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Green human resource management and sustainable workplace: Artificial Intelligence as mediating variable

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Abstract: The purpose of this study is to investigate how Artificial Intelligence (AI) mediates the relationship between Green Human Resource Management (GHRM) practices and the development of sustainable work environments. As sustainability becomes a growing concern in modern workplaces, GHRM has emerged as a vital approach to promoting eco-friendly practices. This study was grounded in the philosophy of positivism and employed an explanatory research design. Data were collected through a survey of 400 employees from eight commercial banks, representing public, private, and development sectors. The sample primarily consisted of a youthful workforce, with most participants holding bachelor's degrees. The findings highlight AI as a critical mediator, enhancing the effectiveness of GHRM practices and promoting sustainable workplace outcomes. This research offers novel insights into AI's role in advancing GHRM and sustainability, particularly in developing nations like Nepal. It emphasizes the importance of integrating AI into HRM models to achieve transformative and sustainable organizational practices, providing practical implications for the banking sector and beyond.
Keywords: *Artificial Intelligence, Employees, Green, Human resource management, Sustainable, Workplace.*

1. Introduction

Green Human Resource Management (GHRM) is a strategic approach to embedding environmental sustainability into human resource policies and practices. It aims to create a workforce that is not only efficient but also environmentally conscious, contributing to sustainable business practices [1]. GHRM integrates eco-friendly principles in areas such as recruitment, training, performance management, and employee engagement [2]. In green recruitment, organizations prioritize candidates who share values of environmental responsibility and utilize virtual interviews or digital application methods to reduce their carbon footprint. Green training and development programs focus on educating employees about environmental management practices, encouraging energy conservation, waste reduction, and sustainable resource utilization within the workplace [3]. Performance management under GHRM emphasizes rewarding eco-friendly behavior and initiatives, linking environmental goals with organizational performance metrics [4]. Furthermore, organizations foster green workplace culture by involving employees in sustainability initiatives such as tree plantations, recycling drives, or reducing plastic usage. GHRM aligns with broader sustainability goals and helps organizations enhance their reputation while contributing to long-term ecological and social well-being [5].

A sustainable workplace integrates environmental, social, and economic principles to foster long-term organizational success and employee well-being. It emphasizes energy efficiency, waste reduction,

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and eco-friendly practices to minimize its ecological footprint [6, 7]. Socially, it promotes employee engagement, diversity, fair compensation, and mental and physical well-being initiatives [8]. Economically, it focuses on cost-effective, long-term strategies such as investing in green technologies and sustainable supply chains [9]. A sustainable workplace encourages a culture of collaboration and shared responsibility, empowering employees to contribute to environmental conservation and creating a positive societal impact [10].

Green Human Resource Management (GHRM) plays a vital role in fostering a sustainable workplace by aligning human resource practices with environmental sustainability goals. Through green recruitment, organizations can attract environmentally conscious individuals whose values align with sustainable practices [11]. Green training and development empower employees with the knowledge and skills to adopt eco-friendly behaviors, such as energy conservation, waste management, and resource optimization, within the workplace [12]. Additionally, GHRM enhances employee engagement by involving them in sustainability initiatives like tree-planting drives, recycling programs, and reducing workplace carbon footprints [13]. Green performance management systems reward employees for contributing to environmental goals, reinforcing a culture of sustainability [14]. Moreover, by integrating sustainable practices into HR policies, such as offering remote work options and promoting public or green transport, GHRM reduces organizational environmental impact. Overall, GHRM bridges the gap between sustainability and workforce management, ensuring that both employees and organizational practices contribute actively to creating a workplace that is environmentally responsible, socially equitable, and economically viable. This integration not only helps organizations comply with environmental regulations but also enhances brand reputation, employee satisfaction, and long- term sustainability.

