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Environmental Performance in the Artificial Intelligence Era: Green HRM Mediation and Green Culture Moderation with Importance-Performance Map Analysis

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Abstract

This study aims to investigate the function of artificial intelligence (AI) in supporting green human resource management (GHRM) practices for improving environmental performance, as well as exploring the reinforcing impact of green culture based on dynamic capability theory insights. Data collection was conducted using structured questionnaires administered to 467 managers working in the palm oil business in West Sumatra, Indonesia with a convenience sampling approach. Partial Least Squares–Structural Equation Modelling (PLS-SEM) and importance–performance map analysis (IPMA) was used to investigate the data. The results suggest that AI significantly improves environmental performance and GHRM, while GHRM also positively affects environmental performance. GHRM mediates the relationship between AI and environmental performance. Green culture strengthens the AI effect on environmental performance but does not significantly moderate the AI and GHRM connection, nor does it produce a significant moderate mediation effect. The proposed model demonstrates that GHRM has moderate explanatory power (R^2 = 0.610) and environmental performance has weak explanatory power (R^2 = 0.290). AI has a moderate effect on GHRM (f^2 = 0.313), whereas the remaining direct effects and other interactions are relatively small. In addition, the model exhibits positive predictive relevance for GHRM (Q^2 = 0.07) and environmental performance (Q^2 = 0.08), although its predictive capability remains relatively limited. The findings highlight the strategic role of AI in enhancing environmental performance both direct and indirect effect via GHRM. A strong green culture further amplifies this effect. This research adds to the integration of AI, GHRM, and green culture within the dynamic capability perspective and provides practical insights relevant to managers and policymakers, to optimize AI-driven HR practices and organizational culture for improved environmental performance.

Keywords: AI, green HRM, green culture, environmental performance, palm oil industry, dynamic capability theory.

1. Introduction

Apart from the exponential expansion in intelligent technology, there are growing global concerns about the profligate use of resources, overabundance of trash and elevated carbon emissions, all of which add to climate change and environmental degradation (Ogbeibu et al., 2024).Given these circumstances, it is demanded for organisations, especially those operating in the environmentally sensitive palm oil sector, to embed sustainability within their operational and strategic agendas to reduce environmental impacts and sustain long-term competitiveness (Wardhani & Rahadian, 2021; Rashid et al., 2025; Limaho et al., 2022). To meet these objectives, companies must embrace new, data-driven methods that promote better environmental management and decision-making. In this context artificial intelligence (AI) has become an important technical tool due to its capacity to analyse huge amounts of data, detect operational inefficiencies, enhance resource use, reduce waste, and encourage sustainable decision making (Lin et al., 2024). Therefore, AI is increasingly seen as a strategic tool not only to enhance organisational efficiency and creativity, but also to improve environmental performance and to integrate economic objectives with environmental sustainability goals (Al Masud et al., 2024; Hossain et al., 2025). Therefore, companies worldwide are increasingly integrating AI into their sustainability strategies to enhance environmental management (Azhar et al., 2025). However, despite its potential advantages, the adoption of AI in conventional industries like the palm oil industry is challenging because of limitations in organisational resources, digital infrastructure, and workforce readiness (Akhtar et al., 2023; Li et al., 2026). These hurdles need further study on how AI may best contribute to organisational results that focus on sustainability.

AI is generally regarded as a component of a more comprehensive system of intelligent technologies, including robotics, smart technologies, and algorithms. Collectively, these systems are classified under the Smart Technologies, Robotics, Artificial Intelligence, and Algorithms (STARA) framework. The STARA framework is a big picture view of how different smart technologies affect the change and long-term success of organizations (Rashid et al., 2025). Robotics, algorithms, artificial intelligence, and other smart technologies are some of the main components of this system that shape the world of organisational digitalization (Ogbeibu et al.,2021, 2024). Nevertheless, AI has garnered the most scholarly focus among the components of the STARA framework because of its broad applicability in sustainability initiatives and data-driven decision-making (John & Pramila, 2023). Consequently, AI has become a prominent focus on environmental performance and sustainability (Azhar et al., 2025; Lin et al., 2024).

A business determines its environmental performance by successfully mitigating its environmental impact through environmentally favourable practices (Al Masud et al., 2024; Hossain et al., 2024). In an endeavour to improve environmental performance, AI functions as a critical catalyst that enables organizations to make data-driven decisions, improve operational efficiency, and optimise resource utilisation, thereby reducing environmental impacts more effectively (Dawra et al., 2024). In this regard, AI also supports the change from conventional human resource management to Green Human Resource Management (GHRM), allowing the incorporation of environmental factors into HRM processes. This change is more than digitalisation and shows a sustainability-oriented approach (Azhar et al., 2025). For example, recruitment and selection procedures can be executed via AI-based systems, training can be administered via digital learning platforms, and employee engagement can be overseen digitally (Dawra et al., 2024). These methods enhance efficiency, diminish resource utilization, and decrease emissions, consequently fortifying the execution of GHRM within enterprises (John & Pramila, 2023; Gusti et al., 2025). This research is based on the restricted empirical investigation that explores simultaneously the interaction of AI, GHRM, and environmental performance, particularly in the setting of the palm oil business. The sector's complex value chain, from upstream plantation operations to downstream crude palm oil (CPO) processing, and significant environmental challenges make this crucial.

Current research, including Azhar et al. (2025), predominantly conceptualizes GHRM through its foundational characteristics, such as green potential, green drive, and green opportunity utilizing the Ability-Motivation-Opportunity (AMO) framework. This viewpoint offers significant theoretical insights but often neglects the practical implementation of GHRM as a collection of tangible and observable HRM activities, including green recruitment, training, and performance management. Empirical studies have not yet investigated the practical use of GHRM, resulting in a notable research deficiency. It is essential to address this gap, as analyzing GHRM at the practice level facilitates a deeper comprehension of how firms convert environmental values into effective HR strategies. This study enhances the current literature by framing GHRM as a comprehensive construct manifested in real HRM practices, thereby providing both theoretical depth and practical significance. Furthermore, previous studies have primarily investigated the relationship between GHRM and overarching intelligent technologies such as STARA (Dawra et al., 2024; John & Pramila,2023; Ogbeibu et al.,2024; Hossain et al., 2025; Al Masud et al., 2024) or have highlighted contextual elements including organizational adaptability, green digital learning, and environmental dynamism (Benzidia et al., 2021). Nevertheless, despite the increasing focus on technology and contextual factors, the significance of organizational culture particularly green culture is predominantly neglected as a vital boundary condition throughout this exchange. Green culture embodies collective attitudes and standards that emphasize environmental sustainability and can improve the efficacy of technological integration implementation (Abbas & Khan, 2023). Organizations with robust green cultures are better positioned to utilize AI to enhance GHRM practices, whereas feeble environmental values may obstruct innovation digitally and diminish performance of the environment (Umrani et al.,2022). Nonetheless, there is scant empirical evidence regarding the moderating role of green culture on the AI, GHRM, and environmental performance nexus.

