AI in sustainable higher education: an interpretive structural model and MICMAC approach

Irene O. Mamites*

College of Education,
Cebu Technological University,
Main Campus,
Cebu, Philippines
Email: irene.mamites@ctu.edu.ph
*Corresponding author

Jose Maria S. Garcia II and Gibe S. Tirol

College of Computer, Information and Communications Technology,
Cebu Technological University,
Main Campus,
Cebu, Philippines
Email: josemariaii.garcia@ctu.edu.ph
Email: gibe.tirol@ctu.edu.ph

Nelson F. Nolon

College of Technology,
Cebu Technological University,
Dumanjug Extension Campus, Philippines
Email: nelson.nolon@ctu.edu.ph

Joy M. Olarte

Department of Education,
Leyte Division,
Region VIII, Leyte, Philippines
Email: joy.olarte001@deped.gov.ph

Ulysis D. Malait and Melanie M. Himang

College of Education,
Cebu Technological University,
Cebu City Mountain Satellite Campus, Cebu, Philippines
Email: ulysisdmalait@gmail.com
Email: melanie.himang@ctu.edu.ph

Abstract: Integrating artificial intelligence (AI) in sustainable higher education practices prove to be beneficial in the teaching and learning process of institutions. With the many probable practices which promote sustainability in higher education, stakeholders must be able to proactively prioritise practices given the lack of resources for the full-blown implementation of sustainable higher education practices. Along this line, this paper employs interpretive structural modelling (ISM) with MICMAC analysis to generate a framework for stakeholders to use in prioritising such practices. A real-life case study in a state university in the Philippines is conducted to understand how AI is integrated in sustainable higher education. Interestingly, the framework points out data collection monitoring systems as the core practice to be tackled by educational institutions.

Keywords: artificial intelligence; sustainable higher education; interpretive structural modelling; ISM; MICMAC analysis; state university.

Reference to this paper should be made as follows: Mamites, I.O., Garcia II, J.M.S., Tirol, G.S., Nolon, N.F., Olarte, J.M., Malait, U.D. and Himang, M.M. (2026) 'AI in sustainable higher education: an interpretive structural model and MICMAC approach', *Int. J. Business and Globalisation*, Vol. 42, No. 1, pp.1–22.

Biographical notes: Irene O. Mamites is an Associate Professor V and Associate Dean for Academic Programs at Cebu Technological University – Main Campus, also serves as the Chair of the Field Study courses and previously led the Diploma in Professional Education and Doctorate Programs. She holds a Bachelor of Secondary Education in Business Technology with a minor in English, Master's in Education (2014), and Doctorate in Development Education (2019). A committed researcher, she has published in Scopus and Web of Science journals as lead and co-author. She has contributed extensively to community training initiatives and authored multiple instructional materials for professional education courses.

Jose Maria S. Garcia II holds a PhD in Technology Management (2005) and Master's in Technician Education major in Electronics Technology (2002) from Cebu Technological University, where he also serves as the Dean of the College of Computer, Information, and Communications Technology and Assistant Campus Director. He earned his BS in Electronics and Communications Engineering (1990) from the University of San Carlos. With 26 years of teaching experience in ICT, he previously served as an Associate Dean of the College of Technology and Campus Director of CTU Dumanjug Extension Campus. He is an active member of PSITE.

Gibe S. Tirol is an Assistant Professor I at Cebu Technological University – Main Campus, where he plays an active role in shaping future IT professionals. He completed his Bachelor of Science in Information and Computer Science at the University of Cebu in 2002 and later earned his Master's in Information Technology from Cebu Institute of Technology – University in 2020. He is currently pursuing his Doctorate in Information Technology at the same institution. With extensive experience in both the IT industry and the academe, he remains dedicated to research, technological innovation, and advancing high-quality IT education.

Nelson F. Nolon is an Instructor III at Cebu Technological University Dumanjug Extension Campus and Chair of the BIT-CT Department. He holds a Master's in Industrial Technology from CTU-Moalboal and teaches programming, fundamentals of programming, computer networks and security, and computer electronics. A licensed Technology and Livelihood Education teacher and certified Trainer in Methodology I, he actively collaborates on research with CTU faculty. His work focuses on AI adoption in higher education and student malware prevention. He has developed a conceptual framework supporting anti-malware adoption, reflecting his strong commitment to technology integration, cybersecurity awareness, and academic advancement.

