM practices. AI-augmented HRM may be supportive for selecting the right person for organizations, especially persons who have digital skills and are used to working in digital environments. According to Russo [68], companies that possess a robust DC are more adept at incorporating sustainable practices into their daily operations. The term "AI-Augmented HRM" describes the application of AI technology to improve employee engagement, performance management, hiring, and talent management. The connection between digital culture and sustainable performance is made possible in large part by these behaviors. By evaluating massive datasets to find the best applicants, AI can expedite the hiring process, minimizing prejudice and raising the caliber of hires [59]. By strengthening the beneficial effects of DC on long-term organizational performance, AI-augmented HRM serves as a mediator. By automating repetitive operations, AI solutions help foster a digital culture and free up HR personnel to concentrate on important projects. A creative and flexible organizational environment is made possible by this change [69]. According to Ulrich and Dulebohn [70], this alignment is essential for long-term success and competitiveness in the digital era. A key function that AI-augmented HRM plays is managing the relationship between digital culture and long-term organizational success.

Furthermore, AI has revolutionized HRM by bringing traditional HR methods into closer alignment with organizational strategy. AI technologies improve several HR tasks, including hiring, onboarding, performance reviews, and employee engagement. According to Jatobá et al. [71], AI-augmented HRM solutions expedite the hiring process by using algorithms that match candidates' talents with job needs, guaranteeing a strategic alignment between personnel and organizational goals. Through the efficient use of human capital to achieve strategic goals, AI-augmented HRM serves as a mediator between organizational strategy and sustainable performance. The way AI technologies enhance personnel management and propel strategic goals is clear evidence of this mediation. Additionally, AI-augmented HRM procedures support sustainability by facilitating more effective resource management and encouraging an innovative and continuous improving culture [62]. In order to ensure long-term success and continued existence, sustainable organizational performance takes into account economic, social, and environmental factors. AI-augmented HRM makes workers more adaptable, creative, and resilient, which promotes sustained performance. AI solutions in HRM may improve employee training and development through individualized learning experiences, as mentioned by Strohmeier and Piazza [72]. This increases productivity and creativity. In addition, due to the extreme completion and intrinsic organizational pressure, organizations are bound to inaugurate AI-augmented HRM for strategic purposes and achieving organizational sustainability. Despite the lack of empirical research linking strategy to AI-enabled HRM, it has been shown that AI-enabled HRM significantly improves SOP [2]. Based on the above discussion and filling the existing research gap, this study assumes the following hypothesis:

H4. *AI-augmented HRM mediates between digital culture and SOP.*

H5. *AI-augmented HRM mediates between organizational strategy and SOP.*

3. Methodology

3.1. Model Development

In the wave of AI and digital transformation, the relationship between AI-augmented HRM and organizational performance is symbiotic, and the integration of technological and management innovation leads to sustainable performance. Moreover, there is only one publication that found that AI-enabled HRM has a positive effect on SOP [2], which has been published recently, but the authors consider AI-enabled HRM to be multidimensional and add employee engagement. Additionally, Prikshat et al. [15] suggested that an advanced conceptual model with AI in HRM needs to be developed for empirical testing, while Chowdhury et al. [25] mentioned that technical and non-technical issues need to be integrated with AI adoption for enhancing performance. Moreover, previous studies have highlighted the importance of a strategic orientation for SOP, but they have not empirically tested the mediation effect of AI-augmented HRM [24]. In addition, organizational culture has a positive effect on SOP, but researchers have not discussed the mediating effect of AI-augmented HRM on the link between DC and SOP [27]. Similarly, digital culture and the digitalization or AI augmentation of HRM are interconnected and need to be theoretically and empirically tested [26]. From the discussion above, it is evident that there is a significant gap in understanding the impact of AI-augmented HRM on sustainable performance in emerging issues. Therefore, this study's objective is to explore the influence of digital culture and organizational strategy on AI-augmented HRM and SOP, focusing on the mediating role of AI-augmented HRM in these relationships (see Figure 1.). This aim informs the selection of the research design, data collection methods, and analytical approach described below. This study, further, taking into account the digital transformational age, has used digital culture and organizational strategy as key independent factors, AI-augmented HRM as a mediator, and SOP as a dependent variable to empirically test this in a developing country. The following Figure 1 shows the present research model:

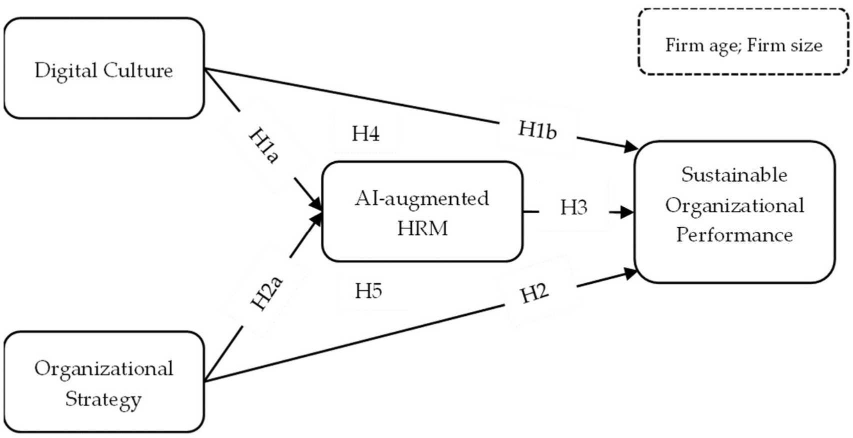

Figure 1. Proposed research model.

3.2. Sampling and Data Collection Methods

The unit of the analysis for this research is employees, and samples were purposively selected from different low, mid-, and upper-level employees who are involved in activities related to HRM. To achieve this purpose, this study focused on collecting data from various financial, insurance, banking, manufacturing, pharmaceutical, wholesale and retail trade, logistics, and service organizations in Bangladesh. To collect data, we have used purposive sampling, where we are involved in HR-related activities to ensure that respondents have some HR-related expertise. Therefore, at the beginning of the study, we provided a short note related to the consent of the participants regarding their participation in the survey, and ensuring they are involved in HR-related activities. In this study, respondents were contacted online (via Facebook Messenger, WhatsApp, Telegram, email, or phone) and in person to collect the response. The time duration of the data collection ranged from June 2024 to July 2024. In this regard, Karim et al. [73] and Shahneaz et al. [74] suggested that for cross-sectional data collection, the period should be a maximum of three months; the total data collection time for this study was two months. We sent 300 questionnaires and received 253 from the respondents. After the screening of improperly completed and invalid questionnaires, and questionnaires with missing information, we finalized 219 questionnaires, resulting in an acceptable response rate of 73.0%. Moreover, this response rate is acceptable in comparison to previous studies' response rate. Previously, Islam et al. [75] attained 60.6%, Amin et al. [76] achieved 52.25%, and Mahmud et al. [77] received 47.2% response rates from studies in Bangladesh. Therefore, the response feedback is quite satisfactory in comparison with the previous response rates.

3.3. Measurement Items and Scaling

First, based on the previous literature review, a structured questionnaire has been prepared to fulfill the research goals. We performed a pilot test with six sample datasets before collecting all the final data. The test showed that the validity questionnaire has a Cronbach's alpha value of -1.29, except for the measurement items of the SOP questionnaire, which were chosen from Akram et al. [78] and Rasool et al. [79] and have a serious problem. Therefore, we have implemented a new set of questionnaires from Kordab et al. [80] to measure SOP and validity, which yielded satisfactory results for both the second-time tested data and an additional five samples. To access the interconnection among DC, OS, AIHRM, and SOP, this research followed Garver and Mentzer [81] and Hoelter's [82] sampling strategy, and used 219 samples to test the research model. To assess each construct of this research, a 5-point Likert scale has been used, which ranges from "strongly disagree" to "strongly agree".

