ACHIEVING SUSTAINABILITY IN THE DIGITAL ERA: THE INFLUENCE OF AI-DRIVEN CAPABILITIES ON ORGANIZATIONAL SUSTAINABILITY

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Abstract

Research Problem: *AI-driven capabilities are a disruptive force that can promote organisational sustainability (OS) and build a sustainable future. Yet the direct and indirect effects of the various components of AI-driven capabilities on the environmental, economic, and social aspects of OS remain poorly understood in contemporary organisations and across different industrial contexts.*
Method/Theory: *The study adopted dynamic capability theory and built a moderated mediation (MODMED) framework to examine how AI-driven capabilities promote OS through green human resource management (GHRM), and how digital literacy moderates the mediation effect. Based on a survey of 310 Chinese enterprises, the proposed framework was empirically tested to examine the hypothesised relationships.*
Results: *AI-driven capabilities positively affect OS; GHRM partially mediates this effect; and digital literacy positively moderates the indirect impact of AI-driven capabilities on OS via GHRM, thereby strengthening firms' overall sustainability performance.*
Key Contribution to Knowledge: *This study enhances the sustainability literature by providing useful information and guidance on how organisations may use AI-driven capabilities to achieve superior sustainability performance, complemented by GHRM and digital literacy, and supported by empirical evidence, mediated by a moderated mediation mechanism.*
Conclusion: *The study extends the sustainability literature by providing useful information and guidance on how organisations may use AI-driven capabilities to improve their sustainability performance, complemented by GHRM and digital literacy, to meet long-term organisational sustainability objectives.*
Recommendation: *The findings offer useful management implications for organisations seeking to increase the adoption of AI-driven capabilities, GHRM, and digital literacy towards achieving the Sustainable Development Goals.*

1. Introduction

Environmental degradation continues, and stakeholders from across the globe call for sustainable business. Organisational sustainability (OS) is the ability of an enterprise to manage the social, environmental, and economic effects associated with it and to maintain and continuously generate long-term business value for the business and for society (Bianchi et al., 2022; Baumgartner &Rauter, 2017). In this way, organisations constrain the scale of consumption, reduce and eliminate waste, and become alert to social, ecological, and economic changes(Yi &Demirel, 2023). OS enables the building of stable relationships with employees, investors, and customers, thereby securing market leadership and position. Consequently, OS strengthens and stimulates long-term economic performance.

Thus, OS needs to be developed, implemented, and protected in depth for organisations to be leaders in a competitive market.OS is only possible when enterprises continue investing in AI and improve AI capabilities (Abulibdeh et al., 2024; Di Vaio et al., 2020; Kar et al., 2022). In terms of dynamic capabilities perspective, the integration of AI based technologies allow firms reconfigure, reassemble and reshuffle their internal resources and external environment in response to the dynamically changing challenges arising from economic, social and environment issues (Pan &Nishant, 2023; Tsolakis et al., 2023). The capability related to AI is conducive to the firms' increased information processing power when it comes to the goals in environment and society issues. A set of capabilities built in dynamic environment is expected to help firms be adaptable to shifts in consumer's preference, changes in customer's need, environment and government regulations (Benzidia et al., 2021; Dohale et al., 2024). OS can also effectively use AI capabilities which support and enhances efficiency for making decisions and foster innovative and efficient operational execution (MohiuddinBabu et al., 2022; Shaik et al., 2023). The direct role of AI-enabled capabilities in achieving OS has not been examined in depth; hence, Research Question 1 was posed: How do *AI-enabled capabilities contribute to the OS?*

While AI and OS have been widely discussed, none of the literature identifies mediators in the relationship between AI capacities and OS. To exploit the AI capabilities of OS to their full potential, green human resource management can implement environmental management principles in hiring the best candidate and in employee training and promotion procedures (Beda-Garcia et al., 2021; Farooq et al., 2022). Effective adoption of OS must also take into account a green culture at the organisational level to embed sustainability values in daily activities and employees' lives (Jernimo et al., 2020). Through GHRM, employees become acquainted with and adapt to the organisation's sustainability goals by inculcating a sense of responsibility, building expertise, and cultivating sustainable thinking patterns through recruitment, performance appraisal, and the reward system (Jernimo et al., 2020), maximising the impact of AI technologies on performance and enhancing the effectiveness of AI-assisted tools in achieving economic performance gains as part of OS while reducing environmental and social footprint (Hao et al., 2024).. According to the dynamic capability view, AI competencies enhance GHRM capacity through data insights, collaboration opportunities, and workflow automation for OS (Dey et al., 2024; Tambe et al., 2019). Regardless, little research has examined how GHRM mediates the relationship between AI

capabilities and firms' OS. Thus, this led to research question 2: *How does GHRM mediate the relationship between AI-enabled capabilities and the OS?*

