Exploring the Impact of Artificial Intelligence Literacy on Green Innovation

Jie Cheng[1,a], Xin Yang[2,b], Harcharanjit Singh Mahinder Singh[3,c], Bo Wang[4,d], Fei Liu[5,e], You Li[6,f]

chengjie@graduate.utm.my[a], andyyang205@qq.com[b], harcharanjit@utm.my[c], wangbo04230423@163.com[d], liufei@axhu.edu.cn[e], liyou@axhu.edu.cn[f]

[1]Suzhi Education Research Center, School of International Education, Anhui Xinhua University, Hefei, 230088, China; Faculty of Management, Azman Hashim International Business School, Universiti Teknologi Malaysia, Johor Bahru, 81310, Malaysia
[2]School of General Education, Hefei Technical College, Hefei, 230012, China
[3]Azman Hashim International Business School, Universiti Teknologi Malaysia, Kuala Lumpur, 54100, Malaysia
[4]School Of Business, Anhui Xinhua University, Hefei, 230088, China
[5]School of Foreign Studies, Anhui Xinhua University, Hefei, 230088, China
[6]School of Culture and Communication, Anhui Xinhua University, Hefei, 230088, China

Abstract. This study explores the relationship between artificial intelligence literacy and green innovation, particularly within the context of growing sustainability concerns. It highlights the moderating influence of green information systems. An online questionnaire survey was administered to manufacturing enterprises certified by ISO 14001 in order to investigate these dynamics. A Structural equation modelling was used to carefully evaluate 288 responses in total. The results demonstrate how artificial intelligence literacy has a significant impact on green innovation and how the presence of green information systems affects how artificial intelligence literacy and green innovation interact. This study provides crucial insights for Malaysian manufacturing companies regarding the fundamental elements that propel green innovation practices.

Keywords: Artificial Intelligence Literacy, Green Information System, Green Innovation

1 Introduction

The global manufacturing industry significantly impacts the environment. Malaysia's manufacturing sector competes globally and increasingly prioritizes sustainable development in line with governmental initiatives. Understanding the factors driving green innovation (GI) can shape policies and encourage eco-friendly technology adoption in Malaysia's manufacturing sector. By embracing artificial intelligence literacy (AIL), companies can lead in sustainable manufacturing, optimizing resource use to align with national sustainability goals. This artificial intelligence-driven approach enhances operational efficiency, reducing waste and energy consumption. Exploring artificial intelligence literacy moderated by a green information system (GIS) is crucial for advancing sustainable practices and positioning the industry as a global leader in environmentally conscious manufacturing.

PMIS 2024, March 15-17, Changsha, People's Republic of China

DOI 10.4108/eai.15-3-2024.2346401

Nonetheless, data highlights Malaysia's industrial sector's poor performance in green innovation, even with the significant 400 billion ringgit allocated for new and ongoing projects in accordance with the 12th Malaysia Plan [1]. Malaysia's position in the Global Innovation Index fell from 33rd in 2020 to 36th in 2021 on a worldwide scale, and it hasn't improved since. Notably, the nation's innovation outputs have declined more sharply, falling from 34th in 2021 to 46th in 2023 [2]. The local government understands that talent and infrastructure, not just innovation, are what give the country a competitive edge. Thus, it is imperative that Malaysia strengthen its innovation capabilities and competencies, particularly given that increased innovation has the potential to expedite the creation of wealth.

Even though green innovation is desperately needed, Malaysia's manufacturing industry has a long way to go before adopting green information systems and artificial intelligence literacy [3]. The primary causes of this shortage are manufacturing firms' antiquated information systems, insufficient investment in technical infrastructure, and a lack of readily available business intelligence tools [4]. Therefore, the limited capacity to generate actionable insights for promoting green innovation may result from the inadequate integration of artificial intelligence literacy and green information systems, which could impede the thorough collecting, handling, and evaluating data.

The present research focuses on one research question: "Can artificial intelligence literacy and green information systems promote green innovation among manufacturers in Malaysia?" It is conducted in the context of a diversified landscape of opportunities and obstacles. In order to investigate this question, the study looks closely at how artificial intelligence literacy directly affects green innovation. In essence, the study looks into how the effectiveness of green information systems might improve the green innovation-artificial intelligence literacy link. In doing so, the study hopes to provide insightful analysis and practical suggestions to decision-makers, business executives, and other stakeholders involved in Malaysia's thriving manufacturing industry.

