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Research paper

Assessing The Role of Artificial Intelligence in Improving The Sustainability of Public Higher AI Education Administration

Xuejie Guo [1] *, Yulin Qin [2], M.K.Zhodro [3], Yuhan Wang [4], Pengfei Zhang [1]

[1] *International Institute of Management and Business,220086, Minsk City,Belarus*
[2] *INTl Interational university,71800, Nilai, Negeri Sembilan, Malaysia*
[3] *Belarusian National Technical University ,220013,Minsk, Republic of Belarus*
[4] *Shinawatra University,99, Bang Toei, Sam Khok District, Pathum Thani 12160, Thailand*
**Corresponding author E-mail: guoxuejie@imb.by*

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Abstract

This study investigates the multidimensional impact of artificial intelligence (AI) on sustainability practices within public higher education institutions. In this paper, sustainability is conceptualized as a three-dimensional construct：environmental, economic, and social educational and this definition guides the study design and interpretation of outcomes. Using an integrated approach that combines extensive literature reviews, quantitative survey data from over 5,000 respondents, and carefully selected case studies, we examine how AI implementations, including personalized learning systems, automated assessment tools, and intelligent tutoring systems, enhance the sustainability of educational practices. Our methodology incorporates both classical statistical methods and novel computational formulas for data reliability and variance analysis. The results demonstrate that AI promotes efficiency, resource optimization, and innovative teaching paradigms, while also unearthing challenges related to ethical issues, scalability, and infrastructural limitations. A deeper dive into subgroup analyses reveals gender differences and disciplinary disparities in attitudes toward AI usage. Ultimately, the study argues that the responsible integration of AI can substantially advance sustainable practices in public higher education if accompanied by rigorous policy and pedagogical strategies.

Keywords: *Artificial Intelligence; Sustainability; Public Higher Education.*

1. Introduction

Sustainability has emerged as a central objective in contemporary energy policy, with buildings worldwide consuming a substantial share of total energy resources. Public higher education institutions—characterized by extensive infrastructures including lecture halls, laboratories, libraries, and dormitories—represent significant energy consumers. In the drive toward creating resilient, sustainable urban environments, these institutions bear both a responsibility and an opportunity to demonstrate best practices in energy management. Artificial intelligence (AI) has recently gained attention as a transformative tool capable of reshaping energy management systems by optimizing operations, reducing wastage, and predicting fluctuating energy demands. At its core, AI leverages algorithms and machine learning (ML) techniques to extract insights from complex datasets, thereby enabling more precise and adaptive energy management solutions. In the context of public higher education, AI-driven approaches hold great promise for reducing operational costs, mitigating environmental impacts, and contributing to broader sustainability goals. [1]

The rapid integration of artificial intelligence in higher education has transformed academic environments, reconfiguring teaching, learning, and administrative processes over the last three decades1. Public higher education institutions face mounting pressures to enhance sustainability amid increasing resource constraints, environmental concerns, and operational challenges. Sustainability—in this context—refers to the ability to manage limited resources efficiently, reduce operational carbon footprints, and build resilient educational infrastructures that meet future demands. AI applications have historically been rooted in fields such as Computer Science and STEM, and their potential in improving operational systems in education is increasingly recognized1. In higher education, AI is not only utilized for profiling, prediction, and intelligent tutoring but also for streamlining administrative tasks and resource allocation. As public universities grapple with financial constraints, there is a growing opportunity to employ AI to achieve operational efficiencies that translate into sustainable practices. [2]