Joy M. Olarte, a Master Teacher III in the Department of Education – Leyte Division, hails from Odiong, Javier, Leyte. She earned her BS in Agriculture major in Agronomy from Visayas State University, Diploma in Basic Education Teaching from Southern Leyte State University, MA in Education major in Science from Asian Development Foundation College, and Doctor of Management in Human Resource Management from Naval State University. With more than a decade of teaching experience, she serves as a trainer of trainers at both regional and division levels and teaches part-time at Cebu Technological University. Her outstanding service has earned multiple distinctions, including the Pasidungog Awards.

Ulysis D. Malait is an Associate Professor II at Cebu Technological University, Cebu City Mountain Satellite Campus. He holds a Doctor in Development Education, Master of Education major in Mathematics, and Bachelor of Science in Industrial Education major in Mathematics. A committed educator and scholar, he has built a career centred on advancing mathematics pedagogy and promoting community development through education. His work reflects a steadfast belief that sustained research is vital to meaningful educational progress, as it drives innovation, strengthens instructional practices, and cultivates transformative learning experiences that prepare future generations for evolving academic and societal demands.

Melanie M. Himang is a Professor VI at Cebu Technological University – Main Campus, Cebu City. She completed her BS in Industrial Technology in 2003, MS in Industrial Technology in 2004, and PhD in Technology Management in 2007, all from Cebu Technological University, and later earned a Special Education License from Virginia Commonwealth University, USA. She currently serves as the Chairman of Research in the College of Computer, Communications, and Information Technology. With over two decades of experience in computer technology, she has produced award-winning research, authored numerous publications, and remained an active member of PSITE.

1 Introduction

Sustainability in higher education has gained increasing attention as institutions respond to global challenges outlined in frameworks such as UNESCO's Decade of Education for Sustainable Development and the Sustainable Development Goals (SDGs) (Seatter and Ceulemans, 2017; Gras-Velazquez and Fronza, 2020; Frank and Ricci, 2023). Embedding sustainability in higher education offers numerous benefits to stakeholders, including improved living conditions and the cultivation of values that promote sustainable lifestyles among students (Kotomina and Sazhina, 2020). A holistic approach to sustainability in higher education not only supports the broader goals of sustainable development but also yields institutional benefits (Filho, 2015). At the basic level, integration can occur through curriculum revisions that embed sustainability principles and the adoption of sustainable campus practices (Vidrevich and Pervukhina, 2023). At a more advanced stage, it involves equipping students with the knowledge, skills, and values necessary for a sustainable future (Sebire and Isabeles-Flores, 2023), supported by emerging technologies such as artificial intelligence (AI).

AI is increasingly recognised as a transformative force in sustainable higher education, with applications that personalise learning, analyse student performance, and adapt curricula to evolving needs (Aggarwal et al., 2023; Lin et al., 2023). These capabilities directly support SDG 4 (quality education) (Fernandes et al., 2024). While some students believe AI could replace university teachers within five years (Okulich-Kazarin et al., 2023), concerns remain regarding privacy, algorithmic bias, and the infrastructure needed for implementation (Lin et al., 2023). Nevertheless, AI integration offers significant opportunities to enhance teaching and learning, empower educators, and contribute to sustainability objectives (Aggarwal et al., 2023; Fernandes et al., 2024). For example, Lee et al. (2024) examined the impact of generative AI on higher education, emphasising the need to remain engaged with evolving research and best practices. Similarly, Suyanarayana et al. (2024) underscored the potential of AI-enhanced digital learning to improve education management systems, address ethical concerns, and provide a roadmap for quality improvement. Despite concerns which shows 10–35% of students perceive AI as a threat to higher education, AI can improve skills, free up instructor time, and enhance performance (Okulich-Kazarin et al., 2024; Tanveer et al., 2020). It also has potential to raise educational quality in developing countries and prepare students for sustainable work environments requiring adaptability, creativity, and emotional intelligence (Bonini, 2020). Beyond pedagogy, AI supports sustainability in higher education through operational innovations, including data collection and monitoring systems (Atymtayeva et al., 2020; Sorour and Atkins, 2024), predictive maintenance (Liz-Domínguez et al., 2019), occupancy-based resource allocation (Sihombing et al., 2020), energy conservation (Garrido-Yserte and Gallo-Rivera, 2020), water-saving technologies (Siddiqui et al., 2021; Soares et al., 2023), resource-efficient policies (Pavlova and Kavčič, 2020), optimised space use (Azizi et al., 2020), renewable energy integration (Almasri et al., 2024; Nazipov et al., 2021), and real-time reporting (Carless et al., 2011). However, with so many possible initiatives, stakeholders may find it difficult to prioritise. This challenge can be addressed using multiple-criteria decision-making (MCDM) methods, which combine quantitative and qualitative approaches to select the best alternatives based on multiple criteria (Majumder and Saha, 2016; Lertprapai, 2013). MCDM techniques such as AHP, TOPSIS, and MAUT allow ranking and comparison of options, and are particularly valuable where objectives conflict or outcomes are uncertain (Bhole and Deshmukh, 2018; Zeleny, 2011).