2 Theoretical Foundation and Framework

Three main concepts are included in this study’s research framework, which is shown in Figure 1: green innovation, green information systems, and artificial intelligence literacy. The main research objective, the characteristics of the variables involved, and the particular correlations under examination should all be taken into consideration when choosing an acceptable underlying theory for the investigation of the links among these constructs. Therefore, the technology acceptance model (TAM) appears suitable, exploring how users accept and adopt technology based on perceived value and usability. In this scenario, artificial intelligence literacy can be viewed through the technology acceptance model, considering how employees' perceptions of the usefulness and ease of using artificial intelligence technologies influence their willingness to embrace artificial intelligence for green innovation. The technology acceptance model framework can help understand how artificial intelligence literacy influences the intention to utilize artificial intelligence in fostering green innovation, moderated by the presence of a green information system. This is in line with the study's objective of understanding the function of technologies related to artificial intelligence in the context of digital 4.0.

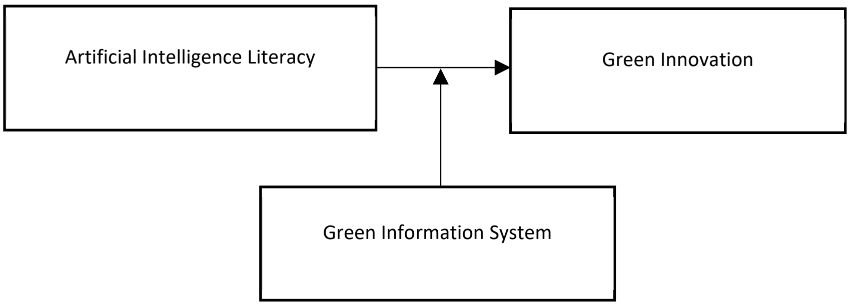

Figure 1: The research framework

3 Hypotheses Development

3.1 Artificial Intelligence Literacy

Artificial intelligence literacy plays a crucial role in driving green innovation across Malaysian manufacturing firms in several ways. Initially, artificial intelligence's data analysis capabilities optimize resource usage, cutting waste, and enhancing energy efficiency in operations [5]. Moreover, artificial intelligence-driven predictive maintenance systems minimize downtime by predicting machinery failures and curbing resource inefficiencies [6]. Second, artificial intelligence-optimized supply chains reduce transportation inefficiencies, thereby lowering carbon emissions in logistics. Artificial intelligence's simulations and modeling aid in crafting eco-friendly product designs, enabling the development of sustainable products with minimal environmental impact [7]. Furthermore, artificial intelligence algorithms excel in pinpointing opportunities for waste reduction and implementing recycling methods within manufacturing, fostering a circular economy model. These artificial intelligence-powered systems diligently monitor emissions, aiding companies in adhering to environmental regulations and curbing their ecological footprint [8]. Additionally, artificial intelligence aids in tracking and ensuring compliance with environmental standards, aligning companies with green protocols [9]. The greater the involvement of manufacturing companies in advancing artificial intelligence literacy among employees, the more substantial their potential for better green innovation. Hence, this hypothesis stands:

H1: Artificial intelligence literacy and green innovation are positively related.

3.2 Green Information System

Enhancing the bond between artificial intelligence literacy and green innovation involves leveraging a green information system (GIS) in multifaceted ways. Initially, green information system consolidates sustainability-related data, including environmental impact and resource usage [10]. Integrating this data with artificial intelligence furnishes comprehensive insights for analytics and decision-making. Green information system offers specialized, eco-focused data sets, vital for artificial intelligence precision in driving green innovation strategies [11]. Moreover, it serves as a platform [12]. Additionally, green information system integration with artificial intelligence enables real-time monitoring of environmental factors, adjusting manufacturing processes promptly for reduced impact [13]. This partnership fosters feedback loops, refining green information system capabilities with artificial intelligence insights for continual green innovation. Furthermore, it automates environmental compliance monitoring using artificial intelligence algorithms to analyze data, ensuring adherence [14]. This combined AI-GIS approach identifies unexplored green innovation opportunities, guiding R&D toward eco-friendly solutions [15]. Besides, being empowered by artificial intelligence, green information system offers decision support, aiding sustainable management choices. Its moderating role ensures that artificial intelligence literacy drives significant green innovation strides [16]. Robust green information system implementation is poised to strengthen the artificial intelligence -green innovation connection. Thus, the proposed hypothesis is:

H2: Green information systems moderates the interaction between artificial intelligence literacy and green innovation.