Public higher education is at the cusp of transformative change as institutions strive to balance academic excellence with the imperative of sustainability. The notion of sustainability in academia now encompasses economic efficiency, social inclusivity, and environmental stew-

ardship. With rapid advancements in artificial intelligence, numerous initiatives seek to exploit AI's adaptive learning models and automated processes to streamline resources and support innovative educational outcomes. Recent research indicates that while AI has been predominantly employed in STEM fields for tasks such as grading automation and predictive analytics, its potential in enriching the humanities and social sciences is gradually emerging. Despite growing enthusiasm, a critical challenge remains: ensuring that the integration of AI does not compromise academic integrity or result in unequal access among different student groups. [3]
The context of this study is grounded in the need for a cross-disciplinary framework that embraces both quantitative experimentation and qualitative insights. Early implementations of AI-based systems have been effective in tailoring learning experiences to individual needs and in optimizing resource allocation. However, divergent attitudes—such as more positive perceptions among technology and engineering students contrasted with caution among humanities and medical students—highlight the complexity of deploying AI solutions in a heterogeneous academic ecosystem. Against this backdrop, our investigation not only examines the technical and operational dimensions of AI in higher education but also critically analyzes its implications on sustainability and ethical practices. [4]

1.1. Conceptual framework of sustainability

To avoid treating sustainability as a single, loosely defined outcome, this study adopts a triple bottom line perspective that frames sustainability in public higher education as a balanced pursuit of environmental, economic, and social/educational value. Environmental sustainability refers to reducing the ecological footprint of campus operations and learning infrastructures, including energy efficiency, resource conservation, and the mitigation of waste and emissions. Economic sustainability emphasizes the ability of institutions to maintain and improve performance under budget constraints through cost-effectiveness, process efficiency, and optimized resource allocation. Social/educational sustainability captures the long-term quality and fairness of educational provision, including equitable access to AI-enabled learning resources, student well-being and engagement, academic integrity, and inclusive teaching and assessment practices.
Consistent with this framework, the study's dependent variable S(sustainability score) is operationalized as a perception-based composite that reflects respondents' overall assessment of how AI adoption contributes to these three sustainability dimensions in their institutional context. In other words, S represents an integrated sustainability perception, rather than a purely environmental metric, allowing the analysis to examine whether AI-enabled innovations improve sustainability holistically while also surfacing trade-offs.

1.2. Research gaps and study contributions

Existing research has documented diverse AI applications in higher education, yet evidence on AI's contribution to sustainability remains fragmented. Gap A is that studies often examine teaching/learning and campus operations separately and employ inconsistent sustainability lenses, making it difficult to build an integrated understanding across environmental, economic, and social/educational outcomes. Gap B is that key enabling conditions—especially teacher preparedness and institutional governance are frequently discussed as context rather than modeled explicitly, leaving unclear whether sustainable benefits depend on structured guidance and accountability.
To address these gaps, this study adopts a triple bottom line framing and operationalizes sustainability as an integrated perception-based outcome (S). Using a large multi-university student survey (N = 5,894) combined with comparative case studies, we test how AI usage (U) and teacher training/support (T) predict sustainability perceptions while controlling for demographic heterogeneity (D) in a regression model. This mixed-methods design provides a concise, data-grounded assessment of both benefits and trade-offs of AI-enabled sustainability in public higher education.