Among MCDM tools, interpretive structural modelling (ISM) and MICMAC analysis are particularly relevant. ISM identifies and structures relationships between factors defining a problem (Attri et al., 2013), producing a hierarchical model based on reachability matrices. MICMAC analysis complements ISM by categorising factors according to their driving and dependence power (Behl et al., 2020). While ISM is widely applied in sustainability-related studies (Ahmad and Qahmash, 2021), manual execution can be error-prone prompting the development of tools such as SmartISM for greater accuracy. ISM-MICMAC has been successfully applied in sectors including supply chain management, IT, and human resources (Gardas et al., 2017), but remains underexplored in sustainable higher education. Within higher education sustainability, ISM has been used to map barriers to green campus operations, which demonstrates the value of structural hierarchies in university contexts, but those studies were not centred on AI as a sustainability lever (Gholami et al., 2020). Meanwhile, current work on AI for sustainability in higher education remains largely descriptive or survey-based and does not employ ISM-MICMAC to expose multilevel interdependencies among AI enablers and sustainability outcomes (Leal Filho et al., 2025). In fact, recent studies on AI in higher education illustrate the gap. For instance, Hughes et al. (2025) explored challenges in generative AI adoption, identifying issues such as risks in LLM training and regulatory shortfalls, yet without employing structural methods to reveal hierarchical leverage points, while Ayyash and Salah (2025) emphasised on AI for energy management in Palestinian universities which integrated theoretical models of adoption but likewise did not apply ISM-MICMAC to map systemic interdependencies. To our knowledge, and based on our review of recent AI in higher education adoption and sustainability literature, no study has yet applied the combined ISM-MICMAC procedure specifically to sustainable higher education with AI as the focal construct, leaving a methodological and substantive gap that this paper addresses. Specifically, this paper aims to address this gap by applying ISM-MICMAC to analyse AI integration practices in the case of a Philippine state university, providing stakeholders with a structured framework for prioritising initiatives and allocating scarce resources effectively.

Finally, this paper aims to address the following research questions:

1. What are the key sustainable higher education practices that must be prioritised by university stakeholders?
2. How do these practices interact, and what hierarchical relationships exist among them?
3. Which practices have the highest driving power and should be prioritised for effective supervision in special education?

2 Methodology

Analysing the practices involved in integrating AI technologies for sustainable higher education can be performed by exploring the structural relationship among such practices following the ISM-MICMAC approach. The first step of accomplishing such goal involves identifying the set of practices that encourage the integration of sustainability practices in higher education including

1 data collection and monitoring systems
2 predictive maintenance
3 occupancy-based resource allocation
4 energy efficiency and conservation measures
5 water conservation techniques
6 resource-saving policies and user education
7 space utilisation optimisation
8 integration of renewable energy sources
9 real-time reporting and feedback.

These factors are defined in detail in table. It is also imperative to note that these factors form part of the decision-making process that the stakeholders of higher educational institutions refer to upon integrating sustainable higher education. By strategically analysing the most apparent factors can suggest how AI technologies can be integrated to sustainable practices in higher education. In order to demonstrate the applicability of ISM-MICMAC approach in analysing the integration of AI in sustainable higher education, a case study in a state university is performed. A detailed overview of the case study and the approach is presented as follows.