4 Methodology

The data gathered from manufacturing firms in Malaysia that are ISO14001 certified and actively engaged in environmental initiatives was analysed using quantitative research methodologies in this study. In keeping with the goals of the study, the use of an online survey questionnaire allowed for thorough statistical evaluation and testing of hypotheses. By focusing on owners/managers as responders, it was possible to obtain feedback from knowledgeable people who are actively involved in directing and carrying out green innovation initiatives within these businesses [17]. Their points of view are essential for understanding organizational tactics and the application of innovation. The survey questionnaire was created using items from previous studies, which guaranteed effectiveness, reliability, and a solid basis for data gathering in this study. An artificial intelligence literacy test was conducted using a four-item scale from [18]. The examination of green information system relied on a six-item scale from [19]. Additionally, a four-item scale measured green innovation [20].

5 Results

Among the 488 surveys distributed, 288 responses were utilized for evaluation, signifying a notable effective response rate of 59.02%. Respondents primarily belonged to the food (8.4%) and fabricated metal (5.7%) sectors, has a penchant for privately held companies (71%). According to this study, a sizable fraction of the participating companies had been in business for more than 21 years (56%), employed more than 200 people (42%), and generated an annual turnover of more than 15 million ringgits (75%).

The Variance Inflation Factor (VIF) test was utilised by the study to evaluate multicollinearity among the independent variables. By measuring the degree to which collinearity among the independent variables affects the variance of an estimated regression coefficient, the VIF test was utilised to assess multicollinearity. Moreover, SMARTPLS, a software for structural equation modeling, was employed to calculate VIF values as part of its analysis. It uses empirical estimation methods based on the regression coefficients to derive the VIF values. Employing SMARTPLS for VIF values instead of mathematical formulas provides practicality and accuracy, making it easier for researchers to obtain VIF values within the context of structural equation modeling without requiring manual calculation. As shown in Table 1, VIF values below 5 for the predictive constructs indicated the absence of collinearity concerns.

Table 1: Variance of inflation factor

	VIF
AIL1	1.896
AIL2	1.758
AIL3	2.258
AIL4	1.664
GI1	4.560
GI2	3.808
GI3	4.677
GI4	4.644
GIS1	4.251
GIS2	4.132
GIS3	2.458
GIS4	2.127
GIS5	2.239
GIS6	2.129

5.1 Measurement Model

The measurement model underwent a thorough assessment, covering construct validity, reliability, and discriminant validity analysis. Illustrated in Figure 2 and detailed in Table 2, 14 constructs exhibited robust item loadings, exceeding the 0.7 threshold. Additionally, these constructs demonstrated strong internal consistency, surpassing Cronbach's alpha values of 0.7. Composite reliability ratings above 0.8, indicating strong reliability, confirming their dependability. Moreover, Robust discriminant validity was confirmed by the average variance retrieved values exceeding 0.5.

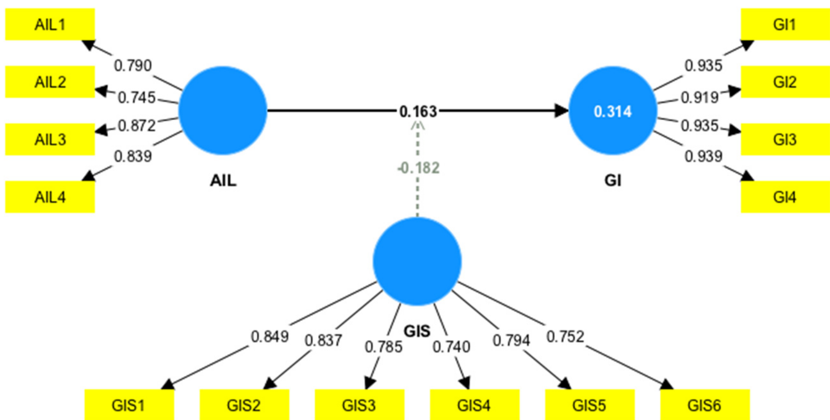

Figure 2: Measurement model item loadings, path coefficient, and R^2 values

Table 2: The construct validity and reliability

Variable	Item Code	Item Loading	Cronbach Alpha (α)	CR	AVE
AIL	AIL1	0.790	0.834	0.886	0.661
	AIL2	0.745			
	AIL3	0.872			
	AIL4	0.839			
GI	GI1	0.935	0.950	0.964	0.869
	GI2	0.919			
	GI3	0.935			
	GI4	0.939			
GIS	GIS1	0.849	0.885	0.911	0.630
	GIS2	0.837			
	GIS3	0.785			
	GIS4	0.740			
	GIS5	0.794			
	GIS6	0.752			