Nevertheless, firms could foster robust sustainability outcomes by leveraging contextual factors that either enhance or mitigate these indirect effects (Liu et al., 2023; Nishant et al., 2020). The contextual factor of the present study is employees' proficiency with digital tools and platforms, which ensures their ability to successfully interact with AI-enabled technology—digital literacy—treated as a moderator that helps realise employees' proficiency in implementing AI-driven sustainability practices (Cetindamar et al., 2021). Working proficiently in digital spaces is imperative to harness the AI tools in GHRM (Ogbeibu et al., 2024); digital literacy skills help employees make the most of insights provided by AI in understanding, processing, and taking consistent action (Zechiel et al., 2024), and proactive pursuit of life-long learning and adaptability to new AI-based objectives reinforce the bond of GHRM with OS (Abulibdeh et al., 2024). Considering the mediating and moderating influences of other factors (Preacher et al., 2007), in this research we study the relation of AI capabilities and OS by the mediation of GHRM and the moderation of digital literacy; thus, it is able to answer the research question 3*: How does digital literacy moderate the indirect relationship between AI capabilities and OS via GHRM?*

By developing a moderated mediation (MODMED) model (Figure 1), the current study contributes to the digital and sustainability literature in three ways: first, by extending theoretical and empirical literature on the association between AI capabilities and OS, since although prior literature recognises how AI enhances firms' productivity (Shaik et al., 2023; Sullivan &Wamba, 2024), more remains to be explored regarding how AI enhances overall economic, environmental, and social performance; second, by bridging the missing link between AI capabilities and OS through the mediating effect of GHRM; and finally, by adding a contingency role for digital literacy, advancing understanding of whether and under what conditions AI capability has a more potent impact on a firm's sustainability via GHRM. This MODMED model (Preacher et al., 2007) presents a broad view of the boundary conditions and scope of influence from AI capability to sustainability.

Figure 1: Conceptual Model

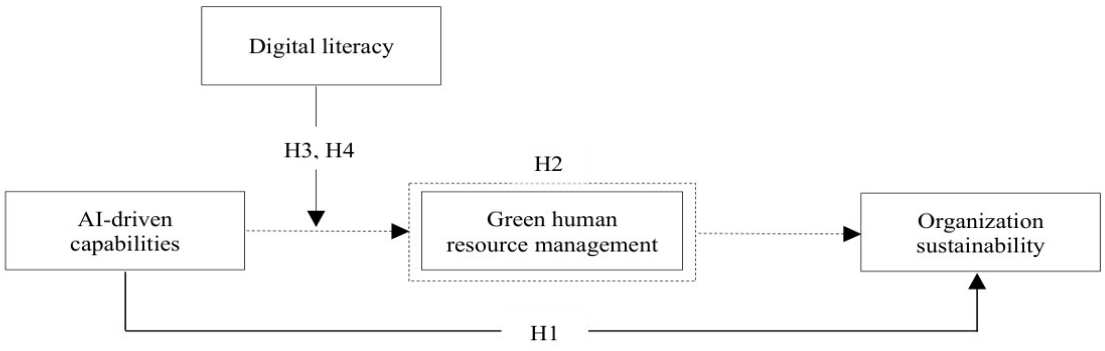


Figure 2: Conceptual model

Note: Dotted arrows show mediation relationship

2. Theory and Hypotheses Developments

2.1 Organisational Sustainability

Long-term organisational sustainability (OS enables the establishment of a long-term OS that considers economic, environmental, and social issues in an organisation's decision-making and functioning (Negri et al., 2021). Sustainable businesses do not simply act to make a profit; rather, they pursue sustainability through operational procedures that have positive social and environmental impacts on today's society and future generations (Fischer et al., 2020). Through waste reduction, emissions reduction, responsible resource use, and the promotion of the circular economy, such companies also value and promote social responsibility by prioritising employees, clients, and the community (Ishaq et al., 2024). By balancing these dimensions, companies that promote OS become more versatile and obtain a stronger competitive advantage in the sustainability market.

A wide range of studies investigate the antecedents of OS. Smith's (2012) research finds that sustainability stems from organisations acquiring knowledge, whereas Carayannis et al. (2015) claim that OS comes from re-revolutionisingorganisations' business models. Other findings indicate that GHRM practices drive sustainability (Jeronimo et al., 2020); knowledge management boosts sustainability (Demir et al., 2023); and green training facilitates the advancement of sustainability (Xie& Zhu, 2020). Despite this extensive research, the effect of AI capabilities has yet to be explored.

2.2 AI Capabilities and Sustainable Organisation: Dynamic Capability View

The DCV suggests that, for organisations to respond and remain competitive in dynamic circumstances, they must demonstrate resource- and competency-based innovation and the adaptation of resources and competencies (Gupta et al., 2020; Teece et al., 1997). Compared to static capability, which focuses on routine tasks, dynamic capability concerns firms' ability to sense opportunities, seize them, and transform organisations to capture them in response to new issues (Schilke et al., 2018)—perceived as crucial for sustaining competitive advantage amid environmental dynamism (Mishra & Singh, 2023), whereas static capability is often inadequate in volatile contexts (Barreto et al., 2024). Dynamic capability is a valuable resource granting organisations the capabilities needed to integrate and orchestrate OS (Chari et al., 2022), enabling firms to face environmental and social challenges and constructively manage sustainability (Yi &Demirel, 2023), mobilising dynamic capabilities and sustainable integration across the value chain to address multiple stakeholder claims while building system stability and sustainability (Chari et al., 2022; Y. D. Lee et al., 2023).