2.1 Case overview

Universities are increasingly striving to apply sustainable higher education practices in response to global sustainability challenges and the UN SDGs. One of the most apparent expectations for higher education institutions is to become leaders in sustainable change, integrating sustainability into their curricula, research, and campus operations. However, universities face numerous challenges in implementing sustainability initiatives, due to a number of resource limitations including lack of institutional support, limited resources, and insufficient trained staff, especially for a state university in a developing country. In the case of this paper, a state university in Cebu, Philippines is considered as a basis for analysing the different aspects revolving around the integration of AI technologies for sustainable higher education. This state university is known for its focus on technology, research, and community service. Furthermore, the university was established in 1911 as a trade school, and became a university in 2009 under Republic Act 9744. Its main campus is in Cebu City, with over 20 satellite campuses across Cebu Province. Currently, the university offers undergraduate, graduate, and doctoral programs in engineering, education, agriculture, fisheries, IT, business, and hospitality management. It emphasises practical skills and is recognised as a Center of Excellence in Fisheries by CHED. The Accrediting Agency of Chartered Colleges and Universities in the Philippines (AACCUP) has also accredited the institution. One of the most pressing issues faced by the university is its transition to provide quality education and engage in community development as a part of the sustainable higher education practices.

Table 1 Sustainable higher education practices in integrating AI technologies to sustainable higher education

Sustainable higher education practices	*Description*
Data collection and monitoring systems	Integrated frameworks or tools designed to gather, organise, and continuously observe data
Predictive maintenance	Proactive maintenance strategy that uses data analysis, machine learning, and IoT technologies to predict when equipment or machinery is likely to fail
Occupancy-based resource allocation	Managing resources based on the actual usage or occupancy of a space
Energy efficiency and conservation measures	Strategies and actions taken to reduce energy consumption, minimise waste, and optimise the use of energy resources
Water conservation techniques	Practices, technologies, and strategies aimed at reducing water usage, minimising waste, and preserving water resources
Resource-saving policies and user education	Strategies aimed at promoting the efficient use of resources, such as water, energy, and materials, through well-designed policies and educational efforts that encourage sustainable behaviour in higher education institutions
Space utilisation optimisation	The process of managing and organising physical spaces in such a way that they are used as efficiently as possible
Integration of renewable energy sources	The process of incorporating renewable energy (RE) technologies such as solar, wind, hydro, geothermal, and biomass into existing energy systems to generate electricity, heat, or fuel
Real-time reporting and feedback	The process of collecting, analysing, and presenting data as it is generated or occurs, allowing for immediate insight and responses

Table 2 Sample SSIM from expert 1's evaluation

Practices	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1		V	V	X	X	V	V	V	V
2			O	V	O	A	V	X	X
3				X	X	A	X	X	O
4					X	A	V	X	X
5						A	X	V	O
6							X	X	V
7								X	X
8									A
9									

Notes: AI technologies for sustainable higher education practices are coded using the following:

1 data collection and monitoring systems
2 predictive maintenance
3 occupancy-based resource allocation
4 energy efficiency and conservation measures
5 water conservation techniques
6 resource-saving policies and user education
7 space utilisation optimisation
8 integration of renewable energy sources
9 real-time reporting and feedback.

To carry out the analysis among practices, eight academic experts were asked to elicit their judgment on the relationship among these practices in relation to integrating AI to sustainable higher education (see Table 1). Note that the choice of eight experts for the ISM analysis is justified on the grounds of expertise, efficiency, and reliability. ISM-MICMAC fundamentally depends on qualitative judgments from domain experts to establish the relationships among variables, and a carefully selected small group enhances both the depth of knowledge and the consistency of responses (Hasan et al., 2024; Noaman et al., 2024). Expanding the panel too much may create unnecessary variability in opinions, making it harder to reach consensus, whereas eight experts strike a practical balance between diversity of perspectives and effective decision-making. This also minimises redundancy, since adding more experts beyond a certain threshold often does not significantly influence the results. Prior studies likewise indicate that panels of five to ten experts are sufficient to produce valid and reliable findings (Nagpal et al., 2015; Gupta et al., 2025). Thus, the inclusion of eight experts ensures an optimal balance of diversity, efficiency, and accuracy, producing meaningful insights while maintaining a manageable process.