Green Human Resource Management (GHRM) plays a transformative role in advancing sustainable workplaces by integrating environmentally friendly practices into core HR functions through the use of Artificial Intelligence [15]. AI-driven tools streamline recruitment by assessing candidates' values and experiences for alignment with eco-conscious objectives, minimizing physical paperwork and facilitating virtual interviews to reduce environmental impact [16, 17]. AI fosters sustainable workplace practices by automating energy-efficient operations, such as optimizing lighting, heating, and cooling systems based on real-time usage patterns. It also enhances training initiatives by offering personalized, engaging learning modules that educate employees about eco-friendly practices, such as waste management and resource optimization [11]. In performance management, AI analytics evaluate employees' contributions to sustainability initiatives, such as energy-saving efforts or participation in green campaigns, enabling fair recognition and rewards.

AI-enabled systems also support remote work and virtual collaboration, reducing the carbon footprint associated with commuting and travel [18, 19]. By leveraging predictive analytics, AI identifies opportunities for sustainability improvement, providing insights to refine strategies and set long-term goals. Automation of routine HR tasks through AI Chabot's and virtual assistants allows HR professionals to focus more on driving strategic green initiatives. The integration of AI in GHRM not only boosts operational efficiency and employee engagement but also aligns human resource practices with the principles of environmental sustainability, transforming workplaces into eco-friendly, future-ready environments. Against this background, this study aims to examine the role of AI as a mediator between GHRM and a sustainable workplace.

2. Objective

To examine the mediating role of Artificial Intelligence between Green Human Resource Management (GHRM) and the development of a Sustainable Workplace.

3. Literature Review

Green Human Resource Management (GHRM) and Sustainable Workplace:

GHRM plays a vital role in fostering a sustainable workplace by aligning human resource policies and practices with environmental goals. Research highlights the significant relationship between GHRM and a sustainable workplace, emphasizing that eco-friendly HR practices such as green recruitment, training, and performance management contribute to reducing organizational environmental impact while promoting employee well-being [11]. GHRM initiatives create a workplace culture centered on energy conservation, waste reduction, and sustainable resource utilization [20]. For example, programs that involve employees in environmental sustainability activities have been shown to enhance their engagement and support for organizational green objectives, ultimately fostering a sustainable and collaborative work environment.

3.1. Green Human Resource Management (GHRM) and Artificial Intelligence (AI)

The integration of Artificial Intelligence (AI) into GHRM significantly enhances its effectiveness and efficiency. Studies reveal a strong relationship between GHRM and AI, as AI-driven tools automate and optimize eco-friendly HR processes such as digital recruitment, virtual interviews, and performance evaluation [21]. AI supports GHRM by providing data-driven insights that enable organizations to develop targeted sustainability initiatives and measure their impact [22]. Moreover, AI-powered learning platforms educate employees on sustainable practices, fostering greater environmental awareness and engagement. By leveraging AI technologies, organizations can streamline GHRM processes and strengthen their commitment to sustainability.

3.2. Artificial Intelligence (AI) and Sustainable Workplace

Artificial Intelligence also exhibits a significant relationship with the development of a sustainable workplace. AI technologies facilitate sustainable practices by automating energy-efficient operations, such as smart lighting and temperature control systems, and optimizing resource utilization [23]. Furthermore, AI enhances employee productivity and engagement by offering virtual collaboration tools and reducing the need for commuting, thus lowering the organization's overall carbon footprint [24]. Predictive analytics powered by AI enable organizations to identify areas for improvement in sustainability and design long-term environmental strategies. Through these capabilities, AI emerges as a key driver in transforming traditional workplaces into environmentally, socially, and economically sustainable spaces.

3.3. Integrated Framework

Existing literature establishes that GHRM, AI, and sustainable workplaces are interconnected. GHRM serves as the foundation for embedding sustainability within HR practices, while AI acts as an enabler, enhancing the execution and monitoring of green initiatives [25]. Together, they contribute significantly to creating sustainable workplaces by integrating environmental, social, and economic considerations into organizational practices. This integrated approach not only enhances operational efficiency but also aligns organizations with global sustainability goals, creating long-term value for businesses and society.