AI-augmented HRM: To assess AI-augmented HRM in this research construct, we have used a single dimension with 8 items, which were adopted from Prikshat et al. [15], considering the use of AI in HRM. But originally, they also adopted items from Mehrabad and Brojeny [83], with the code name AIHRM1; Prikshat et al. [15], with the code name AIHRM2; Cesta et al. [84], with the code name AIHRM3; from Gratton [85], with the code name AIHRM4; Robert et al. [86] and Prikshat et al. [15], with the code name AIHRM5; Huang et al. [87], with the code name AIHRM6; Lawler and Elliot [88], with the code name AIHRM7; and Fan et al. [89] and Li et al. [90], with the code name AIHRM8 (see Appendix A). The example of the first item for the construct is as follows: "For the selection process, our organizations use an AI system that was originally developed based on the Mehrabad and Brojeny [83] questionnaire". *Digital Culture:* To assess DC, this study has used seven items from Junaedi et al. [91]. The purpose of measuring DC was to assess the system of the digital environment that helps with working in a digital arena. An example of an item is "Employees in this organization are encouraged for innovation and adopt new technology". *Organizational Strategy:* To assess and measure OS related to the implementation of digital activities, this study has considered seven items; among them, five items are adopted from Chen et al. [92] and Hakala and Kohtamäki [93], and two items are adopted from Koufteros et al. [94]. An example of these items is "Digitalization is the topmost prioritized element of our company's business strategy". *Sustainable organizational performance:* To measure SOP, this study has six items from Kordab et al. [80]. One sample item is "Our organization provides high-quality services". *Control variables:* Organizational size and age play a crucial role in leveraging AI and technological capabilities effectively. Therefore, this study considers organizational size and age as control variables.

3.4. Demographic Information of the Respondents

Table 1 represents the demographic information of the respondents, including AI tools used for augmented HRM, firm size, firm age, employee age, experience, and employee position. In the case of using AI tools to augment HRM activities, about 45.79% of the respondents use Google AI, 42% use Open AI, about 16.4% use Microsoft research, about 16% use Google Cloud, and the rest of them use Amazon Web Services, Human AI, Open AI Gym, and other AI platforms. In addition, the results depict that among the respondents, about 16% work for small organizations, 14.6% work for medium organizations, and 69.4% work for large organizations. About 55.3% of the organizations are older than 20 years. Around 15.1% of workers have less than 5 years of experience, and 15.9% have between 5 and 10 years of experience. Additionally, 47% of these respondents were between the ages of 30 and 39, 43.4% were between the ages of 20 and 29, and 1.9% were over 50. Most of the respondents (50.2%) had one to five years of experience; 29.7% had six to ten years of experience in a relevant field. Lastly, about 59% were from mid-level positions, and the rest were from lower and higher-level positions.

Table 1. Demographic profile of the respondents.

Variables	Description	Number	%
AI tools used by the respondents ***	Google AI	100	45.79
	Open AI	92	42
	Microsoft Research	36	16.4
	Google Cloud	35	16
	Amazon Web service	7	3.2
	Human AI/Open AI Gym	8	3.7
	Others	35	16
Firm size	Small	35	16.0
	Medium	32	14.6
	Large	152	69.4
Firm age	Less than 5 years	33	15.1
	5–10 years	34	15.5
	11–15 years	16	7.3
	16–20 years	15	6.8
	More than 20 years	121	55.3
Employee age	Below 20 Years	2	0.9
	20 to 29 Years	95	43.4
	30 to 39 Years	103	47.0
	40 to 49 Years	15	6.8
	50 to 59 Years	3	1.4
	More than 60 years	1	0.5
Length of service	Less than 1 year	31	14.2
	1 to 5 years	110	50.2
	6 to10 years	65	29.7
	11 to 15 years	13	5.9
	More than 15 years	31	14.2
Employee position	Lower-level management	65	29.7
	Middle-level management	131	59.8
	High-level management	19	8.7
	Others	4	1.8
Total		219	100%

Notes: *** A single respondent used multiple AI tools.

4. Analysis and Results

4.1. Data Analysis Tools and Techniques

The current study used Microsoft Excel to organize data, and then the data were transformed using SPSS 23. It is to be noted that the SPSS data file has been used for analyzing respondent's demographic details, mean, standard deviations, variance inflation factor (VIF), correlation analysis, Harman's single factor common methods bias test, and input data for AMOS 24 software, which is used for measuring model fit, structural measurement model fit, and path analysis. In this way, a total data test for the final hypothesis has been conducted for achieving research objectives.

4.2. Common Method Biasness Test

At the beginning, to assess the common method biasness, this study tested the Kaiser–Meyer–Olkin (KMO) sampling adequacy, which is 0.942. Using Bartlett's test of sampling sphericity (χ^2 = 4547.196, df = 378, $p < 0.05$), a very high correlation was found among the AIHRM, DC, OS, and SOP, which indicates the suitability of the factor analysis. In addition, common method biasness (CMB) has been conducted with Herman's single factor test to statistically test the biasness [95], and multicollinearity was tested with the variance inflation factor (VIF). The test results of the Herman's single factor test with principal components analysis show that the results of single factors in total variance, explained with a single factor loading value, is 46.849%, which is less than 50% and indicates that there are no bias issues [96]. On the other hand, if the value of VIF ranges from 1 to 3, it indicates there are no multicollinearity problems [97,98]. Therefore, this study has no multicollinearity or CMB issues.

4.3. The Measurement Model

The research tested the measurement and structural model fit, convergent validity, data reliability, discriminant validity, and path coefficient. At first, measurement model validity was established based on the recommended indices. The results revealed χ^2 = 478.144, χ^2/df = 1.968, Goodness of Fit Index (GFI) = 0.847, Adjusted Goodness of Fit Index (AGFI) = 0.814, Root Mean Square Residual (RMR) = 0.042, Root Mean Square Error of Approximation (RMSEA) = 0.067, Comparative Fit Index (CFI) = 0.937, Tucker–Lewis Index (TLI) = 0.928, and Incremental Fit Index (IFI) = 0.937. Based on Doll et al. [99] and Baumgartner and Homburg [100], if the GFI and AGFI are higher than 0.8, they are acceptable. In addition, a value of 0.05 to 0.08 for the RMSEA is acceptable [101]. Therefore, the model is structurally fit for further analysis. Then, the study assessed the convergent validity through the analysis of average variance extracted (AVE) and composite reliability (CR) based on the factor loading, as presented in Table 2. All the loading values are higher than the threshold value of 0.40. However, DC6, DC7, and SOP4 were eliminated due to the low loading below 0.6 and improvement of the model fit. The results of the convergent validity of the study model by conducting tests are as follows: composite reliability (>0.70), average variance extracted (>0.50), and Cronbach's a (>0.70) [102,103]. Additionally, testing the multicollinearity of the model using the variance inflation factor (VIF), where all results range between 0 and 10, is acceptable [104]. Our results demonstrated that all the variance inflation factors (VIFs) were below 3, indicating that there is no multicollinearity issue in this research.

Subsequently, discriminant validity, which implies how much one construct is distinct from another construct, was assessed based on the Fornell–Larcker criterion. To assess the discriminant validity, the square roots of AVE should be higher than the other correlation coefficients [105]. The following Table 3 demonstrates that all the bolded bracketed values exceed the square roots of AVE indices, indicating that there are no discrimination validity issues in this study.

Table 2. The reliability and validity of the constructs.

Variables	Items	Items Eliminated	Loading	Cronbach's α	AVE	AVE	VIF
AI-augmented HRM (AIHRM)	AIHRM1 AIHRM2 AIHRM3 AIHRM4 AIHRM5 AIHRM6 AIHRM7 AIHRM8	None	0.760 0.725 0.778 0.802 0.88 0.853 0.839 0.801	0.938	0.573	0.914	1.372
Digital Culture (DC)	DC1 DC2 DC3 DC4 DC5	2 (DC6; DC7)	0.782 0.824 0.760 0.688 0.697	0.899	0.607	0.885	2.518
Organizational Strategy (OS)	OS1 OS2 OS3 OS4 OS5 OS6 OS7	None	0.685 0.807 0.794 0.827 0.776 0.716 0.739	0.908	0.632	0.923	2.080
Sustainable Organizational Performance (SOP)	SOP1 SOP2 SOP3 SOP5	1 (SOP4, SOP6)	0.788 0.780 0.788 0.704	0.872	0.685	0.897	-

Table 3. Discriminant validity.

Variables	AIHRM	DC	OS	SOP
1. AIHRM	**(0.757)**			
2. DC	0.430 **	**(0.779)**		
3. OS	0.519 **	0.776 **	**(0.795)**	
4. SOP	0.469 **	0.732 **	0.732 **	**(0.827)**
Mean	3.183	3.899	3.913	4.034
Standard Deviation	0.979	0.740	0.729	0.662

Note(s): ** $p < 0.01$; diagonals (in bold) represent the square root of average variance extracted (AVE) while the other entries represent the correlations.