2. Methodology

2.1. Measure

Our quantitative analysis is built upon survey data collected from 5,894 students across multiple public universities, employing a structured questionnaire that rates usage frequency, attitudes, and perceptions regarding AI tools such as ChatGPT and other related chatbots.
To ensure transparency and interpretability of the analytical model. All core constructs were operationalized using multi-item Likert-type measures unless otherwise stated. Unless noted, items were rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), and composite scores were computed by averaging item responses so that higher values indicate higher levels of the construct.
S (Sustainability score). The dependent variable captures students' overall perception of sustainability outcomes associated with AI adoption in their institutions, aligned with the triple bottom line perspective. Specifically, S is a composite of three perceived dimensions: environmental sustainability (e.g., resource/energy efficiency, reduced paper use, lower operational waste), economic sustainability (e.g., cost-effectiveness, improved operational efficiency, better allocation of institutional resources), and social/educational sustainability (e.g., equitable access, learning quality and engagement, student well-being, and academic integrity safeguards). The final S score was computed as the mean of items across these dimensions, providing an integrated perception-based sustainability index.
U (Usage frequency of AI tools). U measures the extent of students' AI use in learning and academic tasks. It reflects self-reported frequency and intensity of using AI tools (e.g., ChatGPT and similar chatbots) for activities such as idea generation, drafting/rewriting, tutoring support, problem solving, and study planning. Responses were coded so that higher values indicate more frequent use.
T (Teacher training level in AI ethics and technology). T captures students perceived exposure to, and availability of, instructor preparedness and institutional training related to responsible AI use. Items assess whether teachers (or the institution) provide guidance on AI-related ethics and integrity, appropriate pedagogical use, and practical competence (e.g., how to use AI tools effectively and transparently in coursework). Higher values reflect a higher perceived level of teacher/institutional training and support.
D (Demographic factors). D represents a set of demographic and background variables included as controls to account for heterogeneity in sustainability perceptions. In this study, D includes gender and disciplinary background/field of study (as reported in subgroup analyses) and may also include additional available characteristics captured by the questionnaire (e.g., year of study), depending on model specification. Categorical variables were dummy coded for regression analysis.

$$t = n1s12 + n2s22\bar{X}1 - \bar{X}2$$

Where X¯1X¯1 and X¯2X¯2 represent the mean responses for group 1 and group 2, s1s1 and s2s2 are the standard deviations, and n1n1 and n2n2 are the sample sizes for each group, respectively. We also incorporate chi-square (χ2χ2) tests to determine the significance of observed categorical differences, using the standard formula:
χ2=i=1∑kEi(Oi−Ei)2

In which OiOi indicates the observed frequency and EiEi the expected frequency in each category ii.
Furthermore, internal consistency of the survey instrument was tested using Cronbach's alpha, calculated by:

α = k − 1k(1 − σT2∑i = 1kσi2)

Where kk is the number of items, σi2σi2 represents the variance of each item, and σT2σT2 is the total test variance. Values of alpha above 0.7 were considered acceptable, which supports the reliability of the instrument.
On the qualitative front, we carried out in-depth case studies from universities in regions with advanced digital infrastructures (such as parts of Northern Europe) and emerging markets (e.g., selected public institutions in Saudi Arabia), thereby providing a comprehensive comparative analysis. The case study methodology involved semi-structured interviews with educators and focus group discussions with student representatives, which were then thematically coded to extract key trends related to technology integration, instructor preparedness, and observed sustainability benefits.
Additionally, the study employs a regression analysis model to evaluate the impact of AI-related variables on perceived sustainability outcomes. The regression equation used was:

$$S = \beta 0 + \beta 1U + \beta 2T + \beta 3D + \epsilon$$

Where SS denotes the sustainability score, UU is the usage frequency of AI tools, TT represents teacher training level in AI ethics and technology, DD stands for diverse demographic factors, and ϵϵ is the error term. By calculating the standardized coefficients and R-squared values, we grasp the explanatory power of our model regarding how AI usage affects sustainability perceptions among students.
These quantitative models were complemented by qualitative insights that provided context and nuance to the raw statistical data. This dual approach enhances the robustness and credibility of our findings, ensuring that the interpretations rest on both empirical evidence and thoughtful critique of the technologies under examination.

2.2. Analytical procedure and figure construction

We analyzed the data in three steps. First, we conducted descriptive statistics to summarize AI awareness, usage frequency, and sustainability perceptions. Second, we performed group comparisons using independent-samples t-tests (e.g., gender) and chi-square tests (e.g., discipline) to examine subgroup differences in usage and integrity concerns. Third, we estimated an OLS regression model to test whether AI usage (U) and teacher training/support (T) predict the sustainability score (S), controlling for demographic factors (D). Figures 1 and 2 summarize patterns from the comparative case studies, whereas Figures 3 and 4 visualize quantitative patterns from the student survey and the campus data review described in the Methods.