The aim of this research is to address notable gaps in the literature while providing several key contributions. Initially, it analyzes the impact of AI on GHRM practices, so enhancing the literature by identifying AI as a pivotal factor in GHRM, a domain that is yet inadequately investigated. Secondly, it examines the direct and indirect impacts of AI on environmental performance, with GHRM acting as a mediating variable, so offering a more profound comprehension of the mechanisms connecting AI and environmental performance. Third, it examines the moderating influence of green culture on the AI, GHRM, and environmental performance linkages, underscoring the significance of corporate values in augmenting the efficacy of AI-driven practices. Fourth, it examines the moderated mediation effect, wherein the indirect influence of AI on environmental performance via GHRM is moderated by green culture. This research utilizes Importance–Performance Map Analysis (IPMA) to pinpoint the most essential elements influencing environmental performance, thereby broadening the contextual framework of AI and sustainability research beyond frequently analysed sectors like hospitality, with a specific emphasis on the palm oil industry (Azhar et al.,2025; Hossain et al., 2025).

This aligns with Dynamic Capability Theory (DCT), which asserts that organizations can improve environmental performance by cultivating and integrating dynamic capabilities: the ability to recognize opportunities and threats (sensing), capitalize on them through strategic initiatives and innovations (seizing), and reorganize internal resources and competencies (reconfiguring/transforming) (Teece et al., 2005). In this context, AI is a technology resource that helps information processing and environmentally oriented decision-making, whereas GHRM is organisational practices that allow the execution of sustainability objectives through human resource management. Moreover, green culture facilitates the alignment and integration of these, allowing organizations to adeptly address environmental concerns.

This paper's structure is as follows. The initial portion presents the research context, aims, and importance of the study. The second part offers an extensive analysis of the pertinent literature and the research hypotheses formulation. The third part outlines the research approach, encompassing data collection procedures and analytical techniques utilized in the study. The fourth part elucidates and analyses empirical findings. The fifth part finishes the paper by summarizing the principal findings, delineating theoretical and practical consequences, and providing recommendations for further investigation.

2. Literature Review and Hypotheses Development

2.1 Theoretical Background

2.1.1 Dynamic Capability Theory (DCT)

Dynamic Capability Theory is built on the Resource-Based View (RBV) by looking at how a business's resources might offer it a long-term edge over its competitors. These resources must have qualities like being unique, rare, valuable, and non-replaceable (Kim et al., 2015;

Hossain et al., 2025). DCT, on the other hand, is all about the capacities to sense, seize, and transform (Teece et al., 2005). Sensing is a company's capacity to spot risks and chances, seizing is an ability of company to act on those risks and chances through strategy and innovation, and transforming is a capability of the business to change its internal resources and skills.

Companies need to be able to change swiftly to stay competitive because technology is changing so quickly (Rahman et al., 2023; Reis et al., 2020). The DCT framework says that firms need to be able to change and adapt to do this (Lin et al., 2024). In this perspective, AI may also help organisations to adapt by improving their information processing, decision-making and operational efficiency, helping organisations to respond more effectively to environmental and operational constraints (Ogbeibu et al., 2024; Azhar et al., 2025). However, AI alone may not be enough to achieve better environmental consequences. Organisations also require sufficient managerial and human resource practices to transform technology capabilities into sustainability-oriented actions. Here, GHRM provides a system for integrating environmental values into recruitment, training, performance management, and employee development (Ogbeibu et al.,2024; Hossain et al., 2025). These practices assist organisations to increase environmental awareness, encourage sustainable behaviour, and aid in the execution of environmental programmes. In addition, a supportive organizational culture can enhance the success of GHRM techniques. Green culture is the set of common environmental values and norms that support the engagement of employees in sustainability-related activities and enable the successful adoption of environmentally responsible practices (Mensah et al., 2025; Mohaghegh et al., 2021; Lin et al., 2024; Hossain et al., 2025). DCT is a useful theoretical lens in this context; to explain how technology resources, organizational practices and cultural elements can collectively contribute to environmental performance.

2.2 Hypotheses Development

2.2.1 AI and Environmental Performance

AI is a type of technology that lets robots operate like people. For example, they can do activities on their own, make decisions on their own, find certain traits, and learn from what they already know (Azhar et al., 2025; Gusti et al., 2024; Rashid et al., 2025; Al Masud et al.,2024). AI becomes an intelligent system that can make decisions on its own and do complicated tasks when it uses a strategy based on the ideas of combination, repetition, and adjustment (Li et al.,2026). Businesses are transforming how they work because of smart technologies like AI, robotics, and algorithms. This technology helps businesses do more environmentally friendly things by using fewer resources, creating less trash, and using less energy (Hossain et al., 2025; Chaudhuri et al., 2024; Hossain et al., 2024). AI can enhance operational efficiency, decision-making, and information processing to facilitate organizational responsivity (Ogbeibu et al., 2024). AI is essential for enhancing environmental performance by allowing organizations to maximize utilization of resources, reduce waste, and enhance energy efficiency (Li & Bian, 2026).

Thus, AI technology capabilities are greatly needed by the palm oil industry because the palm oil industry has a complex value chain that extends from upstream plantation activities to downstream processing operations have significant environmental impacts. Therefore, the role of AI is essential to support environmental monitoring, optimize plantation and processing processes, and improve resource utilization, reducing waste and emissions through real time monitoring and accurate data analytics. According to DCT, firms that utilize technological capabilities like AI are more adept at perceiving and addressing environmental concerns, therefore improving their environmental performance. Considering the reasoning, we put out the following hypothesis:

- H1: AI has a positive relationship with environmental performance

2.2.2 Mediating Role of Green HRM

The implementation of green HRM and environmental awareness go hand in hand. This means that as environmental awareness grows, it becomes increasingly important to business to implement GHRM by incorporating environmental value into employee management thus employees should act sustainably at work (Azhar et al., 2025; Gusti et al., 2025). It has been demonstrated that GHRM practices, such as continuous training, environmental performance evaluation, and green recruitment, increase the environmental performance of employees by enhancing their sustainability-related skills and knowledge (Muisyo, 2021; Hossain et al., 2025). These practices are particularly important in the palm oil industry, because its value chain encompasses plantion, processing, and logistics activities, all of which have an impact on the environment. For example, green training can improve employees' skills in practicing sustainable harvesting. Furthermore, green performance management can encourage plantation workers to minimize excessive chemical use and prevent open burning, which can damage the environment. Thus, GHRM practices can foster environmentally responsible work behaviours.