4.4. Structural Model

The researchers employed AMOS to measure the structural model and to assess the postulated associations. This research has also used bootstrapping of 500 resamples to appraise the statistical significance of path coefficients [106]. The results of the structural model fit were established based on the recommended indices. The results revealed $\chi^2/\mathrm{df} = 2.101$, GFI = 0.994, AGFI = 0.934, RMR = 0.041, RMSEA = 0.071, CFI = 0.996, TLI = 0.970, and IFI = 0.970. In addition, this study assessed the coefficient of determination R2 of the endogenous latent variables, which is the preferred metric for evaluating the structural model [107]. The study explains that 27.1% of the variation in SOP can be explained by AI-augmented HRM. The following Figure 2 shows the outcome of the structural model Fit:

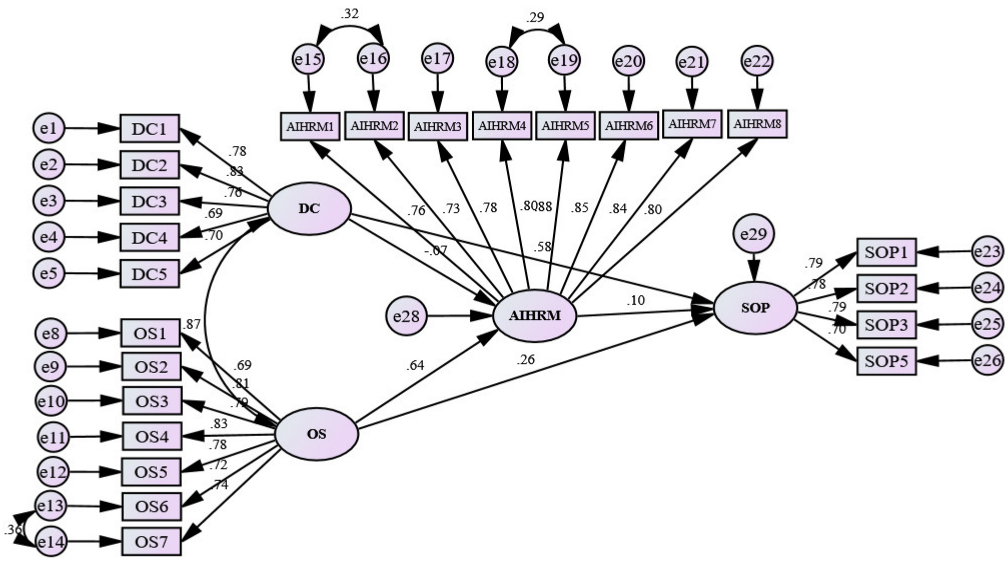

Figure 2. Structural model fit test.

To test the hypothesis, this study has applied 5000 bootstrapping samples to determine the path coefficients and significance of the relationships [108]. At first, the H1a results indicated that DC has an insignificant effect on AI-augmented HRM ($\beta = 0.070$; $p > 0.05$); therefore, H1b was rejected. Then, to assess the hypothesis H1b, the results revealed that DC has a significant effect on SOP ($\beta = 0.403$; $p < 0.05$) (see Table 4). Therefore, H1b is supported. Next, we assessed the hypotheses H2a and H2b. The results proved that OS has a significant effect on AI-augmented HRM ($\beta = 0.465$; $p < 0.05$) and SOP ($\beta = 0.354$; $p < 0.05$). Therefore, H2a and H2b are supported. Next, we tested hypothesis H3. The results proved that AI-augmented HRM has a significant effect on SOP ($\beta = 0.123$; $p < 0.05$) (see Table 4). Therefore, H3 is supported. In addition, we have assessed hypotheses H4 and H5 to test the mediation effect of AI-augmented HRM. The results depicted that AI-augmented HRM insignificantly mediates between DC and SOP ($\beta = 0.008$; $p < 0.05$) and significantly mediates between OS and SOP ($\beta = 0.052$; $p < 0.05$). Therefore, we reject H4 and support H5 (see Table 4). Lastly, in this study, firm age and size have been used as control variables, and the results are as follows: firm age ($\beta = 0.013$; $p > 0.05$) and firm size ($\beta = 0.146$; $p < 0.05$). Therefore, we infer that in Bangladeshi organizations, firm size has a significant role for SOP (see Table 4).

Table 4. Summary of path analysis.

Hypothesis	Pathways	Path Coefficient	95% Confidence Interval		*p*-Value	Decision
			ULC	LLC		
H1a	DC → AIHRM	0.070	−0.122	0.275	0.496	NS
H1b	DC → SOP	0.403 **	0.257	0.550	0.000	S
H2a	OS → AIHRM	0.465 **	0.266	0.651	0.000	S
H2b	OS → SOP	0.354 **	0.197	0.516	0.000	S
H3	AIHRM → SOP	0.123 *	0.027	0.221	0.010	S
Mediation						
H4	DC → AIHRM → SOP	0.008	−0.010	0.042	0.336	NS
H5	OS → AIHRM → SOP	0.052	0.014	0.102	0.006	S
Control						
	Firms age → SOP	0.013	−0.077	0.105	0.787	NS
	Firm size → SOP	0.146	0.062	0.240	0.000	S

Note(s): * $p < 0.05$, ** $p < 0.001$; AIHRM = AI-augmented HRM; DC = digital culture; OS = organizational strategy; SOP = sustainable organizational performance; LLCI = lower limit confidence; ULCI = upper limit confidence; S = supported; NS = non-support.

5. Discussions

This study has successfully addressed the previous research gap and empirically tested the results. We have discussed the findings and their implications in the broadest possible context. The study also highlighted potential future research directions. This research focused on the following two objectives: (1) to explore and empirically test the impact of DC and OS on AI-augmented HRM and SOP; and (2) to evaluate the mediating role of AI-augmented HRM between DC and SOP, as well as OS and SOP. The conceptual relations were also examined based on the RBV and DCV. Notably, this study successfully responds to the research suggestions of Budhwar et al. [3] to use culture and strategy with AI-driven HRM and Chowdhry et al.'s [25] suggestions to use organization culture with AI-driven HRM. The details of the results and discussions are as follows:

Firstly, the results of the empirical test depict that DC has an insignificant influence on AI-augmented HRM (H1a) and SOP (H1b). Though previous studies have theoretically emphasized that DC is vital for enhancing AI-augmented HRM [26], this study proved that DC is not vital for AI-augmented HRM in Bangladesh. These findings also contrast with a previous study by Chew and Sharma [11], which demonstrated that cultural values enhance HRM effectiveness; however, in the case of DC culture, this is not prevalent in developing nations. There are many reasons behind this; first, Bangladesh is a developing country where digital systems are not implemented across organizations. Next, employees of the organizations are comfortable with traditional practices and often resist transitioning from traditional systems to modern digital systems. Then, due to the skills gap and inadequate training programs, employees are afraid of digital tools and techniques. Another reason is that the leaders of Bangladesh may have a lack of vision or clear understanding of digital transformation or prevailing limited resources for the digital transformation, which hinders the advancement of DC. Finally, organizational structure and bureaucracy, along with the lack of a data security system, employee concern about job security, and cultural misalignment, collectively hinder the implementation of DC in organizations of developing countries.

Secondly, OS has a significant positive impact on AI-augmented HRM (H1a) and SOP (H2b), which is inferred due to the organizations' strategic decision to implement AI-augmented HRM. These results also support Prikshat et al.'s [15] assumptions that OS positively influences AI-augmented HRM. The findings also suggest that real-time feedback and performance indicators are provided by AI-augmented HRM, which aids in pinpointing areas for employee growth and coordinating them with corporate objectives. In addition, by offering personalized professional development plans, acknowledging employee contributions, and promoting improved communication, AI can boost employee engagement [60], which lead to increases in employees' work satisfaction and retention rates, which are all factors that support long-term organizational success [10].