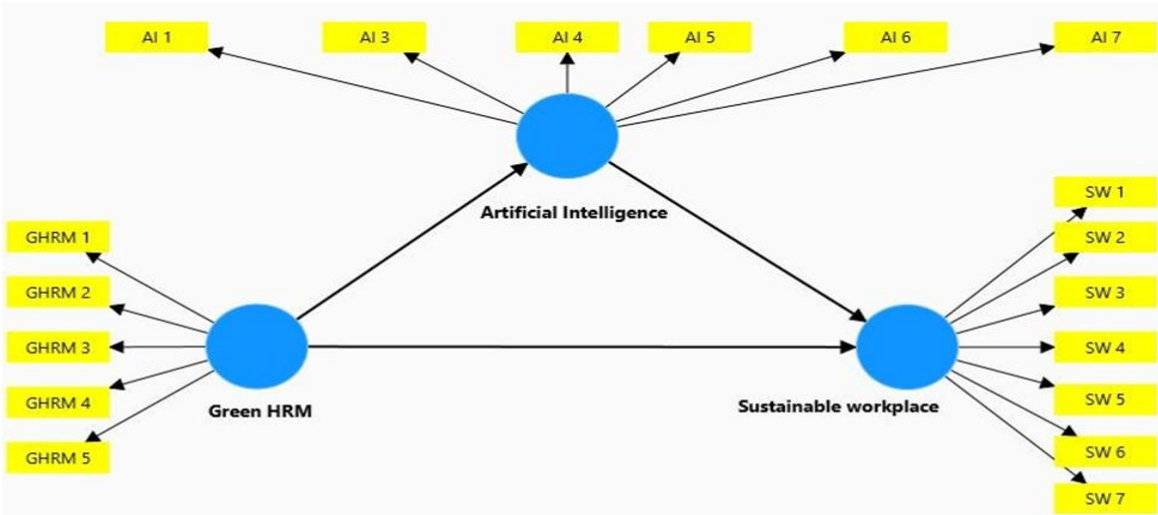

Figure 1.
Framework.

4. Research Methodology

Research Design and Approach: The study is objective in nature and adopts a quantitative research approach to meet its objectives. Quantitative research was chosen to enable systematic data collection and statistical analysis, allowing for precise and replicable insights into the research problem. The research follows a cross-sectional time horizon, meaning data was collected at a single point in time rather than over an extended period. This approach was appropriate given the study's focus on capturing the current perceptions and attitudes of bank employees in Bagmati Province, Nepal, toward the research constructs.

Population and Sampling: The target population for the study comprised employees from commercial banks in Bagmati Province, Nepal. A total of eight banks were selected for inclusion, representing a mix of established private, public, and development banks: Nabil Bank, Siddhartha Bank, Nepal Bank, Agriculture Development Bank, Himalayan Bank, Prabhu Bank, Sanima Bank and NIC Asia Bank. A probabilistic sampling technique was employed to ensure representative participation of employees from these banks. The sample size was calculated using the formula $n=z^2 \times p \times (1-p)/E^2n$. The initial calculated sample size was 385 respondents. Recognizing the possibility of nonresponse or missing data (estimated at 4%), the final sample size was adjusted upward to 400 respondents, ensuring sufficient representation and statistical power.

Data Collection Methods: To collect data from participants, a structured questionnaire was developed. The questionnaire was carefully designed to align with the research objectives and included clear and concise items measured on a 5-point Likert scale. The Likert scale was chosen because it enables respondents to express the intensity of their attitudes, perceptions, or behaviors across predefined categories, ranging from "Strongly Disagree" to "Strongly Agree." Two modes of administration were employed to maximize response rates. Using the KoboToolbox, an advanced and secure online survey platform designed for structured data collection. Printed versions were distributed in person to ensure inclusivity, particularly for participants who might prefer offline methods. All data collection efforts strictly adhered to protocols ensuring anonymity and confidentiality of the respondents.