Technologies like AI can help make GHRM practices like green recruitment, knowledge management, and environmental competencies better. Organisational adaptation can be facilitated by AI, which can enhance the administration of environmentally cognisant employees and facilitate environmentally oriented HR practices from a DCT perspective (Al Masud et al., 2024; Ogbeibu et al.,2024; Vrontis et al.,2023). However, limited research exists that elucidates GRHM as a connection between intelligent technology and environmental sustainability (Ogbeibu et al.,2024; Hossain et al.,2025). Refer to Muisyo (2021), GHRM approaches including green hiring, training, and AI-assisted human resource development that focus on the environment can help sustainability efforts. AI can make HR processes easier by doing things like online interviews, which cut down on paper use and save energy and emissions from travel (Ogbeibu et al.,2024; Dinh et al., 2026).This is in line with DCT, which says that businesses need to be able to adjust to environmental changes to be more resilient and sustainable. As a result, DCT offers a valuable perspective on the ways in which AI as a technological resource and GHRM as an organizational practice can assist organizations in addressing environmental challenges and enhancing their environmental performance. By incorporating AI into HR processes, organizations can enhance their GHRM practices, such as green recruitment, environmental training, and performance management. This, in turn, encourages environmentally responsible employee behavior and supports sustainability objectives. Consequently, GHRM serves as a critical organizational mechanism that enables AI to enhance environmental performance. AI can assist organizations in aligning employee behavior with environmental objectives and improving overall environmental outcomes by facilitating the implementation of sustainability-oriented HR practices. Given this rationale, we suggest the subsequent hypotheses:

- H2: AI has a positive relationship with GRHM
- H2a: GHRM has a positive relationship with environmental performance
- H2b: GHRM mediates the AI and environmental performance relationship

2.2.3 Moderating Role of Green Culture

Long-term sustainability necessitates dynamic capacities, evidenced by a company's dedication to sustainable environmental practices using the establishment of a green culture (Abbas & Khan, 2023; Hooi et al., 2022; Lin et al., 2024). By making environmental principles a part of the organization's fundamental strategy, it can improve environmentally friendly management practices with the help of a strong green culture (Hooi et al., 2022). Additionally, Li and Lin (2024) and Umrani et al.(2022) stress that businesses are using more technologies, including AI, in today's tech-savvy world. In this case, a green culture is an important factor in figuring out if using technology might influence the environment. In this way, a green culture helps to moderate the link between AI and the environment.

Organizations are increasingly requiring adaptation and transformation in their approach to environmental issues. AI can be perceived as a technological resource that facilitates sustainable human resource management practices, thereby supporting organizational adaptation, from the perspective of DCT (Hossain et al.,2025). Strong organizational values, particularly a green culture, can further enhance the efficacy of these practices by motivating employees to endorse environmental objectives and sustainability initiatives (Li & Lin, 2024).Green culture in the palm oil industry is reflected through organizational values that promote adherence to sustainability principles, which are reflected in sustainable palm oil certification standards, both globally through the Roundtable on Sustainable Palm Oil (RSPO) and nationally through the Indonesian Sustainable Palm Oil (ISPO). These values can encourage employees to engage in environmentally responsible operational activities while supporting the effective implementation of AI-based sustainability initiatives. So, companies that care about the environment will be able to strategically employ AI in order to create better use of resources, improve GHRM practices, and do better for the environment (Li & Bian, 2026; Abbas & Khan, 2023; Hossain et al., 2024; John & Pramila, 2023; Dinh et al., 2026). Ogbeibu et al. (2024) also said that combining a green culture with AI as a flexible asset can provide you with a long-term competitive edge. So, better environmental performance happens when GHRM techniques are used with AI and a green culture is used to support them. Consequently, we suggest that:

- H3: Green culture moderates the AI and environmental performance relationship, with high levels of green culture strengthening this relationship.
- H3a: Green culture moderates the AI and GHRM relationship, with high levels of green culture strengthening this relationship.

2.2.4 Green Culture Moderates the Indirect Effect of AI on Environmental Performance through GHRM

Businesses with a robust green culture incorporate environmental principles into their fundamental strategy, thereby promoting environmentally responsible behaviour and improving sustainability-oriented activities among employees (Lin et al.,2024; Raza et al., 2025). Sustainability-oriented activities are made more successful in the context of green culture, with corporate values and employee behavior influencing and reinforcing such efficacy, enabling the improvement of environmental performance. Green culture in the palm oil industry is reflected through sustainability values that are aligned with global and national sustainable palm oil certification standards such as RSPO and ISPO. These standards encourage employees across plantation, processing, and logistics activities to adopt sustainable practices such as sustainable harvesting and proper management of palm oil waste. Thereby strengthening the implementation of AI based GHRM practices and supporting environmental performance.

This is in line with the DCT perspective, which states that to respond to environmental change, an organization needs the ability to reconfigure its resources (Teece et al., 2005). Thus, green culture has a vital role in shaping how organizations execute environmentally oriented human resource practices, including GHRM. Earlier research has indicated that organisational culture can facilitate the adoption of green initiatives and encourage environmental values, thereby supporting the effective implementation of sustainability practices and contributing to enhanced environmental performance(Aggarwal & Agarwala, 2025). From this perspective, green culture enhances the effectiveness of both technological and organizational capabilities by aligning employee behavior with sustainability goals. When integrated with AI, businesses with strong green cultural values are better capable of effectively leveraging AI-driven GHRM practices, thereby improving environmental performance. Accordingly, the indirect impact of AI on environmental performance is enhanced by green culture through GHRM by reinforcing environmentally oriented HR practices and ensuring that technological capabilities are aligned with sustainability objectives. Consequently, green culture serves as a moderating role in the indirect connection of artificial intelligence and environmental performance through GHRM. Drawing from the previously provided explanation, our proposed hypothesis is:

- H4: Green Culture moderates the indirect impact of AI on environmental performance through GHRM

The theoretical framework of this study is based on DCT and is illustrated in Figure 1. From Figure 1, the integration of AI, GHRM, and green culture to enhance environmental performance in the palm oil industry.

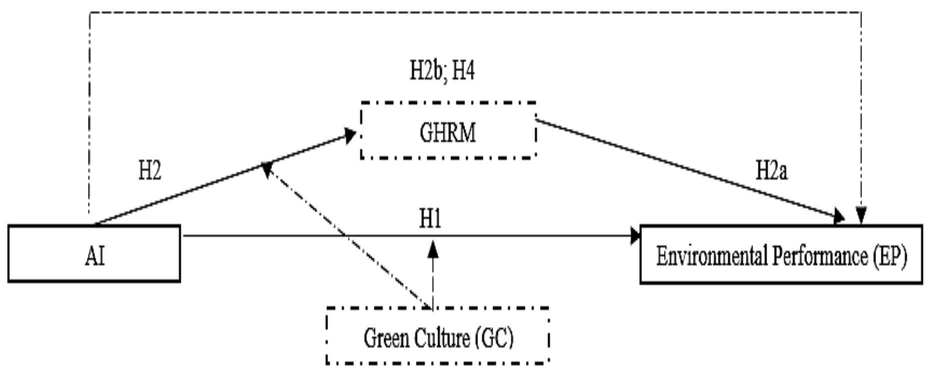

Figure 1: Conceptual Framework

3. Methodology

3.1 Research Design

Deductive research, which is based on developing hypotheses from established theories, is used to develop and test hypothesized relationships between variables (Bougie & Sekaran, 2025). Furthermore, Bell et al. (2022) also explain that a deductive approach is tested using empirical data analysis to determine whether the developed hypothesis is accepted or rejected based on existing theories. Based on these findings, classified as a deductive study grounded in DCT, using the SEM data analysis technique. By employing SEM as a statistical technique, and numerical data to examine theoretical relationships, this study is categorized as a quantitative study. Furthermore, this research is also referred to as causal research because it is based on empirical data to determine whether the hypothesized relationship is proven and to analyze the causal relationship between variables. Similarly, as stated by Blumberg et al.(2014), when a study explains the influence between variables through systematic hypothesis testing, it is considered causal research. Furthermore, because it uses quantitative analysis, a study must have clear operationalization of variables, appropriate measurement methods, and rigorous data analysis procedures to ensure the credibility and validity of the research results (Hair et al., 2022). Based on these criteria, this study is categorized as deductive research with a quantitative approach.