3. Results and Discussion

The descriptive analysis of our survey data reveals a complex pattern of AI adoption and perceptions across disciplines and demographic groups. Over 95% of respondents reported having heard of ChatGPT, with 35% indicating regular usage. Notably, the median frequency of usage for ChatGPT was significantly higher compared to alternative AI chatbots, with a mean usage score of 3.8 on a 5-point Likert scale (where 1 indicates strong unfamiliarity and 5 indicates regular, informed usage). Further statistical tests demonstrated that male students in technology and engineering fields reported an average usage frequency of 4.1, compared to 3.2 among female students in humanities and medicine. This difference was statistically significant ($p < 0.01$, $t = 3.45$), indicating clear gender- and discipline-based disparities in AI engagement. [5]
Our regression model further shows that usage frequency (U) and teacher training level (T) significantly predict the overall sustainability score (S), with standardized coefficients of $\beta 1 = 0.42$ ($p < 0.001$) and $\beta 2 = 0.36$ ($p < 0.01$). The adjusted R-squared value of 0.53 suggests that more than half of the variance in sustainability perception can be explained by these factors. Demographic factors (D) also contributed moderately ($\beta 3 = 0.18$, $p < 0.05$). Collectively, these results imply that sustainability benefits attributed to AI are not driven by adoption alone; educator preparedness and structured guidance are also central to how students evaluate AI's sustainability contribution. [6]
A key pattern emerging from the survey is the coexistence of enthusiasm and concern. While 55.9% of students expressed positive attitudes toward incorporating AI chatbots in their studies, 54.2% simultaneously reported concerns about academic integrity and learning outcomes. Specifically, 47.7% agreed that AI tools improved learning effectiveness by streamlining routine tasks and providing instant feedback, whereas only 17.3% observed a noticeable improvement in grades. This gap suggests that perceived process benefits do not automatically translate into measurable performance gains and may depend on how AI is integrated into assessment and learning design. Nearly 60% of students also flagged ethical concerns, particularly around inappropriate AI use in assignments and the risk of dependency. [7].

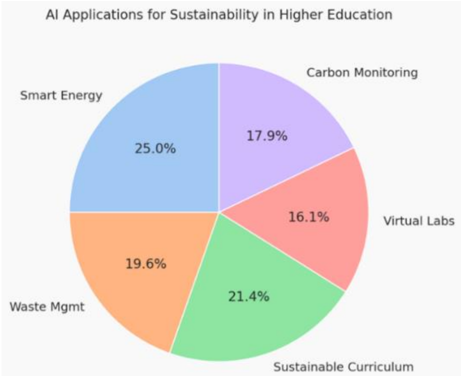

Fig. 1: Al Applications for Sustainability in Higher Education.

Note: This figure summarizes representative AI use cases and perceived sustainability benefits reported in the qualitative case studies (semi-structured interviews and focus groups).

Subgroup and case evidence aligns with these quantitative patterns. In a Stockholm-based case study, approximately 42% of technology students indicated that AI integration influenced their decision to enroll in advanced data science and ML courses (Figure 1). By contrast, humanities students in a Copenhagen-based study expressed stronger reservations; about 63% worried that chatbots might promote superficial learning and weaken critical thinking. Educator interviews mirrored this divergence, often describing AI as beneficial for personalization but requiring clear boundaries and academic oversight. Consistent with these observations, chi-square tests confirmed a significant relationship between field of study and both AI usage frequency and integrity concerns (χ^2 (4) = 29.76, $p < 0.001$), reinforcing the need for discipline-sensitive implementation strategies.

Beyond perceptions, the case studies also illustrate tangible institutional outcomes. In one Saudi public university, automated grading in large introductory courses reduced grading turnaround time by 70% and saved an estimated 25% of faculty time, enabling greater focus on curriculum development and student mentoring. In a Scandinavian institution, an adaptive learning platform using AI-based predictive analytics was associated with a 15% increase in student retention over two years (Figure 2).