Data Analysis: Collected data were analyzed using Smart PLS 4 (Partial Least Squares), a robust tool widely used in social science research. Exploratory Factor Analysis (EFA) was conducted to assess the validity of constructs and ensure the data's structure aligned with theoretical expectations. Structural Equation Modeling (SEM) in Smart PLS enabled examination of complex relationships between variables while accounting for measurement errors. This analytical approach was ideal for uncovering latent constructs and testing the hypothesized relationships in the study.

Ethical Considerations: Ethical integrity was a cornerstone of this study. Several measures were implemented to ensure respect, dignity, and rights of the respondents. Before distributing the questionnaire ethical approval was obtained. At the beginning of the questionnaire, respondents were provided with a detailed explanation of the study's objectives, scope, and purpose. This ensured full transparency. Respondents were explicitly informed that participation was voluntary and that they had the right to withdraw from the study at any time without providing a reason or facing any consequences. Assurances were provided that all responses would remain anonymous and that personal or identifiable information would not be disclosed. These measures collectively enhanced trust and encouraged authentic responses, contributing to the reliability and validity of the study results.

5. Results

5.1. Demographic Information

This study consists of 400 respondents, whose demographic profile provides a comprehensive understanding of their characteristics across gender, age, education, and income levels. Among the respondents, males constitute a majority at 58.8% (n=235), while females represent 41.3% (n=165). In terms of age distribution, the largest group falls within the 21–23 years category, accounting for 45.5% (n=182) of the sample, followed by respondents below 20 years at 28.8% (n=115). Those aged between 24 and 26 years comprise 14.8% (n=59), with the remaining 11.0% (n=44) being above 26 years, indicating a predominantly young respondent base.

Educationally, the majority hold a bachelor's degree (58.5%, n=234), while 23.5% (n=94) have attained a master's degree or higher, and 18.0% (n=72) possess education levels below a bachelor's degree. Regarding income, the largest segment earns between NPR 40,001 and NPR 60,000 (30.3%, n=121). Additionally, 22.0% (n=88) have an income ranging from NPR 60,001 to NPR 80,000, and 19.0% (n=76) report earning more than NPR 80,000. Meanwhile, 17.8% (n=71) fall into the NPR 20,000–40,000 income bracket, and 11.0% (n=44) earn less than NPR 20,000. This demographic overview reflects a diverse sample, representing varied gender, age, educational, and economic backgrounds.

5.2. Measurement Model Analysis

Table 1.
Construct reliability and validity.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Artificial Intelligence	0.807	0.810	0.803	0.507
Green HRM	0.800	0.803	0.800	0.646
Sustainable workplace	0.829	0.832	0.830	0.512

The reliability and validity analysis ensures the measurement scales used in this study are consistent and accurately reflect the underlying constructs, as presented in Table 1. The evaluation was conducted using indicators such as Cronbach's Alpha, Composite Reliability (rho_a and rho_c), and Average Variance Extracted (AVE) for Artificial Intelligence, Cronbach's Alpha value of 0.807 indicates high internal consistency. Similarly, rho_a (0.810) and rho_c (0.803) confirm the composite reliability of the construct, and an AVE of 0.507 suggests adequate convergent validity, indicating that over 50% of the variance is explained by its indicators. For Green HRM, the Cronbach's Alpha of 0.800 also reflects strong internal reliability, with rho_a (0.803) and rho_c (0.800) further supporting this reliability. The AVE of 0.646 signifies a higher level of convergent validity, indicating that a substantial amount of variance is captured by the construct compared to measurement error.