3.2 Procedure for Collecting Data, Population, and Sampling Technique

This study examines the palm oil industry in West Sumatra, Indonesia. We chose this area since it is a big part of the country's economic growth but hasn't been examined enough. This sector also has a lot of problems, the most serious of which is environmental damage (Limaho et al., 2022). Digital transformation, including AI, is crucial for improving environmental sustainability, optimizing resource allocation, and enhancing the effectiveness of program implementation processes. This can be achieved through the strategic role of managers, as they are key decision-makers. Therefore, palm oil managers in West Sumatra, Indonesia, serve as the participants of this study. This is supported by Lin et al.(2024), who argue that the use of technology for sustainability can be realized through the strategic role of managers.

Before giving out the questionnaire, the researchers made sure that the measurements were clear and useful by using items from an earlier study. Professors and PhD students in related subjects then looked over the questionnaire to find and fix any parts that were unclear or confusing. After the review process, the pilot was tested on 10 managers from five different organizations to make sure the instrument was clear before it was employed in the data collection process. The purpose of this pilot study was to assess the clarity of the instrument, including the wording used in the statement items, and to identify any ambiguous language that could make the items difficult to understand and lead to misunderstandings. Therefore, this pilot study was not intended for statistical generalization, but rather to assess instrument clarity. This is supported by Wadood et al.(2021), who stated that to improve the quality of the questionnaire, a pilot study involving a relatively small number of respondents, approximately 10-30, can be conducted before conducting a larger data collection. Furthermore, the respondents involved were managers with similar experience to the target population, allowing their input to be used to evaluate the clarity and understanding of the measurement items. Therefore, involving 10 respondents was deemed appropriate for the initial phase of the research questionnaire testing.

After the questionnaire was refined, it was distributed to the research sample. This study used a non-probability sampling technique with a convenience sampling method due to the difficulty of obtaining a complete sampling frame from the entire target population and limited access to respondents in various organizations. Furthermore, resources and time constraints were also considerations in choosing this method. However, the researcher is aware that the use of this method limits the representativeness of the sample and may introduce bias in generalizing the findings. Therefore, this approach was consciously used as a common methodological choice in exploratory research contexts that are difficult to access through random sampling, not solely due to the ease of accessing respondents.

The distribution process involved sending invitation letters to the managers, which explained the purpose and background of the study. Initially, we contacted several managers directly by phone, then distributed the information online through platforms such as WhatsApp and email obtained from each company's HR department. The relevant parties granted research permission before we carried out this process. Data collecting happened in early July 2025 and took two months to finish. A total of 500 questionnaires were distributed to managers. Of these, 490 questionnaires were returned, while 10 received no response at all. Of the returned responses, 23 were incomplete and therefore excluded from further analysis. Consequently, 467 valid responses were retained and could be used for data analysis. This resulted in a usable response rate of 93%. The final sample size of this study was 467 respondents. This number exceeds the minimum sample size requirement for PLS-SEM. According to Hair et al. (2022), the minimum sample size should be at least ten times the number of paths leading to the endogenous constructs in the research model (structural paths). Therefore, the sample size used in this study is adequate for PLS-SEM analysis.

3.2 Designing a Questionnaire

A research questionnaire with a five-point Likert scale will be used to present questions about AI, which functions as an exogenous variable, GHRM as a mediating variable, green culture as a moderating variable, and environmental performance as an endogenous variable. To ensure that the translation process of the research questionnaire is pertinent to the conditions and guarantees conceptual accuracy and suitability of statements with research respondents, a forward-backward translation method is necessary because the research variable questions are derived from prior research, as indicated in Table 1.

Table 1: Questionnaire Items

Variable	Total Item	Sources
AI	8 Item	Lin et al. (2024)
GHRM	6 Item	Kim et al. (2019)
Green Culture	7 Item	Umrani et al. (2022)
Environmental Performance	6 Item	Lin et al. (2024)

Two proficient translators in both Indonesian and English are needed to modify the translation procedure to fit the Indonesian cultural setting. After that, one should talk to academics and professors to make sure the questionnaire is valid, complete, and important. Only then is it ready to be tested, as described in the appendix.

3.4 Common Method Bias Test

When utilizing surveys to collect data, it's important to use common approach bias because this method tends to get favorable results, or the people answering the questions may not completely comprehend them and may have different levels of knowledge. Satrianto et al. (2023) and Gusti et al. (2024) assert that three steps are essential to mitigate bias in research questionnaires: providing clear instructions or an introduction to the research questionnaire, randomizing the sequence of research variables, and ensuring the confidentiality and anonymity of respondent data. This research employed the Variance

Inflation Factor (VIF) technique on indicators (outer VIF) to identify Common Method Bias (CMB). We chose this strategy because it works better in PLS-SEM than Harman's single-factor test (Kock, 2015). If the outer VIF value is higher than the role of thumb value, which is 3.3, CMB is found (Kock, 2015; Kock & Lynn, 2012). The data in this research were devoid of CMB issues and did not substantially influence the research outcomes, since the range of all VIF values was 1.423 to 2.340, remaining under 3.3, as illustrated in Table 3.

3.5 Data Analysis and IPMA

Data analysis was performed with software for Smartpls to execute PLS-SEM for evaluating intricate models and validating the established theory. It was likewise utilized to look at CMB through outer VIF, check the accuracy of measurements and models of structure, and do IPMA analysis (Hair et al., 2022). IPMA is used to figure out which constructions are crucial and how effectively they work (Ringle & Sarstedt, 2016). This IPMA can show which variables are the most important and which ones still need work (Martilla & James, 1977). The IPMA's results give policymakers and managers a very clear picture of what to do next. They provide a complete plan for making sure that quality keeps getting better (Ringle & Sarstedt, 2016). So, IPMA helps academics, policymakers, and management come up with better plans.