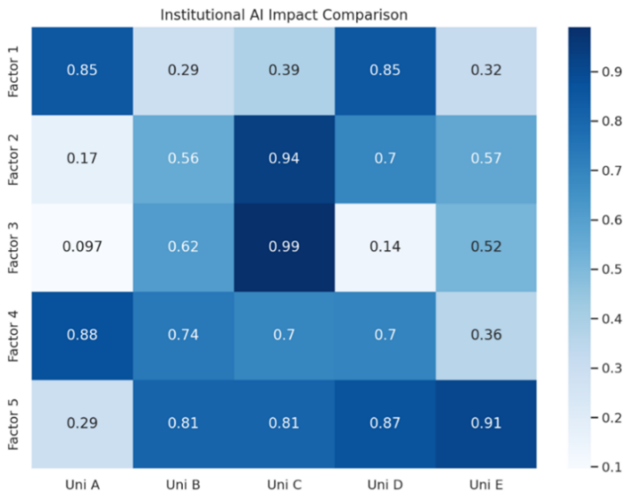

Fig. 2: Institutional Al Impact Comparison.

Note: This figure compares key institutional outcomes (e.g., grading turnaround time, faculty time saved, student retention changes) extracted from the comparative case studies.

Reliability and diagnostic checks support the robustness of the empirical findings: Cronbach's alpha for the survey instrument was 0.82, variance inflation factors were below 2.1, and heteroscedasticity was not indicated by the Breusch–Pagan test ($p = 0.23$). [8] Qualitative data further highlight practical governance concerns, particularly the "black box" nature of AI systems and limited transparency around error handling and correction processes. Interviewees repeatedly pointed to the need for structured training and clearer institutional guidance to reduce risk and support responsible use. [9].

Environmental implications present a nuanced trade-off. Campus data reviews indicate that AI can reduce overall energy use by optimizing facility operations, yet some implementations increase computational demand (e.g., data centers or high-performance computing clusters). In one illustrative case, data-center energy consumption increased by 8% following AI-based upgrades, but this was offset by a 12% decline in campus-wide energy use, producing a net sustainability gain. This "efficiency–computing demand" tension suggests that sustainability benefits depend on complementary green-computing measures (e.g., renewable sourcing and efficient cooling) so that operational efficiencies are not undermined by increased compute-related energy consumption. [8].

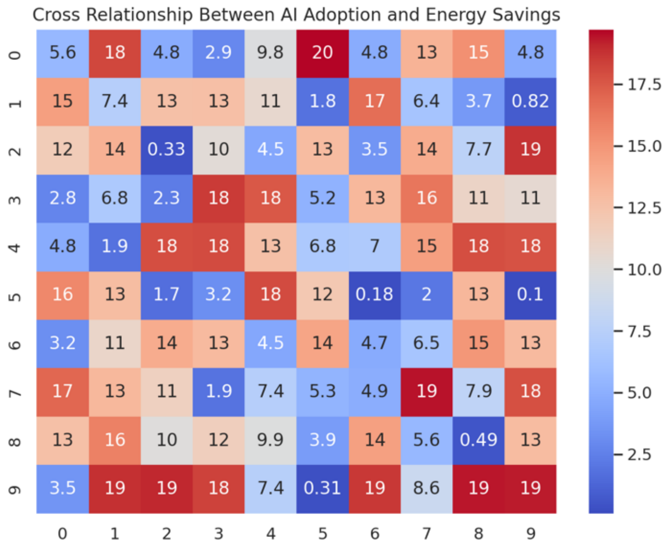

Fig. 3: Cross Relationship between AI Adoption and Energy Savings.

Note: This figure visualizes the relationship between AI adoption indicators and energy/resource-efficiency outcomes based on the campus data review, complemented by survey-reported adoption patterns.