AI capabilities, which constitute the other indispensable dynamic capability for attaining OS (Bag et al., 2021; Zhong et al., 2022), support organisations in effectively realising their environmental, societal and economic opportunities.Companies using dynamic capabilities transform these enormous quantities of data into sustainability opportunities; ensure optimal utilisation of resources and risks which are detrimental to sustainable business practices (Tsolakis et al., 2023). TheseAI Applications make the firm capable of predicting their firm's environmental effects from time to time with respect to factors of air quality, emissions of greenhouse gases, consumption of energy etc. (Benzidia et al., 2021). It supports firms in terms of boosting product quality, firm's performance, decreasing firm's expenditures and bolstering

firm's financial strengths so as to obtain economic, environmental, and social sustainability objectives (Hao&Demir, 2024; Czarnitzki et al., 2023) and improves employees wellbeing by ensuring good working practices, Diversity Practices, employee's remuneration and management of careers of employee (Chang &Ke, 2024). Therefore, AI capability is identified as one of the critical dynamic capabilities for adopting OS and achieving sustainable competitive advantage in the current dynamic business environment.

2.3 AI Capabilities and Organisational Sustainability

Consistent with the DCV, AI-driven capacities are positively related to a company's ability to achieve and sustain multidimensional sustainability (Ortiz-Avram et al., 2024). AI innovation is transforming the environmental perspective on sustainability by supporting companies' resource management and reducing pollution and waste (Di Vaio et al., 2020). Advanced data analytics capture vast amounts of environmental information, producing actionable insights into business environmental impact (Benzidia et al., 2021). Accurate measurements on emission control, optimization in energy consumption, resource depletion reduction, and waste minimisation are available to firms (Ahmad et al., 2021). With a better-defined understanding of their footprints, businesses can transform both production and logistics processes (Richey Jr. et al., 2023) and move from mere compliance to environmentally innovative players (Feng et al., 2024).

In addition, AI enhances economic sustainability aspects by providing process and cost optimization and focusing on the development and implementation of AI to achieve higher economic goals; with the foresight into demand and supply management, it ensures optimal stock storage levels and minimizes costs related to stock holding (Jauhar et al., 2024), meanwhile smoothing out logistics and production operations, and reduce operational risks (Reyes et al., 2023); usingAI to predict future demand trends, cost saving possibilities, and to scout for emerging market opportunities can sustain long-term progress for businesses (Latinovic&Chatterjee, 2022); AI contributes to leaner business operations and better positioned companies, simultaneously working towards sustainability goals (Wamba-Taguimdje et al., 2020).

When dealing with the social dimensions of sustainability, AI holds immense potential; with fairer recruitment practices, enhanced diversity goals, and increased attention to employee well-being, the AI application create a workplace where individuals feel well-regarded and motivated (Malik et al., 2023); to help process employee perception, AI can facilitate better decision making that is aligned with ensuring overall team satisfaction, improving workplace satisfaction and adding value to social Sustainability practices (Budhwar et al., 2022); furthermore AI helps increase work-life balance which significantly contributes to an individual's overall Happiness (Malik et al., 2023); hence AI applications can significantly contribute to human well-being and work quality of life in work environment (Kumar et al., 2024).

H1: AI-driven *capabilities are positively linked with organisational sustainability.*

2.4 The Mediating Role of Green HRM

GHRM practices integrate socially responsible principles across HR activities to enhance a company's sustainability performance (Ogbeibu et al., 2024), including green recruitment, green training and development, green performance management, green rewards,

and green employee engagement, thereby motivating employees to undertake sustainability-related tasks (Yong et al., 2020).

Through green recruitment, firms recruit employees who value and align with sustainability ideas, while green training and development enhance employees' skills to perform environmentally sustainable activities (Usman et al., 2023). GHRM performance management is achieved through recognition and rewards for employees' sustainability-related performance, thereby helping employees continuously engage in sustainable work behaviour (Al-Swidi et al., 2021). Cumulatively, these functions stimulate environmentally friendly behaviour and nurture a green organisational culture that fosters employees' green attitudes and a collectively driven culture for sustainability, contributing to employees' sustainable behaviour (Al-Swidi et al., 2021), green culture (Muisyo& Qin, 2021), and sustainability (Yong et al., 2020).

We extend this research stream by arguing that GHRM plays a central role in translating the effects of AI-driven capabilities into concrete OS by aligning employee behaviour, practices, and mindsets with a firm's sustainability goals. Indeed, with an AI-powered capability to monitor, assess, and optimise environmental, social, and economic conditions (Lee et al., 2024), operationalising the tools calls for workforce engagement with sustainability (Di Vaio et al., 2020). GHRM facilitates the faster integration of these components by aligning sustainability initiatives across the firm's staffing, training, and performance supervision functions and ensuring the workforce possesses the required competencies and motivation for these sustainable practices (Ogbeibu et al., 2024). GHRM leveraging AI-derived capabilities is also an approach to streamlining training towards sustainable resource management and the execution of eco-friendly decisions by workers, so that they practice sustainable behaviours in their work (Hao et al., 2024). This enables a range of sustainability-centric HR practices that are accessible and manageable for workers (Chang &Ke, 2024).

GHRM also allows for the maximisation of opportunities provided by the AI-generated capability for organisational sustainability by creating organisational value that entails the building of a sustainable culture which helps achieve organisational sustainability for the purpose of the environment, society, and economy; measurement of organisational sustainable performances in the company so that HR managers determine the manner AI intelligence is utilised for OS. The incorporation of incentives and motivation programmes related to sustainability can develop employees' engagement with sustainability and contribute to creating a sustainable workplace and enthusiasm for joining a team of collaborators who can jointly manage and run sustainability initiatives, thereby fostering social sustainability (de Oliveira et al., 2023).