Thirdly, the results of the study proved that AI-augmented HRM has a positive effect on SOP (H3), which is similar to the previous findings of Jangbahadur et al. [2]. The body of research on AI applications from an AI-augmented HRM perspective is relatively small, but there are some preliminary indications of empirical evidence from subsidiaries of large multinational technology companies [109–111] or from single-country contexts [112]. AI solutions can offer individualized professional development possibilities, acknowledge employee efforts, and enable personalized communication [62]. Higher employee satisfaction and retention result from these AI-augmented initiatives being aligned with the organization's values and culture through a strategic approach.

Fourthly, while AI-augmented HRM does not significantly mediate between DC and SOP (H4), it does significantly mediate between OS and SOP (H5). This result aligns with the previous discussion again; it needs to be mentioned that the digital culture of Bangladesh is still in developing states; therefore, AI-augmented HRM does not mediate between DC and SOP. Results demonstrated that DC has a positive role for developing SOP in Bangladesh. In addition, the final outcome regarding the mediation effect of AI-augmented HRM between OS and SOP proved that a partially mediating effect can be inferred, and AI-augmented HRM plays a significant role for the interconnection of OS and SOP. AI projects that are well-defined in their approach are more likely to be sustainable in the long term, improve HRM procedures, and correspond with company objectives. Organizations with a strategic vision will be in a better position to fully utilize AI in HRM and achieve long-term success as AI technologies advance.

Moreover, real-time analytics and predictive insights generated by AI systems help organizations make better decisions by allowing them to react proactively to developments in the market [72]. Finally, AI-augmented HRM is essential for bridging the performance gap that exists between organizational strategy and long-term viability. Organizations may attain long-term sustainability by leveraging AI technology to improve HR activities and connect them with organizational goals. In addition, it is proved that the age of the organization does not have a significant controlling effect on SOP; however, larger organizations tend to have higher SOP. Finally, it can be summarized that both DC and OS play significant roles in AI-augmented HRM and SOP in developing countries. Overall, the findings of this study are grounded in the context of Bangladesh, a developing country with unique cultural, organizational, and economic characteristics. While these results provide valuable insights into the interplay between digital culture, organizational strategy, and AI-augmented HRM, they should be interpreted with caution when applied to other developing countries. Future research could extend this investigation to other nations to examine whether these relationships hold across diverse contexts.

5.1. Theoretical Implications

This research unveils several contributions to HRM. First, by applying the RBV and DCV, this empirical test validates the integration logics of DC, OS, and AI-augmented HRM for SOP. Based on the previous findings, there is a limited theoretical explanation of AI-augmented HRM, and very little research related to empirically testing the mediating effects of AI-augmented HRM. On the other hand, a previous study by Jangbahadur et al. [2] theoretically and empirically tested the impact of AI-enabled HRM with a second-order analysis or multidimensional factor effect on SOP. However, this study conducted a single-dimension analysis with items adopted from Prikshat et al. [15], which were originally developed by many researchers separately (see Appendix A). This study covered two theories: the RBV and dynamic capabilities view. Here, DC and OS have considered organizational internal resources and capabilities to achieve SOP, and AI-augmented HRM has been considered based on the dynamic capability view because it enhances organizations' capabilities and responds to organizational change perspectives. Organizational internal resources, DC, and OS are positively supported to make HR dynamic and increase AI-augmented HRM support for SOP. Second, the results can be used to infer that AI-augmented HRM significantly mediates between OS and SOP but not between DC and SOP. Indirectly, this indicates that the dynamic capabilities of AI-augmented HRM make a bridge between OS and SOP, while DC has a direct influencing role for enhancing SOP. Therefore, our results add value to the existing knowledge that dynamic capabilities theory can be used to integrate organizational resources and support continuous development and sustainability for organizations.

5.2. Managerial Implications

These research outcomes have some practical implications that may be supportive of organizations' sustainability as well as their worldwide usefulness. AI is being continuously incorporated by enterprises globally into their systems and business processes in order to automate and expedite a wide range of repetitive jobs. There is a dilemma about whether we will manage the digital culture or make a strategy for facing challenges originating from AI-oriented HRM. The results of this study highlight the significance of DC not significantly driving the adoption AI-augmented HRM, but using AI-augmented HRM in OS to attain individual and organizational goals can lead to the attainment of SOP. This study is particularly supportive of organizations adopting AI for HRM; further, this study supports digital culture adaptation and strategy formulation for AI-augmented HRM tasks, like recruitment, selection, decision-making, training for re-skilling and up-skilling, career planning, job evaluation, turnover, and performance management. Overall, organizations in developing countries are now emphasizing using AI for HRM as a tool for strategic purposes as well as day-to-day operation management to achieve SOP.

5.3. Limitations and Future Research

There are some limitations to this study, which could lead to new directions for research. First, with respect to the user experiences of AI-augmented HRM that were incorporated in the study, these research outcomes are based on middle and top-level employees in the different organizations. Henceforth, it would be prudent to solicit comprehensive input on the same matters from other members of the workforce. Second, this research has considered only one AI-augmented HRM system as a mediating variable and two dependent constructs, which leads to another limitation. Future research related to leadership could explore the digital mindset, social media, innovation, operation capabilities, digital leaders' roles, and other relevant variables. Third, this study was conducted in an emerging nation with cross-sectional limited sample data, but in the future, longitudinal or multipoint data can provide more comprehensive and concrete results to describe real situations. Fourth, this study examined DC and OS to determine the prioritized effect on AI-augmented HRM and SOP. Future studies could ensure the integration of other factors with AI-augmented HRM to match the suitability of the organizations. In addition, this study has not considered any moderating factors, but as AI is mostly related to ethical issues, in the future, ethical AI or digital leadership roles can be considered as moderating determinants. Finally, since this study was conducted solely in an emerging nation, it has limited the generalization scope; therefore, in the future, similar studies can provide more transparent and generalizable results. Overall, it is important to note that while the study offers valuable insights, the sample size of 219 surveys from employees in Bangladesh does not represent the entire workforce of developing countries, let alone the global workforce of approximately 71 million employees. The findings are specific to the Bangladeshi context, and further research with larger, more diverse samples across different regions and industries would help strengthen the generalizability of these results.

6. Conclusions

In the existing literature, it has been discussed that AI helps to improve service quality, cost effectiveness, and organizational effectiveness by reducing substantial operational and capital expenditure [17], improve HR strategies and activities [113], and enhance organizational resources [25]. However, there are a lack of studies that consider the role of DC and OS together in AI-augmented HRM and SOP. This research addresses the gap and responds to the research suggestions of Prikshat et al. [15] and Chowdhury et al. [25] by investigating the integrating impact of DC and OS on SOP while accounting for AI-augmented HRM as a mediator in the relationship. Based on the results, AI-augmented HRM is highly interconnected with OS and SOP. Here, both OS and DC have a significant role for enhancing SOP. Also, AI-augmented HRM partially mediates between OS and SOP. This study highlights how organizations can integrate DC, OS, and AIHRM for the accomplishment of SOP in the digital era. The key finding is that organizations are increasingly focusing on DC and OS to achieve SOP through AI-augmented HRM. Although the findings provide useful insights into the role of digital culture and organizational strategy in AI-augmented HRM and SOP, they are specific to the Bangladeshi context. Further research is recommended to validate these relationships in other developing countries to enhance the generalizability of the results.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su162410843/s1. Ethical clearance certificate; Sample consent form.

Author Contributions: Conceptualization, M.A.M., M.R. and M.M.A.A.M.S.; methodology, M.B.A. and M.A.R.; software, M.B.A.; validation, M.A.R. and V.F.; formal analysis, M.A.M. and V.F.; investigation, M.A.M., M.R., M.B.A. and M.A.R.; resources, M.B.A. and M.A.R.; data curation, M.A.M. and M.R.; writing—original draft, M.A.M., M.R. and M.M.A.A.M.S.; writing—review and editing, M.B.A., M.A.R. and V.F.; supervision, M.M.A.A.M.S. and V.F.; project administration, M.A.M., M.R. and M.M.A.A.M.S. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: This is a perception-based study collected from primary data through survey questionnaires. In this research, ethical standards were maintained to the highest possible extent and before conducting the survey, the researchers applied to the "Research Cell of the University of Barishal, Bangladesh", the local authority for the ethical clearance certificate (ref no: FSB-EC 24-05/2024; e-mail: mshossain@bu.ac.bd), and attached the questionnaire, sampling details, and ethical considerations. After assessing all ethical concerns and guidelines, the committee approved and provided the certificate for furthering the survey process. The ethical clearance certificate is attached as a Supplementary File with the manuscript submission.