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For Sustainable Workplace, Cronbach's Alpha of 0.829 confirms excellent internal consistency. Similarly, rho_a (0.832) and rho_c (0.830) validate composite reliability. The AVE value of 0.512 shows sufficient convergent validity, ensuring that the construct explains a significant proportion of the variance in its items.

These results demonstrate that all three constructs; Artificial Intelligence, Green HRM, and Sustainable Workplace meet the criteria for reliability and validity, reinforcing the credibility of the measurement model in the context of this study.

Table 2.
Model Fit Summary.

	R-square	R-square adjusted
Artificial Intelligence	0.404	0.402
Sustainable workplace	0.595	0.592

The Model Fit Summary provides an overview of the explanatory power of the models tested, as shown in Table 2. For the variable Artificial Intelligence, the R-square value is 0.404, indicating that approximately 40.4% of the variability in the dependent variable can be explained by the independent variables included in the model. The adjusted R-square, slightly lower at 0.402, accounts for the number of predictors and the sample size, suggesting the model retains good explanatory power while controlling for potential over fitting. Similarly, for the Sustainable Workplace, the R-square value is 0.595, demonstrating that 59.5% of the variation in the dependent variable is explained by the predictors. The adjusted R-square is marginally lower at 0.592, signifying a strong fit and minimal penalty for complexity. Together, these metrics suggest that the model for Sustainable Workplace has a better fit and stronger explanatory power compared to the model for Artificial Intelligence.

Table 3.
Discriminant validity.

Heterotrait-Monotrait Ratio (HTMT)			
	Artificial Intelligence	**Green HRM**	**Sustainable workplace**
Artificial Intelligence			
Green HRM	0.446		
Sustainable workplace	0.590	0.706	
Fornell-Larcker Criterion			
	Artificial Intelligence	Green HRM	Sustainable workplace
Artificial Intelligence	0.638		
Green HRM	0.451	0.668	
Sustainable workplace	0.597	0.705	0.642

Discriminant validity ensures that the constructs in a study are distinct from one another, and it has been evaluated here using the Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker Criterion, as presented in Table 3. The HTMT results show values well within acceptable limits, typically below 0.85, indicating distinct constructs. Specifically, the HTMT value between Artificial Intelligence and Green HRM is 0.446, while the value between Artificial Intelligence and Sustainable Workplace is 0.590. The relationship between Green HRM and Sustainable Workplace shows an HTMT value of 0.706, all of which confirm discriminant validity among the constructs. The Fornell-Larcker Criterion also supports this conclusion. According to the criterion, the square root of the Average Variance Extracted (AVE) for each construct (diagonal elements) must be greater than its correlations with other constructs (off-diagonal elements). For Artificial Intelligence, the AVE value is 0.638, exceeding its correlations with Green HRM (0.451) and Sustainable Workplace (0.597). Similarly, for Green HRM, the AVE value is 0.668, greater than its correlations with Artificial Intelligence (0.451) and Sustainable Workplace (0.705). Lastly, Sustainable Workplace also satisfies the Fornell-Larcker Criterion with an AVE value of 0.642, which is higher than its correlations with Artificial Intelligence (0.597) and Green

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HRM (0.705). Collectively, both the HTMT analysis and the Fornell-Larcker Criterion confirm that Artificial Intelligence, Green HRM, and Sustainable Workplace are adequately distinct constructs, demonstrating strong discriminant validity.

Table 4.
Cross-loading.

	Artificial Intelligence	Green HRM	Sustainable workplace	VIF
AI 1	0.647	0.343	0.349	1.578
AI 3	0.580	0.243	0.360	1.431
AI 4	0.729	0.335	0.431	1.534
AI 5	0.620	0.275	0.374	1.825
AI 6	0.528	0.240	0.313	1.513
AI 7	0.702	0.282	0.444	1.323
GHRM 1	0.253	0.620	0.454	1.697
GHRM 2	0.287	0.686	0.498	1.794
GHRM 3	0.326	0.727	0.514	1.588
GHRM 4	0.309	0.653	0.452	1.546
GHRM 5	0.331	0.648	0.433	1.452
SW1	0.398	0.442	0.642	1.561
SW 2	0.393	0.464	0.658	1.657
SW 3	0.392	0.426	0.624	1.535
SW 4	0.416	0.510	0.713	1.686
SW 5	0.406	0.462	0.664	1.613
SW 6	0.318	0.423	0.575	1.277
SW 7	0.349	0.437	0.607	1.537