H2*: Green human resource management practices mediate the relationship between AI-driven capabilities and organisational sustainability.*

2.5 The Moderating Role of Digital Literacy

Digital literacy is the set of knowledge, skills, and competencies an individual needs to successfully manage digital, social, and information technologies and use them effectively in many aspects of life (Nikou et al., 2022), as well as awareness of privacy and security issues (Eynon, 2021). A deep understanding of digital literacy enables employees to learn, apply, and adopt new

emerging technologies, develop skill sets to cope with a constantly adapting digital society, and gain benefit from new digital technologies to be productive (Cetindamar et al., 2021), while fostering awareness of data security, privacy (Irfan et al., 2022), and data ethics concerns (Eynon, 2021)..

We contend that digital literacy moderates the impact of AI capabilities on GHRM by empowering employees' ability to adopt and support AI-supported sustainable initiatives. High levels of digital literacy enable employees to understand and assimilate AI tools to engage with and contribute to GHRM practices (Ogbeibu et al., 2024). This digitally enabled employee can use AI to monitor and assess sustainability practices, contribute to environmental targets, and actively support organisational efforts to further embed the employee in the firm's sustainability processes. Employees with low digital literacy, in contrast, will be unable to participate effectively in AI-driven processes, thereby hindering AI's ability to promote sustainability through GHRM. Thus, a high level of digital literacy complements the impact of a firm's AI capabilities in promoting GHRM.

H3: *Digital literacy moderates the relationship between AI-driven capabilities and green human resource management practices.*

We further hypothesise that the moderating effect of digital literacy on the first-order outcome variable will represent a second-order MODMED effect (Preacher et al., 2007) on OS. The correlation would also be moderated by high digital literacy whereby the extent to which employees successfully leveraging AI potential offered by the GHRM would influence theOS outcomes is determined by their capability to read and understand knowledge generated through the AI mediated processes. High digital literate workforce would employ digitally mediated monitoring tools for carbon print, waste management, consumption of green products and employ knowledge generated through AI application in optimizing the carbon and energyprint of the organization (Ogbeibu et al., 2024).

. On the other hand, low-digitally skilled employees might not be well equipped to work with these interfaces and AI tools, and the impact channel via employee capabilities on GHRM may weaken. Thus, digital literacy strengthens the process by which AI capabilities, via GHRM, impact OS by amplifying that impact.

H4: *The indirect relationship between AI-driven capabilities and organisational sustainability via green human resource management practices is stronger under high digital literacy than under low digital literacy.*

3. Methodology

3.1.Sample and Data Collection

As the empirical context, we chose China, since a complex mixture of environmental, social, and economic problems associated with its speedy industrialisation and urbanisation caused large-scale environmental pollution and soil degradation (Ushie et al., 2023). More than 1 million people annually die from pollution in China; approximately 19.4% of the country's cultivated land was polluted in 2014. These problems also contribute to company losses: German Schaeffler lost $43 million due to pollution by its Chinese suppliers. The Chinese government responded with severe regulatory measures that led to the closure of thousands of plants, implementing policies to address emerging social and environmental problems, accelerate OS, and attract foreign investment in green policies. China is undergoing rapid

transformation driven by AI technology, with digitalisation central to the government's agenda through the policy "Accelerating Digital Development to Build Digital China" (Ye et al., 2022), and is currently second in Digital China status and the largest globally in the AI-powered digital consumers' market (Ma, 2021), making China an appropriate country for studying firms' green strategy performance.

Data were collected from manufacturing companies across China. To ensure accurate linguistic and cultural adaptation and content validity, we followed a standard cross-cultural adaptation procedure (Berry, 1980): an English survey instrument was translated into Chinese by two academic experts in strategic management, with another pair of professors performing a back-translation into English. Content validity was evaluated through a pilot study with 20 CEOs from 10 local companies, whose feedback informed adjustments before the final survey was conducted via face-to-face interviews. To avoid selection bias, the Chinese central government provided a list of companies from local commerce departments, from which we drew 500 firms in each of three regions—East, West, and Central—for a total of 1,500 firms across 23 of the 31 Chinese provinces. We contacted executives at each potential firm to explain the survey's objectives, verify company data, and secure participation via phone or email. Of the list sent to professional researchers, 340 firms agreed to an interview, and five trained interviewers subsequently visited all 340 participating companies.

During interviews, senior managers whose roles were associated with sustainability initiatives—chief executive officers, chairpersons, senior decision-makers, and top managers involved in digital decision processes—were approached to enhance response accuracy. To mitigate common method bias (CMB), we recruited two senior respondents per firm and assured them of confidentiality. Details on the artificial intelligence (AI) competencies and sustainability indexes were obtained from the chairperson or CEO and the R&D manager. Other senior managers reported details of the digital capabilities and GHRM processes. We deleted interviews with a large percentage of missing answers and received 620 complete replies from 310 firms, among which 42.25% were in the East, 30.00% in the Central and 27.75% in the West of China.

Table1. Description of thefirm (N= 310).