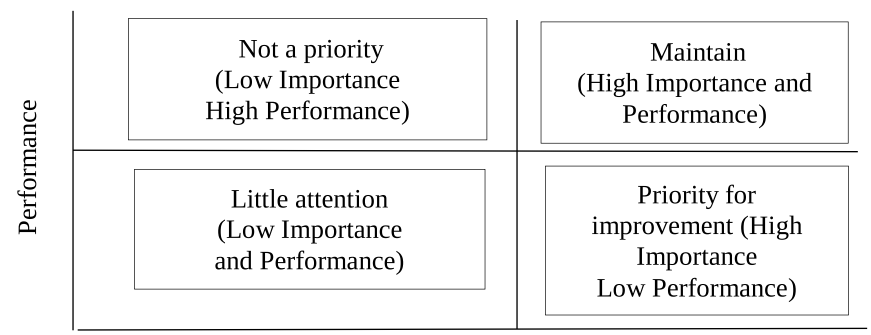

Figure 2: The Four Quadrant Map of IPMA

A four-quadrant map is often used to represent the findings of IPMA (Martilla & James, 1977) . Each quadrant depicts where the variables are based on how important and well they are performing (Ringle & Sarstedt, 2016). Figure 2 shows this in a graphic to make it easier to grasp. This helps policymakers and managers find variables that need to be kept, enhanced, or just need a little attention.

4. Data Analysis

4.1 Respondent Background

There were 467 respondents who answered the survey. Of those, 308 (66%) were male and 159 (34%) were female. Nearly half of the respondents (35%) were aged between 40 and 49 years, and the majority (73%) held a bachelor's degree. In terms of work experience, most respondents (73%) had been working in their current company for 6 to 10 years. In addition, the majority were in lower-level management positions (61%). Regarding departmental distribution, a considerable proportion of respondents (22%) worked in departments related to sustainability.

4.2 Measurement Model Evaluation

Reliability tests, convergent validity, and discriminant validity are all parts of measurement model evaluation. The reliability test's findings revealed that the criteria were good enough because they got rid of various signs, including AI1, AI2, AI3, AI4, GC4, GC5, GC6, GC7, and EP1. These indicators might have made the reliability (α and CR) worse and not added enough to the measurement. The values of the outer loading, Cronbach's alpha (α), and composite reliability (CR) that were left over after this screening all went beyond the 0.7 level (Hair et al., 2022) (See Table 2). As a result, this research can demonstrate convergent validity since the AVE (Average Variance Extracted) value exceeds 0.5 (Hair et al., 2022).

Table 2: Reliability and Convergent Validity of the Constructions

Constructs	Items	Item Loading	α	CR	AVE	Outer VIF
AI	AI5	0.724	0.818	0.880	0.648	1.494
	AI6	0.806				1.728
	AI7	0.847				2.070
	AI8	0.838				1.909
GHRM	GHRM1	0.743	0.865	0.899	0.598	2.033
	GHRM2	0.772				2.184
	GHRM3	0.784				2.123
	GHRM4	0.763				2.190
	GHRM5	0.815				2.269
	GHRM6	0.759				2.222
GC	GC1	0.816	0.742	0.852	0.658	1.479
	GC2	0.762				1.423
	GC3	0.853				1.540
EP	EP2	0.774	0.868	0.905	0.655	1.728
	EP3	0.818				1.972
	EP4	0.844				2.340
	EP5	0.787				1.841
	EP6	0.822				2.187

The Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT) were used to check for discriminant validity, as shown in Table 3. Referring to the criterion of Fornell-Larcker, a concept has discriminant validity if the square root of the Average Variance Extracted (AVE) value is higher than how well it correlates with other constructs (Fornell & Larcker, 1981). Furthermore, in light of HTMT, if HTMT is below 0.85, the concept is considered to possess discriminant validity, as elucidated by Hair et al.(2022). Table 3 shows that this study has discriminant validity since its HTMT values range from 0.554 to 0.848 and it satisfies the criterion of Fornell-Larcker.

Table 3: Discriminant Validity

Constructs	**AI**	**EP**	**GC**	**GHRM**
Fornell-Larcker criteria				
AI	0.805			
EP	0.476	0.809		
GC	0.672	0.456	0.811	
GHRM	0.725	0.483	0.698	0.773
Heterotrait-Monotrait Ratio (HTMT)				
AI				
EP	0.559			
GC	0.843	0.567		
GHRM	0.848	0.554	0.754	-

4.3 Analysis of Confirmatory Composite

In SEM-PLS, confirmatory composite analysis (CCA) looks at composite-based measurement models in two steps: (1) testing use outer loadings to build validity and dependability, composite reliability, AVE, and HTMT, and (2) assessing the model's overall fit using the SRMR, dULS, and dG indices (Hair et al.,2022). SRMR looks at the average variation between the model-reproduced covariance matrix and the real-world covariance matrix. If the value is less than 0.08, it means the models fit well (Hair et al., 2022). At the same time, dULS and dG find the separation of disparity between the model and the data using unweighted and geodesic methods. Neither of them possesses a universal threshold like SRMR does since they depend on the number of indicators, the model's size, and the sample size. As a result, we used bootstrapping to compare the estimated values of dULS and dG with the 95th percentile of the bootstrap distribution. The model is deemed to be a suitable fit if it is smaller (Hair et al.,2022). Table 4's study results reveal that the measurement model and the data support each other well. This means that the structure utilized is good for showing the construct's properties.

Table 4: Analysis of Confirmatory Composite

Index of Model Fit	Model Saturated	Estimation of Models	Results
SRMR	0.070	0.070	Good Fit
d_{ULS}	0.829	0.831	Good Model Fit
d_G	0.344	0.344	Good Model Fit

4.4 Structural Model Evaluation

The model of structure was assessed to examine the hypothesized connections among constructs by assessing path coefficients and their statistical significance with bootstrapping procedures. Statistical significance was determined by employing the bias-corrected and accelerated (BCa) bootstrap technique with 10,000 subsamples and two-tailed t-statistics in Smartpls. A path coefficient was considered significant, and the corresponding hypothesis was accepted, when the test statistic value (t-value) surpassed the critical value of 1.96 and the Probability value (p-value) was below 0.05 (Hair et al.,2022) as reported in table 5.

Table 5: Path Coefficient

Connection	Original Sample	t-value	*p*-value	Results
H_1: AI -> EP	0.250	3.608	0.000	Accepted
H_2: AI -> GHRM	0.480	11.207	0.000	Accepted
H_{2a}: GHRM -> EP	0.200	3.025	0.003	Accepted
H_{2b}: AI -> GHRM -> EP	0.096	2.814	0.005	Accepted
H_3: AI x GC -> EP	0.112	2.090	0.037	Accepted
H_{3a}: AI x GC -> GHRM	0.043	1.084	0.279	Rejected
H_4: AI x GC -> GHRM-> EP	0.009	0.900	0.368	Rejected

Additional analysis was conducted to examine the moderating effect of green culture on the relationship between AI and environmental performance. The results revealed a positive and statistically significant interaction effect between AI adoption and green culture on environmental performance ($\beta = 0.112$, $t = 2.090$, $p = 0.037$), indicating that a strong green culture strengthens the positive influence of AI adoption on environmental performance as seen in Figure 3.