Informed Consent Statement: The researchers collected both oral and written consent from all the respondents who participated in this study. Moreover, approvals were also collected from each organization where the respondents worked during the period of data collection. A sample consent form is attached as a Supplementary File with the manuscript submission.

Data Availability Statement: Data are available within the article.

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Conflicts of Interest: The researchers declare no conflicts of interest.

Appendix A

Table A1. Questionnaire.

Variables	Item Code	Items	Reference(s)
AI Augmented HRM (AIHRM)	AIHRM1	For the selection process our organizations use AI system	Mehrabad and Brojeny [83]
	AIHRM2	For searching candidate data acquisition from résumés our organizations take help from AI	Prikshat et al. [15]
	AIHRM3	AI based training software is used for decision making in crisis situations	Cesta et al. [84]
	AIHRM4	Our organizations take AI's assistance in re-skilling and upskilling	Gratton [85]
	AIHRM5	Our organizations use AI to for performance management and career planning	Robert et al. [86]; Prikshat et al. [15]
	AIHRM6	Our organizations use AI for Job design and workforce planning	Huang et al. [87]
	AIHRM7	In our organizations we use AI as an expert method for the job evaluation system	Lawler and Elliot [88]
	AIHRM8	In our organizations AI methods for employee turnover forecasting	Fan et al. [89]; Li et al. [90]

Table A1. *Cont.*

Variables	Item Code	Items	Reference(s)
Digital Culture (DC)	DC1	Employees in this organization are encouraged for innovation and adopt new technology.	Junaedi et al. [91]
	DC2	Our organizations have a dynamic environment which is quick to respond to technological developments.	
	DC3	Our organizations works in an integrated method for sharing information and ideas by using digital tools.	
	DC4	Our organizations use virtual collaboration system.	
	DC5	Employees of our organizations are comfortable for sharing ideas and providing feedback openly.	
	DC6	Our organizations environment respects the responsible use of technology.	
	DC7	Employees of our organizations are feeling encouraged to participate digitally.	
Organizational Strategy (OS)	OS1	Digitalization is top most prioritize elements of our company's business strategy.	Chen et al. [92]; Hakala and Kohtamäki, [93]
	OS2	Our company investigates the newest trends for the future scenarios to stay competitive.	
	OS3	Digital projects in our organizations have a high importance within our business.	
	OS4	Our organizations are constantly updated and refine our digital strategy.	
	OS5	Our competition and industry experts perceive our organizations as a leader in digital innovation.	
	OS6	Our organizations provide support for the achievement of key strategic objectives.	Koufteros et al. [94]
	OS7	Our organizations improve the prioritization of actions, projects and goals.	
Sustainable Organizational Performance (SOP)	SOP1	Our organization provides high-quality services.	Kordab et al. [80]
	SOP2	Our organizations production and service operational cost is low compared to our competitors.	
	SOP3	Our organization performs well providing effectiveness delivery service.	
	SOP4	Our organization adapts quickly to adjust with unanticipated changes	
	SOP5	Our organization can compete properly in the contemporary market	
	SOP6	Our organization is considered profitable in the industry	

Table A2. Rotated component matrix.

	Component			
	1	**2**	**3**	**4**
AIHRM5	0.833			
AIHRM7	0.823			
AIHRM6	0.814			
AIHRM4	0.805			
AIHRM1	0.804			
AIHRM3	0.788			
AIHRM2	0.764			
AIHRM8	0.757			
OS2		0.791		

Table A2. *Cont.*

	Component			
	1	**2**	**3**	**4**
OS1		0.751		
OS3		0.700		
OS5		0.573		
OS4		0.558		
OS7		0.548		
OS6		0.522		
DC2			0.774	
DC4			0.721	
DC3			0.665	
DC5			0.579	
DC1			0.531	
SOP6				0.724
SOP5				0.702
SOP1				0.631
SOP2				0.615
SOP3				0.615

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 6 iterations.

References

1. Bley, K.; Fredriksen, S.F.B.; Skjærvik, M.E.; Pappas, I.O. The Role of Organizational Culture on Artificial Intelligence Capabilities and Organizational Performance. In *The Role of Digital Technologies in Shaping the Post-Pandemic World*; Papagiannidis, S., Alamanos, E., Gupta, S., Dwivedi, Y.K., Mäntymäki, M., Pappas, I.O., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2022; Volume 13454, pp. 13–24. ISBN 978-3-031-15341-9.
2. Jangbahadur, U.; Ahlawat, S.; Rozera, P.; Gupta, N. The Effect of AI-Enabled HRM Dimensions on Employee Engagement and Sustainable Organisational Performance: Fusion Skills as a Moderator. In *Evidence-Based HRM: A Global Forum for Empirical Scholarship*; Emerald Publishing Limited: Leeds, UK, 2024; *ahead-of-print*. [CrossRef]
3. Budhwar, P.; Malik, A.; De Silva, M.T.T.; Thevisuthan, P. Artificial Intelligence—Challenges and Opportunities for International HRM: A Review and Research Agenda. *Int. J. Hum. Resour. Manag.* **2022**, *33*, 1065–1097. [CrossRef]
4. Leal-Rodríguez, A.L.; Sanchís-Pedregosa, C.; Moreno-Moreno, A.M.; Leal-Millán, A.G. Digitalization beyond Technology: Proposing an Explanatory and Predictive Model for Digital Culture in Organizations. *J. Innov. Knowl.* **2023**, *8*, 100409. [CrossRef]
5. Nicolás-Agustín, Á.; Jiménez-Jiménez, D.; Maeso-Fernandez, F. The Role of Human Resource Practices in the Implementation of Digital Transformation. *Int. J. Manpow.* **2021**, *43*, 395–410. [CrossRef]
6. Singh, G.; Gaur, L.; Agarwal, M. Factors Influencing the Digital Business Strategy. *Pertanika J. Soc. Sci. Humanit.* **2017**, *25*, 1489–1500.
7. Parry, E.; Tyson, S. Desired Goals and Actual Outcomes of E-HRM: E-HRM Goals and Outcomes. *Hum. Resour. Manag. J.* **2011**, *21*, 335–354. [CrossRef]
8. Bondarouk, T.; Brewster, C. Conceptualising the Future of HRM and Technology Research. *Int. J. Hum. Resour. Manag.* **2016**, *27*, 2652–2671. [CrossRef]
9. Thite, M. Future Directions in Electronic/Digital HRM. In *e-HRM*; Routledge: London, UK, 2018; ISBN 978-1-315-17272-9.
10. Stone, D.L.; Deadrick, D.L.; Lukaszewski, K.M.; Johnson, R. The Influence of Technology on the Future of Human Resource Management. *Hum. Resour. Manag. Rev.* **2015**, *25*, 216–231. [CrossRef]
11. Chew, I.K.H.; Sharma, B. The Effects of Culture and HRM Practices on Firm Performance. *Int. J. Manpow.* **2005**, *26*, 560–581. [CrossRef]
12. Aycan, Z.; Kanungo, R.N.; Sinha, J.B.P. Organizational Culture and Human Resource Management Practices: The Model of Culture Fit. *J. Cross-Cult. Psychol.* **1999**, *30*, 501–526. [CrossRef]
13. Wilson, H.J.; Daugherty, P.R.; Morini-Bianzino, N. The Jobs That Artificial Intelligence Will Create. In *What the Digital Future Holds*; The MIT Press: Cambridge, MA, USA, 2018; pp. 97–104. ISBN 978-0-262-34535-4.
14. Maedche, A.; Legner, C.; Benlian, A.; Berger, B.; Gimpel, H.; Hess, T.; Hinz, O.; Morana, S.; Söllner, M. AI-Based Digital Assistants: Opportunities, Threats, and Research Perspectives. *Bus. Inf. Syst. Eng.* **2019**, *61*, 535–544. [CrossRef]