Sample characteristics	**Frequency**	**%**	**Sample characteristics**	**Frequency**	**%**
Firm age			Firm size		
0-10	97	31.29	0-100	90	29.03
11–20	127	40.97	100-200	50	16.13
21-30	50	16.13	200-350	35	11.29
31–40	14	04.52	350-500	90	29.03
41–50	12	03.87	Above 500	45	14.52
Above 50	10	03.23	Education		
Gender			High school	15	04.84
Male	233	75.00	Bachelor	47	15.16

			degree		
Female	77	25.00	Master degree	198	63.87
Revenue (in millions of Naira			PhD	55	17.74
0-20	75	24.19	Firm regions		
11-40	54	17.42	Southern	131	42.25
31–60	43	13.87	Northern	86	27.75
51-80	15	04.84	Central	93	30.00
81-100	61	19.68	Industry		
Above 100	62	20.00	IT	26	08.39
			Energy	42	13.55
Ownership			Chemical	68	21.94
State-owned	186	60.0	Machine	115	37.10
Private	97	31.29	Transportation	25	08.06
Others	27	08.71	Agriculture	34	10.97

3.2. Variable Measurement

Allmeasureswereadaptedfrompreviousresearc handmeasuredonaseven-pointLikertscale, except for most control variables.

3.2.1. Independent variable

The variables for AI adoption capabilities were obtained from the five items developed by Belhadi et al. (2024) and Wamba (2022), covering IT and skills necessary for AI, use of AI to develop self-learning and forecasts, adoption and dispersal of AI throughout business units, and use of AI for creation of new products and services.

3.2.2. Mediating variable

Green human resource management was used and adapted from the existing research (Ishaq et al., 2024; Yong et al., 2020). It consisted of six sub-components: green job analysis and description (3 items); green recruitment (2 items); green selection (2 items); green training (3 items); green performance appraisal (3 items) and green reward system (2 items).

3.2.3. Moderating variable

Digital literacy had five facets according to some previous researchers (Vuorikari et al., 2016; Zahoor et al., 2023), specifically: information literacy (3 items); interaction and collaboration (4 items); content creation (3 items) (Yusop et al., 2022); security (4 items) and problem-solving skills (4 items) (Yusop et al., 2022).

3.2.4. Dependent variable

Laosirihongthong et al. (2013) and Yong et al. (2020) use three dimensions: economic, social, and environmental, to reflect on the OS construct, each dimension with 5 items.Economic performance reflects cost-reduction efforts, such as reduced material, fuel, and waste-management costs; environmental performance reflects measures to prevent contamination, recycle waste, and reduce hazardous waste; and social performance reflects a commitment to employee safety and well-being, the protection of stakeholders' rights, and a contribution to societal well-being.

3.2.5. Control variables.

Following prior research (Jiangetal.,2021), we controlled for firm age (natural log of years since establishment) and firm size (natural log of workforce size) due to their impact onfirm resources and capabilities (Qadeer et al., 2024); state ownership, via a dummy variable (1 for wholly/partly state-owned, 0 for private); and competitive intensity, measured on a scale of 1 (low) to 4 (exceptionally high).

3.3. Construct validity

We used SPSS 24 to examine validity and reliability according to Anderson and Gerbing (1988). All measures produced Cronbach's alpha scores ranging from 0.76 to 0.89, within the accepted benchmark of 0.7 (Hair et al., 2014). For scale validity, we conducted a four-factor confirmatory factor analysis using covariance-based structural equation modelling with AMOS 24. The measurement model achieved adequate fit: $\chi^2/df = 2.315$ ($p < 0.001$), GFI = 0.947, CFI = 0.961, NNFI = 0.957, TLI = 0.916, SRMR = 0.053, and RMSEA = 0.068 (Hair et al., 1998). A principal component analysis with varimax rotation showed significant factor loadings for all items, ranging from 0.7 to 0.95 (Comrey& Lee, 1992), and all scales exceeded the average variance extracted (AVE) threshold, with composite reliability >0.7 (Hair et al., 2014). Discriminant validity was tested using chi-square difference tests between construct pairs, the test for AI capabilities and GHRM ($\chi^2(1) = 7.842$, $p<0.001$) was significant (Anderson &Gerbing, 1988), further ensured because each construct shared less variance than the AVE of the pair (Fornell&Larcker, 1981), with the square roots of the AVEs on the diagonal exceeding correlation coefficients between construct pairs.