Table 3 Initial reachability matrix from expert 1's evaluation

Practices	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*Driving*
1	1	1	1	1	1	1	1	1	1	9
2	0	1	0	1	0	0	1	1	1	5
3	0	0	1	1	1	0	1	1	0	5
4	1	0	1	1	1	0	1	1	1	7
5	0	0	1	1	1	0	1	1	0	5
6	0	1	1	1	1	1	1	1	1	8
7	0	0	1	0	1	1	1	1	1	6
8	0	1	1	1	0	1	1	1	0	6
9	0	1	0	1	0	0	1	1	1	5
Dependence	2	5	7	8	6	4	9	9	6	

Notes: AI technologies for sustainable higher education practices are coded using the following:

1 data collection and monitoring systems
2 predictive maintenance
3 occupancy-based resource allocation
4 energy efficiency and conservation measures
5 water conservation techniques
6 resource-saving policies and user education
7 space utilisation optimisation
8 integration of renewable energy sources
9 real-time reporting and feedback.

The contextual relationships between practices are defined according to (i, j) with the use of directional relationships being V (i.e., when practice i helps achieve practice j), A (i.e., when practice j helps achieve practice i), X (i.e., when both practices helps achieve each other), and O (i.e., when the two practices are not related). As an illustration, suppose the following relationships:

- Space utilisation optimisation helps achieve resource-saving policies and user education; therefore, a rating of V must be given to indicate such relationship.
- Predictive maintenance is achieved through data collection and monitoring systems; therefore, a rating of A must be given to indicate such relationship.
- Water conservation techniques and energy efficiency and conservation measures helps achieve each other; therefore, a rating of X must be given to indicate such relationship.
- Space utilisation optimisation and real-time reporting and feedback are not related; therefore, a rating of O must be given to indicate such relationship.

The results of the structural self-interaction matrix (SSIM) for expert 1 are shown in Table 2.

Table 4 Aggregated initial reachability matrix

Practices	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*Driving*
1	1	1	1	0	1	1	0	0	1	6
2	0	1	0	0	0	0	0	0	1	2
3	0	0	1	1	0	1	0	1	0	4
4	0	1	0	1	1	0	1	0	0	4
5	0	0	0	0	1	0	0	1	0	2
6	0	0	0	1	1	1	1	0	1	5
7	0	0	1	0	0	0	1	0	1	3
8	0	0	0	0	0	0	0	1	0	1
9	0	1	1	0	0	0	0	1	1	4
Dependence	1	4	4	3	4	3	3	4	5	

Notes: AI technologies for sustainable higher education practices are coded using the following:
1 data collection and monitoring systems
2 predictive maintenance
3 occupancy-based resource allocation
4 energy efficiency and conservation measures
5 water conservation techniques
6 resource-saving policies and user education
7 space utilisation optimisation
8 integration of renewable energy sources
9 real-time reporting and feedback.

2.2 Develop the initial reachability matrix

The initial reachability matrix is generated by converting the SSIM into a numerical matrix following the rules:

- A rating of V in the SSIM in cell (i, j) converts that cell (i, j) to 1 and the counterpart (j, i) to 0 in the initial reachability matrix.
- A rating of A in the SSIM in cell (i, j) converts that cell (i, j) to 0 and the counterpart (j, i) to 1 in the initial reachability matrix.

- A rating of X in the SSIM in cell (i, j) converts that cell (i, j) to 1 and the counterpart (j, i) also to 1 in the initial reachability matrix.
- A rating of O in the SSIM in cell (i, j) converts that cell (i, j) to 0 and the counterpart (j, i) also to 0 in the initial reachability matrix.

Given the conversion rules presented above, the SSIM (see Table 2) accomplished by expert 1 is converted into its corresponding initial reachability matrix (see Table 3). Note that an initial reachability matrix will be created for each of the eight experts tapped in this paper. Therefore, these initial reachability matrices will then be aggregated to come up with only one initial reachability matrix representing the unified judgment of experts. To aggregate, a general rule of thumb is implemented such that, if in every cell, the sum of the initial reachability matrix is equal to or more than two-thirds of the total number of experts, then that cell will have a value of 1. Otherwise, the value becomes 0. Aggregating the initial reachability matrices of experts results to an aggregated initial reachability matrix presented in Table 4. It is also important to note that transitive links may be present in the aggregated initial reachability matrix; therefore, Table 5 reflects the final reachability matrix considering the transitive links (i.e., matrix cells with asterisk).