15. Prikshat, V.; Islam, M.; Patel, P.; Malik, A.; Budhwar, P.; Gupta, S. AI-Augmented HRM: Literature Review and a Proposed Multilevel Framework for Future Research. *Technol. Forecast. Soc. Change* **2023**, *193*, 122645. [CrossRef]
16. Castellacci, F.; Viñas-Bardolet, C. Internet Use and Job Satisfaction. *Comput. Hum. Behav.* **2019**, *90*, 141–152. [CrossRef]
17. Wirtz, B.W. *Digital Business Models: Concepts, Models, and the Alphabet Case Study*; Springer: Berlin/Heidelberg, Germany, 2019; ISBN 978-3-030-13005-3.
18. Azadeh, A.; Zarrin, M. An Intelligent Framework for Productivity Assessment and Analysis of Human Resource from Resilience Engineering, Motivational Factors, HSE and Ergonomics Perspectives. *Saf. Sci.* **2016**, *89*, 55–71. [CrossRef]
19. Azadeh, A.; Abdolhossein Zadeh, S. An Integrated Fuzzy Analytic Hierarchy Process and Fuzzy Multiple-Criteria Decision-Making Simulation Approach for Maintenance Policy Selection. *Simulation* **2016**, *92*, 3–18. [CrossRef]
20. Torres, E.N.; Mejia, C. Asynchronous Video Interviews in the Hospitality Industry: Considerations for Virtual Employee Selection. *Int. J. Hosp. Manag.* **2017**, *61*, 4–13. [CrossRef]
21. van Esch, P.; Black, J.S.; Ferolie, J. Marketing AI Recruitment: The next Phase in Job Application and Selection. *Comput. Hum. Behav.* **2019**, *90*, 215–222. [CrossRef]
22. Sitzmann, T.; Weinhardt, J.M. Approaching Evaluation from a Multilevel Perspective: A Comprehensive Analysis of the Indicators of Training Effectiveness. *Hum. Resour. Manag. Rev.* **2019**, *29*, 253–269. [CrossRef]
23. Pejic-Bach, M.; Bertoncel, T.; Meško, M.; Krstić, Ž. Text Mining of Industry 4.0 Job Advertisements. *Int. J. Inf. Manag.* **2020**, *50*, 416–431. [CrossRef]
24. Wang, Y. The Impact of Digital Strategic Orientation on Enterprise Sustainable Performance Against the Background of 2030 Sustainable Performance Goal. *Math. Probl. Eng.* **2022**, *2022*, 2263222. [CrossRef]
25. Chowdhury, S.; Dey, P.; Joel-Edgar, S.; Bhattacharya, S.; Rodriguez-Espindola, O.; Abadie, A.; Truong, L. Unlocking the Value of Artificial Intelligence in Human Resource Management through AI Capability Framework. *Hum. Resour. Manag. Rev.* **2023**, *33*, 100899. [CrossRef]
26. Muzaffar, R.; Muzaffar, S.; Muzaffar, Z. Digital Culture and the Transformational Impact of E-HRM in the Era of Digital Transformation. In *New Strategy Models in Digital Entrepreneurship*; IGI Global: Hershey, PA, USA, 2024; pp. 320–329. ISBN 9798369337431.
27. Srisathan, W.A.; Ketkaew, C.; Naruetharadhol, P. The Intervention of Organizational Sustainability in the Effect of Organizational Culture on Open Innovation Performance: A Case of Thai and Chinese SMEs. *Cogent Bus. Manag.* **2020**, *7*, 1717408. [CrossRef]
28. Connelly, C.E.; Fieseler, C.; Černe, M.; Giessner, S.R.; Wong, S.I. Working in the Digitized Economy: HRM Theory & Practice. *Hum. Resour. Manag. Rev.* **2021**, *31*, 100762. [CrossRef]
29. Agrawal, A.; Gans, J.S.; Goldfarb, A. What to Expect from Artificial Intelligence. *Mit Sloan Manag. Rev.* **2017**, *58*, 23–26. Available online: http://mitsmr.com/2jZdf1Y (accessed on 21 October 2021).
30. Huang, C.; Wang, X. Financial Innovation Based on Artificial Intelligence Technologies. In Proceedings of the 2019 International Conference on Artificial Intelligence and Computer Science, Wuhan, China, 12–13 July 2019; Association for Computing Machinery: New York, NY, USA, 2019; pp. 750–754.
31. Radcliffe-Brown, A.R. Historical Note on British Social Anthropology. *Am. Anthropol.* **1952**, *54*, 275–277. [CrossRef]
32. Lubis, F.R.; Hanum, F. *Organizational Culture*; Atlantis Press: Amsterdam, The Netherlands, 2020; pp. 88–91.
33. Giannini, T.; Bowen, J. Digital Culture. In *Museums and Digital Culture: New Perspectives and Research*; Springer: Cham, Switzerland, 2019; pp. 3–26. ISBN 978-3-030-11835-8.
34. Mithas, S.; Tafti, A.; Mitchell, W. How a Firm's Competitive Environment and Digital Strategic Posture Influence Digital Business Strategy. *MIS Q.* **2013**, *37*, 511–536. [CrossRef]
35. Hall, D.J.; Saias, M.A. Strategy Follows Structure! *Strateg. Manag. J.* **1980**, *1*, 149–163. [CrossRef]
36. Bharadwaj, A.; Sawy, O.; Pavlou, P.; Venkatraman, N. Digital Business Strategy: Toward a Next Generation of Insights. *MIS Q. Manag. Inf. Syst.* **2013**, *37*, 471–482. [CrossRef]
37. Tambe, P.; Cappelli, P.; Yakubovich, V. Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *Calif. Manag. Rev.* **2019**, *61*, 15–42. [CrossRef]
38. Upadhyay, A.K.; Khandelwal, K. Applying Artificial Intelligence: Implications for Recruitment. *Strateg. HR Rev.* **2018**, *17*, 255–258. [CrossRef]
39. Gamage, G.; De Silva, D.; Mills, N.; Alahakoon, D.; Manic, M. Emotion AWARE: An Artificial Intelligence Framework for Adaptable, Robust, Explainable, and Multi-Granular Emotion Analysis. *J. Big Data* **2024**, *11*, 93. [CrossRef]
40. Binns, R. Algorithmic Accountability and Public Reason. *Philos. Technol.* **2018**, *31*, 543–556. [CrossRef]
41. Mihardjo, L.; Sasmoko, S.; Alamsyah, F.; Elidjen, E. The Influence of Digital Leadership on Innovation Management Based on Dynamic Capability: Market Orientation as a Moderator. *Manag. Sci. Lett.* **2019**, *9*, 1059–1070. [CrossRef]
42. Barney, J.B. Strategic Factor Markets: Expectations, Luck, and Business Strategy. *Manag. Sci.* **1986**, *32*, 1231–1241. [CrossRef]
43. Özçelik, G.; Aybas, M.; Uyargil, C. High Performance Work Systems and Organizational Values: Resource-Based View Considerations. *Procedia—Soc. Behav. Sci.* **2016**, *235*, 332–341. [CrossRef]
44. Zahra, S.A.; Hayton, J.C.; Salvato, C. Entrepreneurship in Family vs. Non–Family Firms: A Resource–Based Analysis of the Effect of Organizational Culture. *Entrep. Theory Pract.* **2004**, *28*, 363–381. [CrossRef]
45. Fareed, M.; Noor, W.; Isa, M.; Mohd Salleh, S.S.M. Developing Human Capital for Sustainable Competitive Advantage: The Roles of Organizational Culture and High Performance Work System. *J. Econ. Perspect.* **2016**, *10*, 655–673.