Table 2. Descriptive statistics and correlations

Main variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Competitive intensity	-																		
2. Firm age	0.002	-																	
3. Firm size	0.004	0.014*	-																
4. State ownership	-0.002	-0.007	0.010	-															
5. AI-driven capabilities	0.192*	-0.005	-0.012	-0.017	0.871														
6. DL information literacy	0.014	0.030	-0.014	-0.155*	0.210**	0.854													
7. DL interaction and collaboration	0.012	0.021	0.004	0.010	0.251**	0.301***	0.863												
8. DL digital content creation	-0.011	-0.014	-0.003	0.001	0.254**	0.254**	0.247**	0.844											
9. DL safety	-0.004	-0.006	-0.012	-0.101	0.305***	0.211**	0.241**	0.248**	0.891										
10. DL problem-solving	0.021	0.002	0.005	-0.015	0.281**	0.189*	0.174*	0.169*	0.210**	0.893									
11. GHRM green analysis and job description	-0.011	-0.020	0.012	-0.010	0.351***	0.259**	0.182*	0.201**	0.135*	0.187*	0.851								
12. GHRM green recruitment	0.005	0.006	0.001	0.020	0.311***	0.235**	0.231**	0.204**	0.267**	0.194*	0.189*	0.839							
13. GHRM selection	0.010	0.005	0.015	0.007	0.258**	0.261**	0.274**	0.221**	0.234**	0.278**	0.233**	0.274**	0.870						
14. GHRM training	-0.010	-0.110	-0.014	0.100	0.268**	0.268**	0.234**	0.277**	0.268**	0.274**	0.310**	0.318**	0.301***	0.902					
15. GHRM green performance assessment	0.021	0.011	0.005	0.008	0.355***	0.331***	0.247**	0.236**	0.270**	0.272**	0.172*	0.161*	0.210**	0.210**	0.866				
16. GHRM green rewards	-0.020	-0.015	-0.022	-0.011	0.287**	0.221**	0.195**	0.224**	0.226**	0.298**	0.211**	0.311**	0.341***	0.282**	0.252**	0.911			
17. OS economic performance	0.121*	0.132*	-0.114*	-0.221*	0.458***	0.310***	0.179**	0.189*	0.169*	0.247**	0.225**	0.223**	0.245**	0.269**	0.247**	0.264**	0.871		
18. OS environmental performance	0.110*	-0.102*	-0.023	0.051	0.335***	0.326***	0.161*	0.169*	0.124*	0.168*	0.185*	0.178*	0.199*	0.258**	0.247**	0.278**	0.471**	0.879	
19. OS social performance	0.132*	-0.014	-0.011	-0.005	0.335***	0.347***	0.184*	0.247**	0.268**	0.220**	0.247**	0.168*	0.318***	0.299**	0.341**	0.324**	0.374**	0.441**	0.875
Mean	2.541	2.452	1.462	1.621	5.234	4.684	4.057	5.214	4.689	4.012	4.892	5.229	5.128	4.985	5.181	4.552	5.061	4.668	5.275
S.D.	0.485	0.654	0.584	0.754	0.948	0.785	0.641	0.628	0.568	0.874	0.759	0.837	0.713	0.847	0.680	0.481	0.696	0.920	0.594

Notes: eLog taken; *p < 0.05; **p < 0.01; 2-tailed. Diagonal elements are square roots of the AVE values; N = 310.
DL = digital literacy; OS = organizational sustainability.

3.1. Common Method Bias

We used several procedures to detect and reduce potential CMB. Harman's single-factor test using CFA (Podsakoff, 2003) produced four factors with eigenvalues above 1.0, explaining 68.48% of total variance, with the single highest-contributing factor explaining 26.14%, well below the critical 50% threshold. We also applied a marker variable (MV) test (Lindell& Whitney, 2001), using job satisfaction as the MV. After adjusting the correlations of all latent constructs to the smallest positive correlation (r = 0.002) between the MV and the others, all latent variable correlations remained significant, indicating that CMB would not be an issue.

4. Results

Table 2 abovesummarises means, standard deviations, and correlations of the variables. Table 2 shows the moderated hierarchical regression results. Controls alone create models 1 and 4 as baselines. AI capability and its interaction with digital literacy were added in models 2 and 3, respectively. AI capability and its joint interaction with GHRM form models 5 and 6.

4.1. Main Effect Testing

In line with H1, there is a positive correlation between AI capabilities and OS. The outcomes of Model 5 in Table 3 show that the implementation of AI significantly affects decisions regarding the achievement of the OS ($\beta = 0.254$, $p < 0.001$), supporting H1.

Table 3. Regression Results

	GHRM			Organizational sustainability		
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Control variables						
Firm age[e]	0.021 (0.103)	0.026 (0.101)	0.025 (0.101)	0.104 (0.210)	0.111 (0.213)	0.115 (0.214)
Firm size[e]	-0.113* (0.011)	-0.115* (0.012)	-0.126* (0.023)	-0.024 (0.231)	-0.025 (0.235)	-0.027 (0.241)
Competitive intensity	0.125* (0.024)	0.123* (0.026)	0.121* (0.023)	0.172* (0.012)	0.153* (0.016)	0.162* (0.021)
State ownership	0.012 (0.204)	0.013 (0.206)	0.013 (0.205)	-0.026 (0.325)	-0.025 (0.323)	-0.027 (0.326)
Main effects						
AI-driven capabilities		0.184** (0.013)	0.201** (0.010)		0.254*** (0.000)	0.136* (0.016)
Digital literacy			0.105* (0.021)			
Mediating effect						
GHRM						0.301*** (0.005)

	GHRM			Organizational sustainability		
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Moderating effect						
AI-driven capabilities × digital literacy			0.270*** (0.002)			
Model summary						
R^2	0.146	0.235	0.302	0.175	0.263	0.372
ΔR^2		0.089***	0.067***		0.088***	0.109***
F value	5.537***	7.495***	11.943***	4.537***	9.741***	10.480***

Notes: *p < 0.05; **p < 0.01; ***p < 0.001. 2-tailed. N = 310. eLog taken.