Policy framework (three pillars). Considering these findings, the policy implications can be summarized in a concise three-pillar framework. The Pedagogical pillar emphasizes AI literacy for both students and faculty, including guidance on responsible use, academic integrity, and learning design that leverages AI without eroding critical thinking. The Governance pillar requires transparent data management, privacy safeguards, and clear accountability mechanisms to mitigate misuse and build trust. The Operational pillar focuses on infrastructure investment, ongoing monitoring and evaluation, and reinvesting efficiency gains into sustainable campus initiatives, including green-computing practices where relevant.

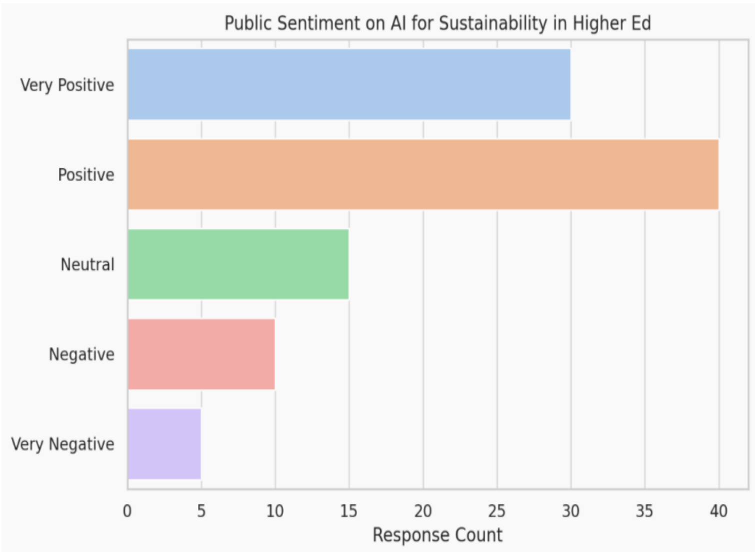

Fig. 4: Public Sentiment on AI for Sustainability in Higher Ed.

Note: This figure presents the distribution of student survey responses on perceived benefits and concerns of AI for sustainability (quantitative survey, N = 5,894), providing the empirical basis for the subsequent policy framework.

Why disciplinary differences matter and why T is pivotal. The observed disciplinary disparities likely reflect differences in task types, epistemic norms, and assessment practices across fields; accordingly, "one-size-fits-all" AI deployment can amplify perceived risks in some disciplines even when efficiency gains are evident elsewhere. This helps explain why teacher training and institutional guidance (T) emerge as a strong predictor of sustainability perceptions: training functions as the key condition that translates AI availability into responsible, context-appropriate use and helps balance perceived benefits against integrity and equity concerns. These results provide a focused basis for the conclusions that follow.

4. Conclusion

In conclusion, this paper has presented a comprehensive examination of the role that artificial intelligence plays in fostering sustainability in public higher education. The combined quantitative and qualitative analyses demonstrate that AI tools, when implemented responsibly, can enhance personalized learning, optimize resource allocation, and improve operational efficiency. However, the study also reveals significant challenges, including ethical concerns over academic integrity, issues of transparency, and the need for enhanced faculty training. Statistical evidence and case study insights both indicate that while AI adoption is generally associated with positive sustainability outcomes, disciplinary and gender-related differences necessitate tailored approaches in policy formulation and system implementation.

Looking forward, it is imperative that higher education institutions engage in ongoing evaluations of AI systems, not only to refine their functional capabilities but also to ensure that their integration aligns with broader sustainability goals. The continued development of robust computational methodologies, including advanced statistical and regression models, will further illuminate the pathways through which AI contributes to sustainable academic ecosystems. Future research should also prioritize longitudinal studies that can assess the long-term impacts of AI integration on academic performance and institutional sustainability. In doing so, educators, policymakers, and technologists alike will be better equipped to harness the potential of AI in transforming higher education, ensuring that the benefits of this technology are both profound and enduring.