46. Shin, J.; Mollah, A.; Choi, J. Sustainability and Organizational Performance in South Korea: The Effect of Digital Leadership on Digital Culture and Employees' Digital Capabilities. *Sustainability* **2023**, *15*, 2027. [CrossRef]
47. Paiva, E.L.; Roth, A.V.; Fensterseifer, J.E. Organizational Knowledge and the Manufacturing Strategy Process: A Resource-Based View Analysis. *J. Oper. Manag.* **2008**, *26*, 115–132. [CrossRef]
48. Mollah, M.A.; Choi, J.-H.; Hwang, S.-J.; Shin, J.-K. Exploring a Pathway to Sustainable Organizational Performance of South Korea in the Digital Age: The Effect of Digital Leadership on IT Capabilities and Organizational Learning. *Sustainability* **2023**, *15*, 7875. [CrossRef]
49. Mollah, M.A.; Amin, M.B.; Debnath, G.C.; Hosain, M.S.; Rahaman, M.A.; Abdullah, M. Nexus among Digital Leadership, Digital Transformation, and Digital Innovation for Sustainable Financial Performance: Revealing the Influence of Environmental Dynamism. *Sustainability* **2024**, *16*, 8023. [CrossRef]
50. Teece, D.J.; Pisano, G.; Shuen, A. Dynamic Capabilities and Strategic Management. *Strateg. Manag. J.* **1997**, *18*, 509–533. [CrossRef]
51. Eriksson, T. Processes, Antecedents and Outcomes of Dynamic Capabilities. *Scand. J. Manag.* **2014**, *30*, 65–82. [CrossRef]
52. Böhmer, N.; Schinnenburg, H. Critical Exploration of AI-Driven HRM to Build up Organizational Capabilities. *Empl. Relat. Int. J.* **2023**, *45*, 1057–1082. [CrossRef]
53. Basu, S.; Majumdar, B.; Mukherjee, K.; Munjal, S.; Palaksha, C. Artificial Intelligence–HRM Interactions and Outcomes: A Systematic Review and Causal Configurational Explanation. *Hum. Resour. Manag. Rev.* **2023**, *33*, 100893. [CrossRef]
54. Castells, M.; Fernandez-Ardevol, M.; Qiu, J.L.; Sey, A. *Mobile Communication and Society: A Global Perspective*; MIT Press: Cambridge, MA, USA, 2009; ISBN 978-0-262-26230-9.
55. Martínez-Caro, E.; Cegarra-Navarro, J.G.; Alfonso-Ruiz, F.J. Digital Technologies and Firm Performance: The Role of Digital Organisational Culture. *Technol. Forecast. Soc. Change* **2020**, *154*, 119962. [CrossRef]
56. Haffar, M.; Al-Karaghouli, W.; Djebarni, R.; Al-Hyari, K.; Gbadamosi, G.; Oster, F.; Alaya, A.; Ahmed, A. Organizational Culture and Affective Commitment to E-Learning' Changes during COVID-19 Pandemic: The Underlying Effects of Readiness for Change. *J. Bus. Res.* **2023**, *155*, 113396. [CrossRef]
57. Grover, V.; Tseng, S.-L.; Pu, W. A Theoretical Perspective on Organizational Culture and Digitalization. *Inf. Manag.* **2022**, *59*, 103639. [CrossRef]
58. Bersin, J.; Tsui, A.P.Y. Digital Transformation of Human Resource Management in the Era of Disruptive Technology. In *Transformational HRM Practices for Hong Kong*; Hong Kong University Press: Hong Kong, China, 2020; pp. 170–190. ISBN 978-988-8900-05-3.
59. Chamorro-Premuzic, T. *Personality and Individual Differences*; John Wiley & Sons: Hoboken, NJ, USA, 2016; ISBN 978-1-118-77303-1.
60. Haenlein, M.; Kaplan, A.; Tan, C.-W.; Zhang, P. Artificial Intelligence (AI) and Management Analytics. *J. Manag. Anal.* **2019**, *6*, 341–343. [CrossRef]
61. Westerman, G.; Bonnet, D.; McAfee, A. *Leading Digital: Turning Technology into Business Transformation*; Harvard Business Press: Boston, MA, USA, 2014; ISBN 978-1-62527-247-8.
62. Huang, M.-H.; Rust, R.T. Artificial Intelligence in Service. *J. Serv. Res.* **2018**, *21*, 155–172. [CrossRef]
63. Mazzei, L.A. Voice Without a Subject. *Cult. Stud. Crit. Methodol.* **2016**, *16*, 151–161. [CrossRef]
64. Cascio, W.F.; Montealegre, R. How Technology Is Changing Work and Organizations. *Annu. Rev. Organ. Psychol. Organ. Behav.* **2016**, *3*, 349–375. [CrossRef]
65. Balyan, A.K.; Ahuja, S.; Sharma, S.K.; Lilhore, U.K. Machine Learning-Based Intrusion Detection System for Healthcare Data. In Proceedings of the 2022 IEEE VLSI Device Circuit and System (VLSI DCS), Kolkata, India, 26–27 February 2022; pp. 290–294.
66. Vrontis, D.; Christofi, M.; Pereira, V.; Tarba, S.; Makrides, A.; Trichina, E. Artificial Intelligence, Robotics, Advanced Technologies and Human Resource Management: A Systematic Review. In *Artificial Intelligence and International HRM*; Routledge: London, UK, 2023; ISBN 978-1-00-337708-5.
67. Malik, M.S.; Ali, K.; Kausar, N.; Chaudhry, M.A. Enhancing Environmental Performance through Green Hrm and Green Innovation: Examining the Mediating Role of Green Creativity and Moderating Role of Green Shared Vision. *Pak. J. Commer. Soc. Sci. (PJCSS)* **2021**, *15*, 265–285.
68. Russo, M.V. *Environmental Management: Readings and Cases*; SAGE: New York, NY, USA, 2008; ISBN 978-1-4129-5849-3.
69. Marler, J.H.; Boudreau, J.W. An Evidence-Based Review of HR Analytics. *Int. J. Hum. Resour. Manag.* **2017**, *28*, 3–26. [CrossRef]
70. Ulrich, D.; Dulebohn, J.H. Are We There yet? What's next for HR? *Hum. Resour. Manag. Rev.* **2015**, *25*, 188–204. [CrossRef]
71. Jatobá, M.; Santos, J.; Gutierriz, I.; Moscon, D.; Fernandes, P.O.; Teixeira, J.P. Evolution of Artificial Intelligence Research in Human Resources. *Procedia Comput. Sci.* **2019**, *164*, 137–142. [CrossRef]
72. Strohmeier, S.; Piazza, F. Domain Driven Data Mining in Human Resource Management: A Review of Current Research. *Expert Syst. Appl.* **2013**, *40*, 2410–2420. [CrossRef]
73. Karim, M.; Bin Amin, M.; Ahmed, H.; Hajdu, Z.; Popp, J. The Influence of Leadership Styles on Employee Performance in Telecom Companies of Bangladesh. *Probl. Perspect. Manag.* **2023**, *21*, 671–681. [CrossRef]
74. Shahneaz, M.A.; Amin, M.B.; Eni, L.N. The Interplay between the Psychological Factors and Entrepreneurial Intention: An Empirical Investigation. *J. Asian Financ. Econ. Bus.* **2020**, *7*, 139–146. [CrossRef]
75. Islam, M.S.; Rubel, M.R.B.; Rimi, N.N.; Amin, M.B.; Quadir, P. Attaining Sustainable Excellence: Investigating the Impact of Sustainable Scm and Circular Economy on Green Garment Industry in Bangladesh. *Sustain. Futures* **2024**, *8*, 100234. [CrossRef]
76. Amin, M.B.; Asaduzzaman, M.; Debnath, G.C.; Rahaman, M.A.; Oláh, J. Effects of Circular Economy Practices on Sustainable Firm Performance of Green Garments. *Oeconomia Copernic.* **2024**, *15*, 637–682. [CrossRef]