4.2. Mediating Effect Testing

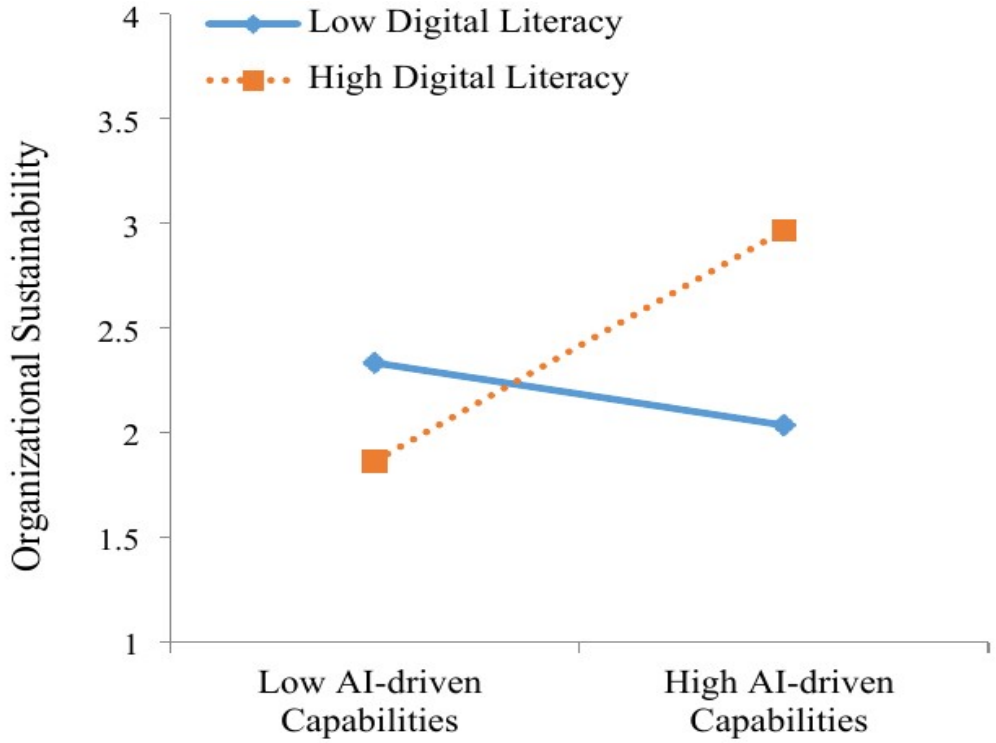
H2 posits that GHRM mediates the relationship between AI capabilities and OS. Using Baron and Kenny's (1986) approach, we test our prediction by examining the four conditions. Firstly, artificial intelligence functionality has a substantial effect on GHRM (β = 0.184, p < 0.01), thereby representing Condition 1. Secondly, for Model 5, the impact of AI is very significant (β = 0.254, p < 0.000), fulfilling Condition 2. Thirdly, the significant relationship between GHRM and OS (β = 0.301, p< 0.001) met Condition 3 in Model 6. Last but not least, for Model 6, where GHRM is added, the coefficient for AI capabilities on OS is reduced to a significant level (β=0.136, p<0.05), thus meeting Condition 4. As this result is consistent with Baron and Kenny's (1986) criteria, it provides partial support for H2.

These findings were substantiated by performing the Sobel test and the Monte Carlo Method for Assessing Mediation (MCMAM). The Sobel test yielded (z = 2.34, p < 0.01), confirming the mediation effect of GHRM, and the MCMAM analysis, with a 95% confidence level (0.068 - 0.276), validated the mediation effect of GHRM.

4.3. ModeratedMediating Effect Testing

AI Capabilities and GHRM: According to H3, there is an indirect relationship between AI capabilities and GHRM, mediated by digital literacy. To test H3, a hierarchical moderated regression analysis was performed. Mean centring was applied in order to prevent multicollinearity (Aiken & West, 1991). In Table 3, for the results concerning AI capabilities, the AI capabilities scores interacted with digital literacy in a positive and statistically significant manner (β = 0.270, p < 0.001). This provided support for H3. To explore the interaction effect, we conducted a simple slopes test at the high (+1 SD) and low (−1 SD) levels of digital literacy. Low digital literacy is associated with low GHRM, whereas the positive relationship between AI capabilities and GHRM remains higher under high digital literacy (as shown in Figure 2).

Figure 2: The moderating effect of digital literacy



To investigate H4, that digital literacy has moderated the indirect effect of AI capability on OS via GHRM, we perform parametric bootstrapping using the MCMAM approach suggested by Selig and Preacher (2008) with the PROCESS macro. From Table 4, with 5,000 bootstrap replications and 95% CI, we found a significant conditional indirect effect (Cheung & Lau, 2017), supporting H4. In other words, the indirect effect of AI capabilities on OS via GHRM under high digital literacy (β =0.215, 95% CI = [0.069, 0.364]) is much more robust and substantial than the indirect effect under low digital literacy (β = 0.039, 95% CI = [[-0.033, 0.125]). This supports our prediction in H4.