The cross-loading table evaluates the degree to which individual indicators are associated with their assigned constructs compared to others, ensuring indicators have the highest loadings with their respective constructs, as shown in Table 4. In this analysis, items linked to Artificial Intelligence (e.g., AI1 to AI7) exhibit higher loadings with their intended construct, ranging from 0.528 to 0.729, compared to their loadings with Green HRM (0.240–0.343) and Sustainable Workplace (0.313–0.444). This suggests that these indicators are more strongly associated with Artificial Intelligence. Similarly, indicators for Green HRM (e.g., GHRM1 to GHRM5) display higher loadings on their own construct (0.620–0.727) compared to Artificial Intelligence (0.253–0.331) and Sustainable Workplace (0.433–0.514), confirming their proper alignment with the Green HRM construct.

For the Sustainable Workplace construct, indicators SW1 to SW7 exhibit stronger loadings on their assigned construct (0.575–0.713) compared to their loadings on Artificial Intelligence (0.318–0.416) and Green HRM (0.423–0.510). These patterns confirm that all items load highest on their respective constructs, reinforcing construct validity. Additionally, the Variance Inflation Factor (VIF) values, ranging from 1.277 to 1.825, are well below the typical threshold of 5, indicating no significant multicollinearity issues among the indicators. This overall cross-loading pattern demonstrates the discriminant validity and reliability of the measurement model, ensuring that indicators effectively measure their respective constructs without excessive overlap.

5.3. Structural Model Analysis

Table 5.
Indirect effect.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Artificial Intelligence-> Sustainable workplace	0.323	0.327	0.064	5.081	0.000
Green HRM -> Artificial Intelligence	0.364	0.370	0.068	5.367	0.000
Green HRM -> Sustainable workplace	0.576	0.580	0.043	13.376	0.000

The results of the indirect effect analysis indicate significant relationships between the variables, as shown in Table 5. The indirect path from Artificial Intelligence to Sustainable Workplace shows an original sample value of 0.323, demonstrating a moderate positive effect. This effect is statistically significant with a T-statistic of 5.081 and a p-value of 0.000, confirming its robustness. The relationship between Green HRM and Artificial Intelligence reveals an indirect effect with an original sample value of 0.364. This effect is also significant, as evidenced by a T-statistic of 5.367 and a p-value of 0.000, indicating that Green HRM has a meaningful and statistically supported influence on Artificial Intelligence.

Finally, the strongest indirect effect is observed between Green HRM and Sustainable Workplace, with an original sample value of 0.576. The exceptionally high T-statistic of 13.376 and a p-value of 0.000 underline the significant contribution of Green HRM to the development of Sustainable Workplaces. Across all relationships, the low standard deviations suggest the stability and precision of these estimates, highlighting the pivotal roles of Green HRM and Artificial Intelligence in enhancing workplace sustainability.

5.4. Mediating Analysis Results

Table 6.
Results of Mediating.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decisions
Green HRM -> Artificial Intelligence -> Sustainable workplace	0.117	0.123	0.039	3.027	0.002	partial mediation

Mediating analysis explores the extent to which a mediating variable explains the relationship between an independent variable (IV) and a dependent variable (DV), as summarized in Table 6. In this analysis, the mediating role of Artificial Intelligence (AI) between Green HRM (the IV) and Sustainable Workplace (the DV) was examined. The results show that Artificial Intelligence partially mediates the relationship between Green HRM and Sustainable Workplace, with an indirect effect value (Original Sample, O) of 0.117. The T-statistic of 3.027 and a p-value of 0.002 indicate that this mediating effect is statistically significant. The positive value of the indirect effect highlights that Green HRM practices contribute to the creation of Sustainable Workplaces indirectly through AI.