77. Mahmud, A.; Ding, D.; Hasan, M.; Ali, Z.; Amin, M.B. Employee Psychological Reactions to Micro-Corporate Social Responsibility and Societal Behavior: A Structural Equation Modeling Analysis. *Curr. Psychol.* **2023**, *42*, 17132–17146. [CrossRef]
78. Akram, M.S.; Goraya, M.A.S.; Malik, A.; Aljarallah, A.M. Organizational Performance and Sustainability: Exploring the Roles of IT Capabilities and Knowledge Management Capabilities. *Sustainability* **2018**, *10*, 3816. [CrossRef]
79. Rasool, S.F.; Samma, M.; Wang, M.; Yan, Z.; Zhang, Y. How Human Resource Management Practices Translate Into Sustainable Organizational Performance: The Mediating Role Of Product, Process And Knowledge Innovation. *Psychol. Res. Behav. Manag.* **2019**, *12*, 1009–1025. [CrossRef] [PubMed]
80. Kordab, M.; Raudeliūnienė, J.; Meidutė-Kavaliauskienė, I. Mediating Role of Knowledge Management in the Relationship between Organizational Learning and Sustainable Organizational Performance. *Sustainability* **2020**, *12*, 10061. [CrossRef]
81. Garver, M.S. Logistics Research Methods: Employing Structural Equation Modeling to Test for Construct Validity—ProQuest. *J. Bus. Logist.* **1999**, *20*, 33–57.
82. Hoelter, J.W. The Effects of Role Evaluation and Commitment on Identity Salience. *Soc. Psychol. Q.* **1983**, *46*, 140–147. [CrossRef]
83. Mehrabad, S.M.; Brojeny, F.M. The Development of an Expert System for Effective Selection and Appointment of the Jobs Applicants in Human Resource Management. *Comput. Ind. Eng.* **2007**, *53*, 306–312. [CrossRef]
84. Cesta, A.; Cortellessa, G.; De Benedictis, R. Training for Crisis Decision Making—An Approach Based on Plan Adaptation. *Knowl. Based Syst.* **2014**, *58*, 98–112. [CrossRef]
85. Gratton, L.C. New Frontiers in Re-Skilling and Upskilling. *MIT Sloan Manag. Rev.* **2019**, *61*, 1. Available online: https://sloanreview.mit.edu/article/new-frontiers-in-re-skilling-and-upskilling/ (accessed on 21 October 2021).
86. Robert, L.P.; Pierce, C.; Marquis, L.; Kim, S.; Alahmad, R. Designing Fair AI for Managing Employees in Organizations: A Review, Critique, and Design Agenda. *Hum. Comput. Interact.* **2020**, *35*, 545–575. [CrossRef]
87. Huang, M.-H.; Rust, R.; Maksimovic, V. The Feeling Economy: Managing in the Next Generation of Artificial Intelligence (AI). *Calif. Manag. Rev.* **2019**, *61*, 43–65. [CrossRef]
88. Lawler, J.J.; Elliot, R. Artificial Intelligence in HRM: An Experimental Study of an Expert System. In Proceedings of the 1993 Conference on Computer Personnel Research, St Louis, MO, USA, 1–3 April 1993; Association for Computing Machinery: New York, NY, USA, 1993; pp. 473–480.
89. Fan, C.-Y.; Fan, P.-S.; Chan, T.-Y.; Chang, S.-H. Using Hybrid Data Mining and Machine Learning Clustering Analysis to Predict the Turnover Rate for Technology Professionals. *Expert Syst. Appl.* **2012**, *39*, 8844–8851. [CrossRef]
90. Li, J.; Bonn, M.A.; Ye, B.H. Hotel Employee's Artificial Intelligence and Robotics Awareness and Its Impact on Turnover Intention: The Moderating Roles of Perceived Organizational Support and Competitive Psychological Climate. *Tour. Manag.* **2019**, *73*, 172–181. [CrossRef]
91. Junaedi, A.T.; Renaldo, N.; Yovita, I.; Veronica, K.; Sudarno, S. Digital Culture as a Moderating Factor in Increasing Digital Literacy. *Reflect. Educ. Pedagog. Insights* **2023**, *1*, 116–127.
92. Chen, Y.; Wang, Y.; Nevo, S.; Jin, J.; Wang, L.; Chow, W.S. IT Capability and Organizational Performance: The Roles of Business Process Agility and Environmental Factors. *Eur. J. Inf. Syst.* **2014**, *23*, 326–342. [CrossRef]
93. Hakala, H.; Kohtamäki, M. Configurations of entrepreneurial- customer- and technology orientation: Differences in learning and performance of software companies. *Int. J. Entrep. Behav. Res.* **2011**, *17*, 64–81. [CrossRef]
94. Koufteros, X.; Verghese, A.; Lucianetti, L. The Effect of Performance Measurement Systems on Firm Performance: A Cross-Sectional and a Longitudinal Study. *J. Oper. Manag.* **2014**, *32*, 313–336. [CrossRef]
95. Harman, H.H. *Modern Factor Analysis*, 3rd ed.; U Chicago Press: Oxford, UK, 1976; p. 487.
96. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.-Y.; Podsakoff, N.P. Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [CrossRef]
97. Kock, N.; Lynn, G. Lateral Collinearity and Misleading Results in Variance-Based SEM: An Illustration and Recommendations. *J. Assoc. Inf. Syst.* **2012**, *13*, 546. [CrossRef]
98. Kock, N. Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach. *Int. J. e-Collab. (IJeC)* **2015**, *11*, 1–10. [CrossRef]
99. Doll, W.J.; Xia, W.; Torkzadeh, G. A Confirmatory Factor Analysis of the End-User Computing Satisfaction Instrument. *MIS Q.* **1994**, *18*, 453–461. [CrossRef]
100. Baumgartner, H.; Homburg, C. Applications of Structural Equation Modeling in Marketing and Consumer Research: A Review. *Int. J. Res. Mark.* **1996**, *13*, 139–161. [CrossRef]
101. Kim, H.; Ku, B.; Kim, J.Y.; Park, Y.-J.; Park, Y.-B. Confirmatory and Exploratory Factor Analysis for Validating the Phlegm Pattern Questionnaire for Healthy Subjects. *Evid Based Complement Altern. Med* **2016**, *2016*, 2696019. [CrossRef] [PubMed]
102. Hair, J.F.; Sarstedt, M.; Ringle, C.M.; Mena, J.A. An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research. *J. Acad. Mark. Sci.* **2012**, *40*, 414–433. [CrossRef]
103. Henseler, J.; Ringle, C.M.; Sinkovics, R.R. The Use of Partial Least Squares Path Modeling in International Marketing. In *New Challenges to International Marketing*; Sinkovics, R.R., Ghauri, P.N., Eds.; Advances in International Marketing; Emerald Group Publishing Limited: Leeds, UK, 2009; Volume 20, pp. 277–319. ISBN 978-1-84855-469-6.
104. Hair, J.F., Jr.; Sarstedt, M.; Hopkins, L.; Kuppelwieser, V.G. Partial Least Squares Structural Equation Modeling (PLS-SEM): An Emerging Tool in Business Research. *Eur. Bus. Rev.* **2014**, *26*, 106–121. [CrossRef]

105. Fornell, C.; Larcker, D.F. Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *J. Mark. Res.* **1981**, *18*, 382–388. [CrossRef]
106. Hair, J.F., Jr.; Black, W.C.; Babin, B.J.; Anderson, R.E. *Multivariate Data Analysis*, 7th ed.; Pearson: Upper Saddle River, NJ, USA, 2009; ISBN 978-0-13-813263-7.
107. Chin, W.W. Commentary: Issues and Opinion on Structural Equation Modeling. *MIS Q.* **1998**, *22*, vii–xvi.
108. Hair, J.F.; Astrachan, C.B.; Moisescu, O.I.; Radomir, L.; Sarstedt, M.; Vaithilingam, S.; Ringle, C.M. Executing and Interpreting Applications of PLS-SEM: Updates for Family Business Researchers. *J. Fam. Bus. Strategy* **2021**, *12*, 100392. [CrossRef]
109. Del Giudice, M.; Scuotto, V.; Papa, A.; Tarba, S.Y.; Bresciani, S.; Warkentin, M. A Self-Tuning Model for Smart Manufacturing SMEs: Effects on Digital Innovation. *J. Prod. Innov. Manag.* **2021**, *38*, 68–89. [CrossRef]
110. Jaiswal, D.; Kaushal, V.; Kant, R.; Kumar Singh, P. Consumer Adoption Intention for Electric Vehicles: Insights and Evidence from Indian Sustainable Transportation. *Technol. Forecast. Soc. Change* **2021**, *173*, 121089. [CrossRef]
111. Malik, M.J.; Ahmad, M.; Kamran, M.R.; Aliza, K.; Elahi, M.Z. Student Use of Social Media, Academic Performance, and Creativity: The Mediating Role of Intrinsic Motivation. *Interact. Technol. Smart Educ.* **2020**, *17*, 403–415. [CrossRef]
112. Nguyen, T.-M.; Malik, A. A Two-Wave Cross-Lagged Study on AI Service Quality: The Moderating Effects of the Job Level and Job Role. *Br. J. Manag.* **2022**, *33*, 1221–1237. [CrossRef]
113. Vrontis, D.; Makrides, A.; Christofi, M.; Thrassou, A. Social Media Influencer Marketing: A Systematic Review, Integrative Framework and Future Research Agenda. *Int. J. Consum. Stud.* **2021**, *45*, 617–644. [CrossRef]