Table 4. Conditional indirect effect of AI capabilities on organizational sustainability under digital literacy

Moderator	Level (± 1SD)	Boot indirect effect	Boot SE	95% bias corrected CI
Digital literacy	Low -1SD	0.039	0.030	[-0.033, 0.125]
	Medium	0.053	0.022	[0.038, 0.172]
	High +1SD	0.215	0.048	[0.069, 0.364]

5. Discussion

Building on the DCV framework, this study investigates how AI capabilities influence OS through the mediating effect of GHRM and the moderating effect of digital literacy. Our results confirmed the positive impact of AI capabilities on OS. GHRM, as a mediating variable, has a significant indirect effect on the AI capabilities–OS relationship, and digital literacy, as a moderating variable, moderates this relationship.

5.1. Theoretical contributions

This study makes three contributions to the literature. First, it enhances theoretical and empirical insights on how AI capabilities contribute to OS. Despite prior work recognising AI's contributions to firm performance (Shaik et al., 2023; Sullivan &Wamba, 2024), innovation (Dong et al., 2024), competitive advantage (Kemp, 2024), and productivity (Czarnitzki et al., 2023), its relationship with environmental, economic, and social sustainability has received scant attention. Our evidence highlights that firms achieve their environmental targets and pursue sustainability initiatives whilst simultaneously driving improvements in organisational performance through the effective use of AI for managing large amounts of environment-related data and optimising resources and processes (Zechiel et al., 2024). Further, AI-facilitated intelligence draws an organisation ahead in preparing to address societal and environmental problems by recognising stakeholders' requirements and legal directives, and illustrates how organisations can transform towards sustainability to achieve social impact.

Second, this study clarifies how AI capabilities exert indirect influence on OS via operations of GHRM. While most extant work shows the positive effects of AI capabilities on significant global sustainability concerns (Kar et al., 2022; Nishant et al., 2020), few studies have documented the indirect ways in which it operates to attain sustainability outcomes. The study shows that GHRM has a profound mediating effect in connecting AI capabilities to sustainability: these capabilities affect sustainability indirectly by facilitating sustainable GHRM implementation and by linking organisational culture and strategy to the sustainability agenda. Using the sustainable applications of recruitment, training and development processes (Ogbeibu et al., 2024), organisations can attain practicable and reliable sustainable practices, encompassing economic, social, and environmental dimensions, to present concrete empirical evidence of the critical mediating function of GHRM linking AI capabilities to OS (Yong et al., 2020).

Third, the present study has also contributed to the literature on green HRM and sustainability by establishing the mediating and moderating effects of digital literacy in AI-enabled organisational settings. Although AI capability influence sustainability indirectly via the avenue of GHRM, this relationship is mediated by employee digital literacy, that allows them translate AI enabling sustainability outputs to more practical actionable sustainable solutions. Extending existing models in terms of moderator and mediator (Preacher et al., 2007) this study advances comprehensive explanation how an organisation may make use of their AI capabilities to strive for sustainability through focusing not only technology but also the core condition – the employee skill for that, digital competence. Similarly, the result confirms digital literacy is an enabler for adaptability and innovation of the employee during the process of adoption of AI (Zahoor et al., 2023).

5.2.Managerial implications

Firstly, for a company to perform well across environmental, economic, and social dimensions, managers must deploy AI capabilities across these dimensions. AI-based solutions enhance organisations' ability to deploy resources effectively, reduce operational costs, and promote inclusion among workers (Abulibdeh et al., 2024). The adoption of AI can help optimise the use and consumption of resources (Dong et al., 2024). From a social perspective, managers can promote the adoption of AI with the intent to build a caring, safe, and healthy workplace (Camilleri, 2024).

Second, since AI is at the forefront of capabilities in firm innovation, managers are aware that GHRM can help utilise the firm's AI capabilities for boosting sustainability across environmental, economic and social facets. To gain greater leverage from AI capabilities to boost the OS, managers can design green training to enable staff to capitalise on AI assistance and can link financial rewards to sustainability practices to motivate the utilisation of such AI tools.

Finally, managersmustidentifydigitalliteracyasacrucialfocusareatoleverageAI'simpactonOS within the GHRM framework, strengthening firm performance across sustainability dimensions.

To strengthen digital skills within the context of GHRM, managers are advised to enhance their employees' digital literacy. Through programmes that marry digital learning initiatives and sustainability aims, and by engaging their staff in such activities, it will stimulate innovation and achieve high sustainability. These practices will involve conducting specialised training programmes, activities and workshops. This strengthens digital capabilities and sustainability orientation among employees within the scope of GHRM, leading to more favourable engagement with AI applications for sustainability (Ogbeibu et al., 2024; Chaudhuri et al., 2024).

5.3. Limitations and future avenues

Despite making original contributions, this study has limitations that should be addressed in subsequent research. First, due to its cross-sectional design, this study cannot establish causality between the study variables; although this limitation is minimized by employing multiple-informant methods and relevant statistical controls, a longitudinal design could be useful for future studies.

Second, among other important variables such as the CEO's digital literacy (Filatotchev et al., 2023) and leadership's digital competence and capability (Zhao et al., 2024), only digital literacy is examined as a moderator. Furthermore, this research demonstrates that GHRM mediates the relationship between AI capabilities and OS; future studies may explore an organisation's efficiency (Roy &Khastagir, 2016) and agility (Ahmed et al., 2022) as alternative mediators. Finally, by considering AI capabilities and OS from an emerging country such as China, the present study may not be generalisable to other economic and political settings; future research could test our proposed framework using a representative sample of firms operating in different economic and political environments.

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