There were no cross-loading problems, as shown by Table 3's results, which show that every construct's item loading surpassed the cross-loading thresholds. Table 4 demonstrates that each variable's square root of the average variance extracted (AVE) outperformed its correlations with other variables, indicating compliance with the Fornell–Larcker criterion. Furthermore, Table 5 displayed ratios of Heterotrait-Monotrait correlations greater than 0.85 for all variables. Together, these tests affirmed the absence of concerns regarding discriminant validity.

Table 3: The cross loadings

	AIL	GI	GIS	GIS x AIL
AIL1	0.790	0.237	0.402	-0.209
AIL2	0.745	0.239	0.338	-0.125
AIL3	0.872	0.337	0.482	-0.204
AIL4	0.839	0.428	0.585	-0.373
GI1	0.376	0.935	0.477	-0.387
GI2	0.342	0.919	0.475	-0.389
GI3	0.376	0.935	0.442	-0.414
GI4	0.406	0.939	0.497	-0.416
GIS1	0.377	0.373	0.849	-0.478
GIS2	0.371	0.347	0.837	-0.478
GIS3	0.331	0.308	0.785	-0.351
GIS4	0.375	0.303	0.740	-0.442
GIS5	0.644	0.541	0.794	-0.395
GIS6	0.518	0.438	0.752	-0.348
GIS x AIL	-0.302	-0.431	-0.520	1

Table 4: The Fornell–Larcker criterion

	AIL	GI	GIS
AIL	0.813		
GI	0.403	0.932	
GIS	0.579	0.508	0.794

Table 5: The Heterotrait-Monotrait ratio of correlations

	AIL	GI	GIS	GIS x AIL
AIL				
GI	0.426			
GIS	0.607	0.526		
GIS x AIL	0.305	0.442	0.554	

5.2 Structural Model

After conducting bootstrapping in Smart PLS V.4 to evaluate the measurement model, all three research hypotheses were tested. Figure 2 presented the path coefficients. Table 6 depicted the corresponding t-values and p-values. The t-test and p-value are statistical methods used in research to determine the significance of relationships or differences between groups or variables. T-test is straightforward to perform and applicable to various scenarios, and it can be effective with relatively small sample sizes. P-value offers a numeric measure of the strength of evidence against the null hypothesis and provides a standardized way to interpret statistical significance. It also supports decision-making by indicating whether results are likely due to chance or a real effect. Within the structural model, H1 exhibited a path coefficient of 0.163, a t-value of 2.835, and a p-value of 0.005. The p-value of smaller than 0.05 indicated that H1 is supported. In the analysis of moderation results, H2 displayes a path coefficient of 0.182, with t-value of 3.235, and p-value of 0.001. H2 was validated with p-value below 0.05.

Table 6: The direct relationship and moderating relationship

Hypothesis	Effect	Standard Deviation	t-Value	p-Value	Decision
H1	AIL → GI	0.058	2.835	0.005	supported
H2	GIS x AIL → GI	0.056	3.235	0.001	supported

The coefficient of determination (R^2) indicates a moderate level of explanatory power for the research model concerning green innovation. More specifically, approximately 31.4% of the variance in green innovation is explained by the prediction ability of the model. It is important to note, nevertheless, that Approximately 68.6% of the variability in green innovation remains unexplained, underscoring the impact of other variables on this outcome. Figure 3 illustrates how the green information system has a major influence on the artificial intelligence literacy-green innovation link. The graphic illustrates a stronger interaction in which the dependent variable is influenced by the independent and moderating variables in turn, producing an effect that goes beyond simple additive impact. This implies that there is a stronger correlation between artificial intelligence literacy and green innovation at better green information system.

On the other hand, artificial intelligence literacy has less of an impact on green innovation at weak green information system.