Moreover, the findings suggest that Green HRM not only has a direct influence on Sustainable Workplace outcomes (as indicated by other analyses) but also leverages AI as a key facilitator in this process. This underscores the interconnectedness of the constructs and emphasizes the critical role of technology, such as AI, in amplifying the effectiveness of Green HRM initiatives to achieve workplace

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sustainability. The analysis confirms partial mediation, as Artificial Intelligence explains part of the relationship between Green HRM and Sustainable Workplace, while a direct effect still exists.

6. Discussion

Recent studies have increasingly emphasized the critical role of Artificial Intelligence (AI) and Green Human Resource Management (GHRM) practices in fostering sustainable workplaces. A prominent study by Garg, et al. [26] explored the application of AI in enhancing environmental sustainability through GHRM practices. Their findings highlighted that AI-powered GHRM strategies offer organizations the capacity to meet social responsibility commitments, forge economic partnerships, and streamline operational processes. This study underscored that AI tools can be employed in various GHRM domains such as talent acquisition, workforce management, and employee engagement, ultimately leading to improved organizational sustainability. The integration of AI within GHRM was seen as a mechanism to bridge gaps in environmental initiatives, aligning operational practices with eco-friendly policies. By adopting these strategies, organizations could not only achieve cost efficiency but also reduce their ecological footprints.

Additionally, the research accentuated that AI can provide predictive analytics and decision-making capabilities, which are essential for implementing effective green policies and assessing their long-term impact [26]. Similarly, studies highlighted at platforms such as the Web of Conferences delved into how AI technologies contribute to the adoption and optimization of environmentally friendly initiatives within human resource management. These studies stressed AI's pivotal role in enhancing GHRM practices by enabling better resource utilization, fostering sustainable employee behaviors, and streamlining processes for greater eco-efficiency [27]. The integration of AI was noted to offer HR practitioners novel tools to monitor compliance with green policies, automate sustainability reporting, and create an inclusive workplace culture focused on sustainability. Such findings consistently support the view that AI facilitates a systematic approach to embedding sustainability into HR processes, thereby elevating the operational and strategic importance of GHRM.

Building upon these perspectives, this study explores the mediating role of AI in bridging GHRM and the establishment of sustainable workplaces. Unlike prior research that primarily examined the direct integration of AI with GHRM, our findings demonstrate that AI not only complements GHRM practices but also acts as a significant mediator. This intermediary role allows AI to enhance the effectiveness of GHRM initiatives in driving sustainability outcomes. For instance, our study provides evidence that AI can streamline the execution of GHRM initiatives while simultaneously amplifying their impacts by identifying and resolving barriers to sustainable practices. This unique finding emphasizes that AI-driven insights help fine-tune GHRM activities, ensuring that they align more effectively with organizational sustainability goals. By serving as a bridge, AI supports a cohesive integration of environmental, social, and operational dimensions of workplace sustainability.