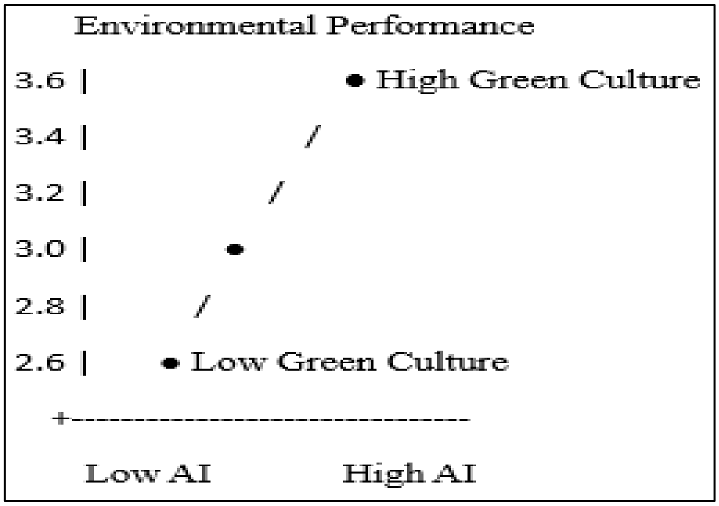

Figure 3: Interaction Effect of AI and Green Culture on Environmental Performance

From Figure 3 shows a steeper interaction slope at higher levels of green culture suggesting that organizations with well- established green cultural values are better able to leverage AI adoption to enhance their environmental performance. In other words, the positive effect of AI on environmental performance is amplified when supported by a strong green culture within organization. In contrast, the interaction effect on GHRM was not statistically significant ($\beta = 0.043$, $t = 1.084$, $p = 0.279$). Thus, these results indicate that no meaningful interaction pattern can be observed.

The coefficient of determination (R2), which shows the percentage of variance in the endogenous variables described by the exogenous constructs, was used to evaluate model fit. Refer to Hair et al. (2022), R^2 values are classified as weak (0.19), moderate (0.33), and substantial (0.67). The results indicate that AI, green culture, and GHRM explain 29% of the variance in environmental performance ($R^2 = 0.290$), which can be considered weak explanatory power. Additional external factors not included in the present model likely influence environmental performance, making this finding reasonable. In contrast, AI and green culture explain 61% of the variance in GHRM ($R^2 = 0.610$), representing a moderate level of explanatory power. These findings suggest that the model demonstrates adequate predictive capability, particularly in explaining variations in GHRM.

Effect size (f^2) was examined to evaluate the power of the relationships among constructs, with values of 0.02, 0.15, and 0.35 signifying, respectively, small, medium, and large effects (Hair et al., 2022). The f^2 value was calculated by evaluating the change in the coefficient of determination (R^2) when a specific exogenous construct was omitted using the model, thereby reflecting the construct’s unique contribution to the endogenous variable. Larger f^2 values indicate a greater substantive impact on the explained variance within the structural model. The results indicate that AI exerts a medium effect on GHRM ($f^2 = 0.313$), suggesting that AI represents a relatively strong predictor of GHRM and that its exclusion would substantially reduce the R^2 of GHRM. In contrast, the direct effect of AI on environmental performance is classified as small ($f^2 = 0.036$), indicating a limited contribution to the explained variance in environmental performance. Similarly, the effect of GHRM on environmental performance is small ($f^2 = 0.022$), implying that its unique contribution is modest relative to other predictors in the model. The moderating effect of green culture on the AI and environmental performance nexus is also small ($f^2 = 0.025$), suggesting that although the interaction may be statistically significant, its practical magnitude is limited. Furthermore, the interaction effect of AI × green culture on GHRM is very small ($f^2 = 0.007$), indicating a negligible practical impact and aligning with its statistical non-significance. It should be noted that effect sizes are calculated only for direct relationships; therefore, no f^2 values are reported for indirect (mediated) effects, as mediation is evaluated through the significance of indirect paths using bootstrapping procedures (Hair et al., 2022).

Finally, predictive relevance was evaluated with the Stone Geisser Q^2 criterion to examine the prediction accuracy of the model. In PLS-SEM, the interpretation of Q^2 generally follows the Hair et al. (2022)'s guidelines, whereby Q^2 values greater than zero indicate predictive relevance, with thresholds of 0.02, 0.15, and 0.35 representing the predictive relevance of small, medium, and large respectively. The results reveal Q^2 values of 0.07 for GHRM and 0.08 for environmental performance. As both values exceed zero but remain below 0.15, the model demonstrates small yet positive predictive relevance. These findings suggest that the structural model possesses limited but acceptable predictive capability in explaining GHRM and environmental performance.

4.5 IPMA Evaluation

To supplement the PLS-SEM findings, an IPMA was done to further investigate the impacts of AI, GHRM and GC on EP. IPMA concurrently assesses the relevance (total effects) and performance of each construct in respect to the target construct. In IPMA, significance values are the entire impact obtained from the structural model, including direct and indirect (mediated) effects on Environmental Performance. These total effects thus provide a more holistic estimation of the overall contribution of each component to EP than the direct path coefficients alone (Ringle & Sarstedt (2016). Table 6 and figure 4 present the importance and performance values of the constructs.

Table 6. IPMA Results

Construct	Importance (Total Effect)	Performance
AI	0.325	75
GHRM	0.125	73
GC	0.225	75

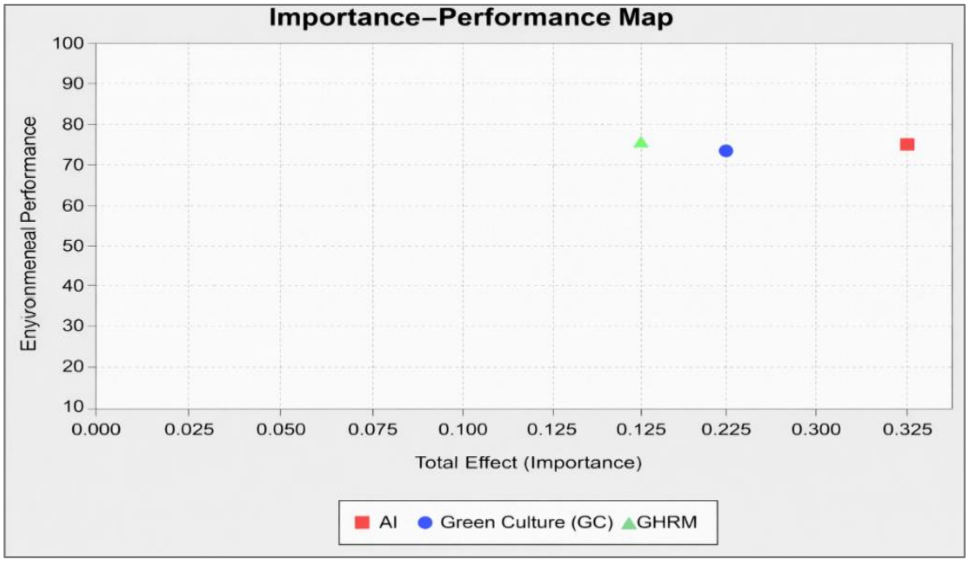

Figure 4: IPMA Results for Environmental Performance

As shown in Table 6 and figure 4, the impact of AI on EP is the greatest (total effect value is 0.325). This suggests that a one-unit rise in AI is related to an increase of 0.325 units in the EP on the latent construct scale. GC has a total impact of 0.225 which shows that a one unit increase in GC boosts EP by 0.225 units. On the other hand, GHRM has the lowest overall impact of 0.125. This means that if GHRM is increased by one unit, EP will rise by 0.125 units. The AI and the GC both scored 75 on performance, but the GHRM had a slightly lower score of 73. This shows that the implementation level of AI and GC is considerably greater than GHRM in the examined organizations. The overall IPMA findings imply that AI has the greatest impact on EP, followed by GC and GHRM accordingly in terms of total effect sizes (0.325 > 0.225 > 0.125). However, the performance ratings are less varied amongst the constructs, with GHRM being the lowest implementation level among the three variables.