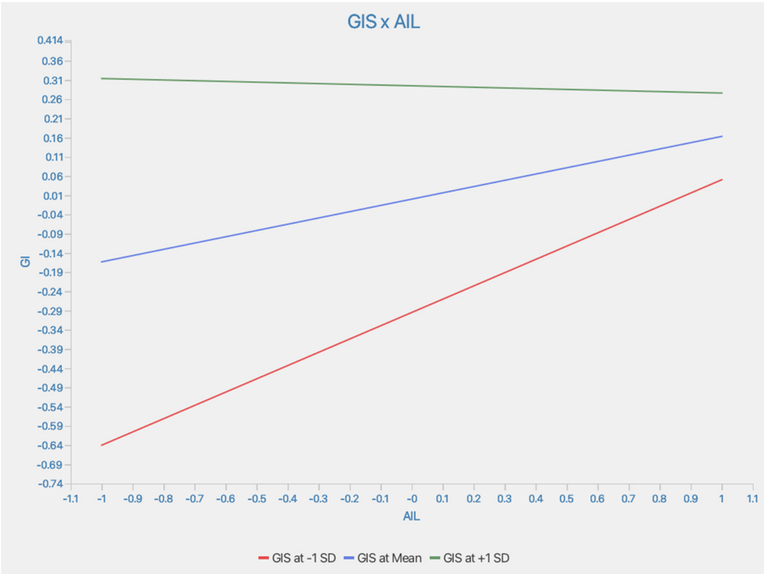

Figure 3: Interaction plot of GIS x AIL

6 Discussion

H1 proposed a positive association between artificial intelligence literacy and green innovation, aligning with a previous study [21]. The correlation underscores that empowering employee with artificial intelligence literacy enables effective utilization of artificial intelligence tools and insights. Leveraging artificial intelligence 's capabilities informed by such literacy facilitates organizational shifts toward sustainability, fostering innovation, and competitiveness while curbing environmental impact. This underscores the significance of investing in artificial intelligence learning practices, particularly for nurturing green innovation [22]. Furthermore, the relationship between artificial intelligence literacy and green innovation in manufacturing offers diverse advantages, from operational efficiency and cost reduction to market positioning and sustainable practices. Adopting artificial intelligence literacy for green innovation not only yields environmental advantages but also fortifies a company's resilience, competitiveness, and stakeholder trust over time [15]. Additionally, conducting a thorough analysis of a company's unique context yields crucial insights, laying a strong groundwork for informed decisions regarding artificial intelligence investments. It aids in devising tailored strategies, mitigating risks, and maximizing the impact of artificial intelligence initiatives on organizational success.

Additionally, enhancing artificial intelligence literacy in manufacturing companies involves implementing structured training programs, organizing workshops, fostering internal knowledge sharing, collaborating with artificial intelligence experts, conducting pilot projects, promoting continuous learning culture, and integrating artificial intelligence proficiency into performance evaluation. Particularly, workshops offer opportunities for hands-on learning, discussions, and exchange of ideas related to artificial intelligence applications in manufacturing. Conducting pilot projects enables practical experimentation and validation of artificial intelligence solutions in real-world manufacturing settings. These strategies collectively contribute to improving artificial intelligence literacy and leveraging artificial intelligence effectively in manufacturing operations.

H2 suggested that the link between artificial intelligence literacy and green innovation is moderated by the green information system. The results provide compelling evidence for the moderating effect of the green information system in this respect. Acting as a facilitator, the green information system maximizes the potential of artificial intelligence literacy to drive green innovation. It offers the structured framework and data infrastructure necessary to effectively harness AI capabilities for sustainable practices within manufacturing firms. This emphasizes how important it is for Malaysian manufacturers to increase their green information systems' efficacy in order to support their green innovation initiatives [23]. However, optimizing a green information system to effectively moderate the relationship between AI literacy and green innovation is a time-consuming process. It demands technological integration, employee training, and ongoing enhancements, rendering it complex. Additionally, a robust green information system relies on high-quality, integrated data. Challenges related to data accuracy, reliability, and compatibility across systems can impede its effectiveness as a moderator. Moreover, implementing and maintaining such a system can be resource-intensive, posing limitations in terms of budget, skilled personnel, or technological infrastructure, affecting its moderating capacity. Overcoming these challenges necessitates a comprehensive understanding of the organizational context, strategic planning, continuous evaluation, and adaptable systems to effectively moderate the relationship between artificial intelligence literacy and green innovation.