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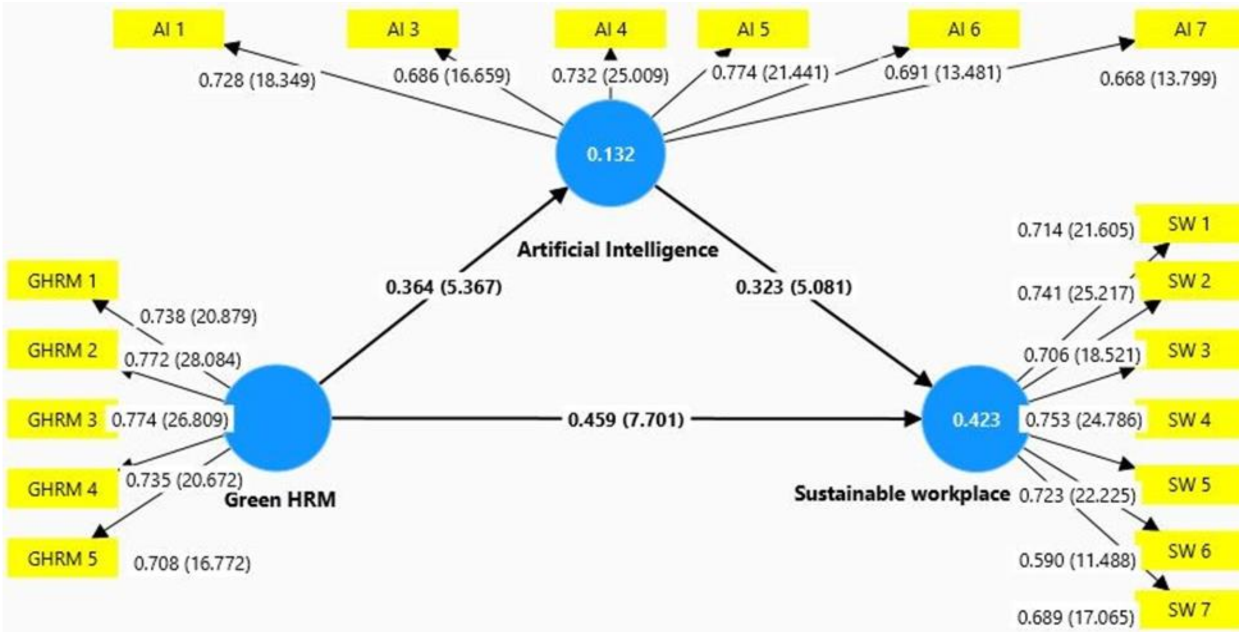

Figure 2.
PLS Model of Study.

Our findings also reinforce the importance of strategically aligning AI applications with GHRM practices to achieve holistic sustainable development objectives. Through empirical analysis, we have demonstrated the partial mediation effect of AI, whereby it significantly influences the relationship between GHRM and the development of sustainable workplaces. This revelation is particularly valuable as it unravels the indirect pathways through which AI promotes workplace sustainability. By illuminating this nuanced interplay, our research contributes to the existing literature by advancing a deeper understanding of the AI-GHRM-sustainability nexus. Additionally, these findings carry practical implications for organizations seeking to leverage AI for greener HR practices, suggesting a structured approach to incorporate AI in their GHRM strategies. Thus, our research not only expands the theoretical framework of sustainability in HR practices but also provides actionable insights for businesses striving to integrate technology with green initiatives for a sustainable future.

7. Conclusion

The study examines the role of Artificial Intelligence (AI) as a mediator in the relationship between Green Human Resource Management (GHRM) and Sustainable Workplace outcomes. The analysis confirms that AI partially mediates this relationship, indicating that it significantly contributes to translating GHRM practices into workplace sustainability. The findings highlight that GHRM not only has a direct impact on creating sustainable workplace outcomes but also enhances these outcomes indirectly through the integration of AI. This emphasizes the interconnectedness of GHRM and AI, showcasing how technological innovations play a critical role in amplifying the effectiveness of GHRM initiatives. The study concludes that incorporating AI within GHRM frameworks enhances their ability to promote sustainable practices, demonstrating the importance of leveraging AI for achieving workplace sustainability. Partial mediation indicates that while AI plays a substantial role in the relationship, other influencing factors also exist.

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Institutional Review Board Statement:

Ethical approval was obtained from the Nepal Philosophical Research Center's Ethics Committee on January 20, 2024, with reference number (Ref-1/20/24-0032).

Transparency: This study was carried out honestly and ethically, with data collection and all procedures clearly explained and followed.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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