5. Discussion and Recommendations

This study explains the moderation mediation model specifically describing how AI can contribute to environmental performance through GHRM with green culture as its reinforcement based on DCT. Referring to this aim, the results of this study show that AI has a positive and significant effect on environmental performance, which supports H1. These results are in line with the DCT perspective, AI is a strategic technological resource that helps organizations identify inefficient resource use, predict environmental problems and optimize production processes. With the capabilities of AI, organizations can reduce energy and raw material waste and reduce emissions and waste which ultimately impact the environment. This is reinforced by the study by Li and Bian (2026), ESG performance of companies in China is optimal through environmental and governance practices as a result of AI adoption. AI improves sustainable development performance through operational efficiency and resource utilization (Li et al., 2026; Hossain et al., 2025; Chaudhuri et al., 2024; Hossain et al., 2024; Ogbeibu et al., 2024). Thus, consistent findings from various countries and industrial sectors show that AI is a strategic resource capable of improving organizational capabilities in dealing with environmental problems.

The research results support H2, H2a, and H2b which show that AI and GHRM have a positive effect on environmental performance. In addition, GHRM acts as a mediator that bridges the influence of AI on environmental performance. These findings provide empirical support for DCT which emphasizes the importance of technological resources for organizational excellence as manifested by the ability to manage them. In this study, GHRM function as a mechanism that translates AI technology capabilities into environmentally friendly behaviours, activities, and work practices. Organizations through GHRM practices such as green recruitment and selection, green training, green performance, green compensation and others can encourage employees to be active in environmental conservation. To create environmental conservation, not only using AI directly, but also using AI indirectly can improve environmental performance through GHRM because AI first helps organizations in improving GHRM practices, which then GHRM encourages environmental performance. The results of this study are supported by (Dinh et al., 2026; Ogbeibu et al.,2024; Al Masud et al., 2024; Vrontis et al.,2023) that human resources are an important capability to form a mechanism that connects innovation technology and organizational sustainability performance. Previous empirical studies are strengthened by this study by showing that the function of GHRM is important in the context of developing countries, where employee engagement and behavioral change determine the success of sustainability transformation.

For the moderation effect, this study partially supports the proposed hypothesis. This study accepts H3, which means that green culture strengthens the relationship between AI and environmental performance. This shows that organisations that have environmental values, norms, and beliefs tend to be better able to use AI to achieve environmental sustainability. In DCT's view, green culture is organizational values that strengthens the effectiveness of technological resources. When organizations have a culture that supports sustainability, information and recommendations from AI will be easier to translate into environmentally friendly actions. This finding extends the study (Lin et al., 2024) that the effectiveness of technology in supporting environmental sustainability can increase due to the influence of an environmentally oriented organizational culture. In addition, H3a and H4 are not accepted because green culture does not moderate the relationship between AI and GHRM as well as the relationship between AI and environmental performance through GHRM. A possible explanation for these results is that the implementation of GHRM practices is more influenced by formal organizational policies, top management commitment, and structural support than by organizational culture. While a green culture can support environmental sustainability, it may not necessarily strengthen AI-based GHRM practices without adequate organizational support, systems, and policies. In addition, the limited interaction between AI and green culture arises because the implementation of AI itself is accompanied by various challenges such as high investment costs, technological complexity, limited infrastructure and workforce unpreparedness to adopt the technology. These challenges may reduce the organization's ability to optimally integrate AI into organizational values, thus weakening the interaction between AI and green culture, in influencing GHRM practices. Thus, organizational culture alone is not sufficient to strengthen the successful integration of AI into GHRM practices. For AI to be effective in GHRM practices, organizations require not only structural support such as policies, commitment, and resources but also adequate technological and infrastructure readiness. Consequently, the moderating relationship becomes statistically insignificant. Furthermore, IPMA results show that AI has the highest level of importance followed by green culture and GHRM on environmental performance. These results show that AI is the most influential factor in improving environmental performance. This is supported by Li and Bian (2026) and Li et al.(2026) that AI functions to increase organizational efficiency and sustainability. Furthermore, green culture has a significant enough impact on environmental performance, although GHRM has a low level of importance and performance, but it still can be improved to strengthen its contribution to environmental performance. Thus, this study expands the implementation of DCT by showing that the integration between AI, GHRM, and green culture plays an important role in improving environmental performance, especially in developing countries.

5.1 Theoretical Implications

This study extends DCT by explaining that improved environmental performance results from the synergy between technological and organizational capabilities. Strategic technological capabilities such as AI not only help companies respond effectively to environmental challenges but also strengthen GHRM practices. This finding suggests that the benefits of AI are derived not only from its technological capabilities but also from its ability to support organizational capabilities. In addition, the GHRM as an organizational capability contributes positively to environmental performance. Thus, to maximize environmental outcomes, technological capabilities alone are not sufficient, but human resource capabilities are required to translate AI-based resources into effective environment practices. Therefore, GHRM is a factor that bridges AI and environmental performance so that this research supports the DCT view that there is a need for combination, integration and configuration of complementary capabilities to achieve environmental sustainability. Additional insights are also provided by this study regarding the conditions that influence the application of DCT. Green culture has been shown to strengthen the effect of AI on environmental performance, indicating that environmentally oriented organizational values can increase the effectiveness of technological capabilities in achieving environmental sustainability. This result is in line with the DCT perspective that strategic capabilities are highly dependent on the values of the organization in which the capabilities are implemented. On the other hand, the results of this study indicate that green culture does not moderate the influence of AI on GHRM, thus differing from previous studies which suggest that organizational culture consistently strengthens the relationship between technological capabilities and management practices. Furthermore, this study also did not find a significant moderate mediation effect. This suggests that cultural values alone are insufficient to influence how AI is internalized into human resource management practices; rather, it relies heavily on organizational mechanisms, competencies, and support. This result is consistent with DCT, which emphasizes that resources not only determine the value of a capability but also depend on organization's ability to integrate them effectively.