7 Conclusion, Limitations, and Future Directions

The study's conclusions point to a complex relationship between corporate intelligence and promoting green innovation, highlighting the critical role that green information systems play as mediators in this relationship. Using business intelligence technologies has a positive impact on introducing and promoting innovative and environmentally conscious practices in Malaysia's manufacturing sector, particularly when it is led by a strategically integrated green information system. According to the research, the creation and implementation of green innovation projects can be significantly impacted by adopting business intelligence, which is tempered by the specialised capabilities of green information systems. When combined with the eco-centric framework and green information systems, business intelligence's analytical and data-driven capabilities have the potential to drive technological advancements, product innovation, market positioning that is in line with sustainability goals, and sustainable strategies.

Through an empirical investigation and validation of the interactions between green information systems, and green innovation in Malaysia's manufacturing sector, the research significantly advances theoretical frameworks and practical applications. Including the green information system as a moderator also helps to clarify how green technologies, especially eco-centered systems, can moderate the link between data-driven insights and sustainable innovation emergence. Moreover, the useful lessons learned from this research provide essential direction for integrating green information systems and business intelligence into production settings. These revelations offer methods for maximising these technologies, encouraging the creation of long-lasting inventions. By fusing data-driven decision-making with environmentally conscious technologies, adopting the research's suggestions could give businesses a competitive edge and promote green innovation. Moreover, the research facilitates the pragmatic application of sustainability concepts in industrial settings, empowering corporations to uphold environmental accountability by clever tactics and innovations.

It is imperative to recognise the constraints of the present research. The reliability of self-reported measurements may have limits, and response biases may be introduced if survey-based data collection is the only method used. Supplementing with diverse data collection methods like interviews or observations could offer more robust insights. Moreover, this study's timeframe constraints mean that technological advancements or changes in sustainability practices post-data collection might affect the findings' applicability. Additionally, the observed associations may be impacted by unconsidered external variables like changes in the global market or the state of the economy.

Subsequent research in the manufacturing sector of Malaysia may examine the effect of green digital learning orientation, cultural intelligence, leadership, social networks, platform empowerment, technological capabilities, and education on green innovation. Other possible mediators between green innovation and business intelligence also can be explored, including data analytics capabilities, stakeholder engagement, and knowledge management systems. Moreover, there are interesting moderators towards green innovation to be examined using quantitative research methods. For example, gender discrimination, financial support, power distance, and cultural distance. Future research endeavours may concentrate on certain forms of green innovation activities that are impacted by business intelligence and green information systems. Examples include waste reduction methods, eco-design, the use of renewable energy sources, and sustainable supply chain practices. Last but not least, future research can study different types of innovation in one framework, including technological innovation, marketing innovation, and business model innovation. These forms of green innovation can occur independently or in combination, and they play a crucial role in driving environmental sustainability and competitiveness in today's economy.

Acknowledgments. 2022 Major Research Project of Philosophy and Social Science at Hefei Technical College, Grant no: 2022AH040299. 2022 Science and technology innovation project, Grant no: S202212216163, S202212216174. 2023 Provincial Project at Suzhi Education Research Center of Anhui Xinhua University, Grant no: SK2023AH051785.

References

[1] Ishak, N. F., & Thiruchelvam, V. (2024). Sustainable innovations in Malaysia's public procurement: strategic policy initiatives and coherences. *International Journal of Innovation Science*, *16*(2), 338-372.

[2] WIPO. (2022). Global Innovation Index 15th Edition.

[3] Ordóñez de Pablos, P., & Zhang, X. (2023). *5G, Artificial Intelligence, and Next Generation Internet of Things: Digital Innovation for Green and Sustainable Economies: Digital Innovation for Green and Sustainable Economies*. IGI Global.