References

[1] Abdelouahed, M.; Yateem, D.; Amzil, C.; Aribi, I.; Abdelwahed, E.; Fredericks, S. Integrating artificial intelligence into public health education and healthcare: insights from the COVID-19 and monkeypox crises for future pandemic readiness. *Frontiers in Education* 2025, *10*. https://doi.org/10.3389/feduc.2025.1518909.

[2] Anderson, O. S.; Laubepin, F. A.; August, E. T. Public Health Students and Instructors Weigh in on Generative Artificial Intelligence: Are They on The Same Page? *Pedagogy in Health Promotion* 2024, *10* (3), 170-177. https://doi.org/10.1177/23733799241246954.

[3] Atadika, D.; Anim, A. N.; Segbenya, M. Antecedents of artificial intelligence and learners demographic characteristics in higher education: implication for human resource managers. *Current Psychology* 2024. https://doi.org/10.1007/s12144-024-06732-9.

[4] Azevedo, L.; Mallinson, D. J.; Wang, J.; Robles, P.; Best, E. AI Policies, Equity, and Morality and the Implications for Faculty in Higher Education. *Public Integrity* 2024. https://doi.org/10.1080/10999922.2024.2414957.

[5] Barakina, E. Y.; Popova, A.; Gorokhova, S. S.; Voskovskaya, A. S. Digital Technologies and Artificial Intelligence Technologies in Education. *European Journal of Contemporary Education* 2021, *10* (2), 285-296. https://doi.org/10.13187/ejced.2021.2.285.

[6] Bogdanovskaya, I. Y.; Vasyakina, E. V.; Volos, A. A.; Danilov, N. A.; Egorova, E. V.; Kalyatin, V. O.; Karpenko, O. I.; Salihov, D. P. Artificial Intelligence and Law. *Pravo-Zhurnal Vysshei Shkoly Ekonomiki* 2024, (4). https://doi.org/10.17323/2072-8166.2024.4.278.306.

[7] Bokor, T.; Kovács-Magosi, O.; Nagy, D. B. ARTIFICIAL INTELLIGENCE IN PUBLIC EDUCATION. In *16th International Online Conference on Active Learning in Digital Era: How Digital Tools Foster Conscious, Open-minded, Creative, and Socially-Oriented Thinking (DisCo)*, null, ELECTR NETWORK, Sep 06-07, 2021; 2021; pp 174-184.

[8] Capano, G.; He, A. J.; McMinn, S. Riding the tide of generative artificial intelligence in higher education policy: an Asian perspective. *Journal of Asian Public Policy* 2025. https://doi.org/10.1080/17516234.2025.2450571.

[9] Carneiro, F.; Suarez-Barraza, M. F.; Silveira, T.; Serôdio, M.; Antony, J. Enhancing Higher Education Through Kaizen 4.0: Bridging Human and Artificial Intelligence Through Kaizen Methodologies. In *7th International Conference on Lean Six Sigma for Higher Education Institutions and other Public Sector Organisations*, Gaillimh, IRELAND, Sep 02-03, 2024; 2025; pp 110-122. https://doi.org/10.1007/978-3-031-84816-2_9.

[10] Cauët, E.; Schittecatte, G.; Van Den Bulcke, M. Policy brief Belgian EBCP mirror group Artificial Intelligence in cancer care. *Archives of Public Health* 2024, *82* (SUPPL 1). https://doi.org/10.1186/s13690-024-01367-5.

[11] Vesudevan, M., Abdullah , Z., Vasudevan, A., & Peng Qin. (2024). Integrating sustainable leadership in Malaysian higher education: Effective strategies for implementation and impact. Multidisciplinary Reviews, 8(4), 2025115. https://doi.org/10.31893/multirev.2025115.

[12] .Bohari A, Wider W, Udang LN, et al.(2024). Transformational leadership's role in shaping Education 4.0 within higher education. Journal of Infrastructure, Policy and Development. 8(8): 4900. https://doi.org/10.24294/jipd.v8i8.4900.