5.2 Practical Implications

These results offer a practical guide for palm oil administrators to implement environmentally oriented human resources management and digital transformation. In practice, AI is unable to provide optimal benefits independently; therefore, its successful implementation necessitates the incremental incorporation of human resources, technological capabilities, and organizational support.

Palm oil companies may implement AI to facilitate environmental management in their mill operations and plantation activities. To facilitate more effective environmental monitoring, AI can be employed to detect potential fires and deforestation, optimize resource utilization, and enhance the efficacy of production processes and refuse management. AI is a decision-support instrument that offers real-time information to administrators and employees through user-friendly digital interfaces or applications. This information is the foundation for workers to make timely operational decisions and take appropriate action. Therefore, the implementation of AI is not intended to replace the role of field workers; rather, it serves as a supporting instrument that enhances the accuracy and efficacy of work. The success of its implementation is contingent upon the workforce's involvement and competence.

The integration of digital and sustainability competencies into recruitment, training, performance appraisals, and reward systems is necessary to enhance GHRM practices. Recruiting employees with digital literacy and environmental awareness, providing training on how to interpret and utilize AI-generated information in environmental management activities, and incorporating technology utilization and environmental performance targets into key performance indicators as a basis for providing rewards and performance evaluations are all viable options for doing so. This step is crucial to guarantee that employees are capable of not only utilizing AI-related technologies, but also utilizing the information generated by AI to promote environmentally friendly work practices and the attainment of the company's sustainability objectives.

Moreover, organizations must establish organizational values that are conducive to the implementation of technology for environmental sustainability by incorporating these values into their operational activities. Nevertheless, these endeavors should not be dependent solely on slogans or symbols that reflect environmental concerns; they should be internalized through formal policies and mechanisms, such as the establishment of environmental objectives and performance indicators. Consequently, a green culture serves as a foundation for the enhancement of the organization's environmental performance. Consequently, an integrated and synergistic approach that integrates AI adoption, GHRM practices, and an environmentally driven organizational culture is necessary to enhance environmental performance in the palm oil industry. This comprehensive approach enables companies to effectively employ technology while simultaneously guaranteeing that the workforce possesses the requisite skills, commitment, and literacy to implement these technologies to advance the company's environmental sustainability objectives.

5.3 Limitations of the Study and Future Research

The present study focused on the palm-derived oil business to improve internal validity and increase data reliability. However, this study results are not widely generalizable. To gain a deeper comprehension of the AI utilization effect on environmental performance through GHRM, with green culture as a reinforcing factor, it is advised that future research examine a variety of industries, including manufacturing, services, logistics, digital technology, and others. West Sumatra, Indonesia, which has a collectivist society, is where this study was carried out. The development of a green culture that improves environmental performance is greatly influenced by an awareness of cultural differences. Thus, other cultural kinds such individualistic cultures, power distance, masculinity, and femininity should be investigated in future studies. Since this study only examines the mediating mechanisms of GHRM, it presents potential for future development in the analysis of technological transformation for environmental performance. Other mediating variables that might offer a more thorough explanation are still up for investigation. Moreover, the findings show that the moderating effect of green culture on the AI and GHRM connection or the AI and environmental performance connection through GHRM is not significant, future research could examine other factors influencing environmental performance and revisit the green culture role in various contexts. The cross-sectional design of this research measures associations between variables at one moment in time, which limits causal inferences. Besides that, cross-sectional design can give rise to the potential for common method bias. Furthermore, future studies are urged to use longitudinal study methodologies and different data sources to better capture the dynamic evolution of organizational skills and to give deeper insights into the processes via which AI contributes to sustained environmental. Additionally, this study examined managers' perspectives; future research should examine all organizational levels to provide a more thorough picture.

5.4 Conclusion

Environmental performance improvement in the palm oil industry is grounded in the theoretical framework of DCT, therefore this study provides empirical support for DCT. The results of this study indicate that AI significantly improves GHRM practices and environmental performance. Furthermore, GHRM has a significant positive effect environmental performance, thereby mediating the relationship between AI and environmental performance. This means that an organization's human resource management capabilities play a crucial role in translating technological capabilities into environmental sustainability.

On the other hand, green culture strengthens the positive effect of AI on environmental performance, which means that the success of AI in supporting environmental sustainability is highly dependent on the values of an environmentally oriented organization. However, it is not proven that green culture moderates the relationship between AI and GHRM nor does it strengthen the indirect effect of AI on environmental performance through GHRM. This suggests that although green culture is important in an organizational value, its contribution is more evident in directly strengthening environmental outcomes rather than influencing organizational practices. Overall, this study extends DCT by explaining that environmental performance can be achieved through the integration of strategic technological capabilities, organizational capabilities, and a supportive organizational value. Therefore, successful environmental sustainability requires not only technology but also the internalized of this into organizational practices supported by strong environmental values.

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Declaration of AI Use

ChatGPT was used to assist in improving the clarity and readability of the manuscript. The authors take full responsibility for the accuracy, integrity, and originality of the content.

Data Availability

The datasets are available from the corresponding author upon reasonable request.

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Appendix: Questionnaire Items

Artificial Intelligence (AI)

1. Artificial intelligence has the potential to improve our organization's ability to make decisions.
2. Artificial intelligence makes it simple for our business to combine data from several sources.
3. Artificial intelligence is frequently used to aid users or decision-makers in comprehending difficult information.
4. Artificial intelligence allows us to examine production issues and concentrate on ongoing improvement by breaking down information.
5. Artificial intelligence decreases industrial waste, prolongs the life cycle of machines, and speeds up our ability to adapt to more efficient operations.
6. To maximize resource consumption and make better use of assets, our organization employs artificial intelligence.
7. Businesses have recycling choices thanks to artificial intelligence.

8. Our business can better respond to shifts in the energy supply, use resources more efficiently, and adjust to customer demands thanks to artificial intelligence.

GHRM

1. My firm offers sufficient training to advance environmental management as a fundamental corporate principle.
2. When evaluating an employee's performance, my firm considers how well they are performing at being environmentally conscious
3. My firm links awards and salary to eco-friendly behaviour by its employees.
4. In hiring and selection, my firm takes environmental management and personal identity into account.
5. Employees are fully aware of the company's environmental policy.
6. My firm promotes employee involvement in generating ideas for environmental sustainability.

Green Culture (GC)

1. Every employee at my company receives information about the significance of environmental sustainability
2. Social sustainability is a top priority for every department in my company.
3. My company has a clear policy statement that calls for social sustainability in all facets of its operations.
4. In my organization, social sustainability is a top focus
5. One of my core corporate values is social sustainability.
6. My organization is committed to maintaining social sustainability.
7. My company puts a lot of effort into projecting a social sustainability image.

Environmental Performance (EP)

1. Our business has lower air emissions than our primary rivals.
2. Our business has less wastewater than our primary rivals.
3. Our business has decreased solid waste when compared to our primary rivals.
4. Our business uses fewer hazardous, damaging, and poisonous materials than our primary competitors.
5. Our business has fewer environmental incidents than our primary rivals.
6. Our business environmental situation is better than that of our primary competitors.