[4] Mohamad, A. (2015). *Information Technology Investment and Manufacturing Firm Performance: The Moderating Effect of Decentralized Decision Making* (Doctoral dissertation, Universiti Sains Malaysia).
[5] Akerkar, R. (2019). *Artificial intelligence for business*. Springer.
[6] Ran, Y., Zhou, X., Lin, P., Wen, Y., & Deng, R. (2019). A survey of predictive maintenance: Systems, purposes and approaches. *arXiv preprint arXiv:1912.07383*.
[7] Wang, Z., & Liao, H. T. (2020, April). Towards the eco-design of Artificial Intelligence and Big Data applications: a bibliometric analysis of related research. In *IOP Conference Series: Materials Science and Engineering* (Vol. 806, No. 1, p. 012039). IOP Publishing.
[8] Yavari, A., Mirza, I. B., Bagha, H., Korala, H., Dia, H., Scifleet, P., ... & Shafiei, M. (2023). ArtEMon: Artificial Intelligence and Internet of Things Powered Greenhouse Gas Sensing for Real-Time Emissions Monitoring. *Sensors*, *23*(18), 7971.
[9] Liu, W., Zhao, J., Du, L., Padwal, H. H., & Vadivel, T. (2021). Intelligent comprehensive evaluation system using artificial intelligence for environmental evaluation. *Environmental Impact Assessment Review*, *86*, 106495.
[10] Gholami, R., Watson, R. T., Hasan, H., Molla, A., & Bjorn-Andersen, N. (2016). Information systems solutions for environmental sustainability: How can we do more?. *Journal of the Association for Information Systems*, *17*(8), 2.
[11] Kirchner-Krath, J., Morschheuser, B., Sicevic, N., Xi, N., von Korflesch, H. F., & Hamari, J. (2024). Challenges in the adoption of sustainability information systems: A study on green IS in organizations. *International Journal of Information Management*, 102754.
[12] Brezulianu, A., Geman, O., Arif, M., Chiuchisan, I., Postolache, O., & Wang, G. (2021). Epidemiologic Evolution Platform Using Integrated Modeling and Geographic Information System. *Computers, Materials & Continua*, *67*(2).
[13] Leonov, S., Yarovenko, H., Boiko, A., & Dotsenko, T. (2019). Prototyping of information system for monitoring banking transactions related to money laundering. In *SHS Web of Conferences* (Vol. 65, p. 04013). EDP Sciences.
[14] Xie, M. W., Jia, Y. C., Lv, F. X., & Chang, S. X. (2016). A comprehensive information system for landslide monitoring based on a three-dimensional geographic information system. In *Green building, environment, energy and civil engineering* (pp. 305-310). CRC Press.
[15] Wang, Q., Sun, T., & Li, R. (2024). Does artificial intelligence promote green innovation? An assessment based on direct, indirect, spillover, and heterogeneity effects. *Energy & Environment*, 0958305X231220520.
[16] Tian, H., Zhao, L., Yunfang, L., & Wang, W. (2023). Can enterprise green technology innovation performance achieve "corner overtaking" by using artificial intelligence?—Evidence from Chinese manufacturing enterprises. *Technological Forecasting and Social Change*, *194*, 122732.
[17] Relf, V. E., Morgan, E. R., Hodgkinson, J. E., & Matthews, J. B. (2012). A questionnaire study on parasite control practices on UK breeding Thoroughbred studs. *Equine Veterinary Journal*, *44*(4), 466-471.
[18] Chai, C. S., Lin, P.-Y., Jong, M. S.-Y., Dai, Y., Chiu, T. K. F., & Qin, J. (2021). Perceptions of and Behavioral Intentions towards Learning Artificial Intelligence in Primary School Students. Educational Technology & Society, 24(3), 89–101.
[19] Liu, Z., Wang, H., & Li, P. (2018). The antecedents of green information system and impact on environmental performance. International Journal of Services, Economics and Management, 9(2), 111.
[20] Zameer, H., Wang, Y., Yasmeen, H., & Mubarak, S. (2022). Green innovation as a mediator in the impact of business analytics and environmental orientation on green competitive advantage.

Management Decision, 60(2), 488–507.
[21] Mhlanga, D. (2021). Artificial intelligence in the industry 4.0, and its impact on poverty, innovation, infrastructure development, and the sustainable development goals: Lessons from emerging economies?. *Sustainability*, *13*(11), 5788.
[22] Buhmann, A., & Fieseler, C. (2023). Deep learning meets deep democracy: Deliberative governance and responsible innovation in artificial intelligence. *Business Ethics Quarterly*, *33*(1), 146-179.
[23] Chiang, C. T. (2024). A systematic literature network analysis of green information technology for sustainability: Toward smart and sustainable livelihoods. *Technological Forecasting and Social Change*, *199*, 123053.