Table 5 Final reachability matrix

Practices	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*Driving*
1	1	1	1	1*	1	1	1*	1*	1	9
2	0	1	1*	1*	1*	1*	1*	1*	1	8
3	0	1*	1	1	1*	1	1*	1	1*	8
4	0	1	1*	1	1	1*	1	1*	1*	8
5	0	0	0	0	1	0	0	1	0	2
6	0	1*	1*	1	1	1	1	1*	1	8
7	0	1*	1	1*	1*	1*	1	1*	1	8
8	0	0	0	0	0	0	0	1	0	1
9	0	1	1	1*	1*	1*	1*	1	1	8
Dependence	1	7	7	7	8	7	7	9	7	

Notes: AI technologies for sustainable higher education practices are coded using the following:
1 data collection and monitoring systems
2 predictive maintenance
3 occupancy-based resource allocation
4 energy efficiency and conservation measures
5 water conservation techniques
6 resource-saving policies and user education
7 space utilisation optimisation
8 integration of renewable energy sources
9 real-time reporting and feedback.

2.3 Level partitioning

In order to come up with the structural partitioning of the AI technologies for sustainable higher education practices, the practices are classified into sets based on its directional relationships with respect to other practices. In here, the final reachability matrix is used to identify the reachability set and antecedent set for each practice. A reachability set is comprised of the practices which includes itself and others that it helps to achieve. On the other hand, antecedent set is composed of the practices which includes itself and others through which it is attained. After identifying the reachability and antecedent set of each practice, the intersection set is then developed by taking the common practices between the reachability and antecedent sets. The intersection set firstly found then covers the bottommost level in the ISM framework. Then, the process is repeated for multiple iterations until all of the practices have been assigned to a certain level. As an example, the level 1 partitioning is presented in Table 6 while the final level partitioning is shown in Table 7.

2.4 Develop the ISM-based model

In this step, the ISM-based model is developed according to the level partitioning generated in the previous step. For instance, level 1 partitioning showed that practice 8 (integration of renewable energy sources) is assigned to level 1 of the ISM framework. Following such pattern, the final level partitioning shown in Table 7 is plotted accordingly into the ISM framework (see Figure 1). After plotting the levels of the practices, the arrows from one to another are then identified based on the final reachability matrix. The relationship between practice i and j is denoted graphically by an arrow pointing from i to j. Note further that the bottom level (i.e., denoted as level 4) practice is considered as the root cause which enables the attainment of the top-level practices. In order to complete the analysis of AI technologies for sustainable higher education practices, the driving and dependence power of every practice according to the MICMAC analysis is performed. The results of the MICMAC analysis are summarised in Figure 2.

Table 6 Level partitioning showing iteration 1

Practices	*Reachability set*	*Antecedent set*	*Intersection set*	*Level*
1	1, 2, 3, 4, 5, 6, 7, 8, 9	1	1	
2	2, 3, 4, 5, 6, 7, 8, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	
3	2, 3, 4, 5, 6, 7, 8, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	
4	2, 3, 4, 5, 6, 7, 8, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	
5	5, 8	1, 2, 3, 4, 5, 6, 7, 9	5	
6	2, 3, 4, 5, 6, 7, 8, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	
7	2, 3, 4, 5, 6, 7, 8, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	
8	8	1, 2, 3, 4, 5, 6, 7, 8, 9	8	1
9	2, 3, 4, 5, 6, 7, 8, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	

Notes: AI technologies for sustainable higher education practices are coded using the following:

1 data collection and monitoring systems
2 predictive maintenance
3 occupancy-based resource allocation
4 energy efficiency and conservation measures
5 water conservation techniques
6 resource-saving policies and user education
7 space utilisation optimisation
8 integration of renewable energy sources
9 real-time reporting and feedback.

Table 7 Final level partitioning

Practices	*Reachability set*	*Antecedent set*	*Intersection set*	*Level*
1	1	1	1	4
2	2, 3, 4, 6, 7, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	3
3	2, 3, 4, 6, 7, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	3
4	2, 3, 4, 6, 7, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	3
5	5	1, 2, 3, 4, 5, 6, 7, 9	5	2
6	2, 3, 4, 6, 7, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	3
7	2, 3, 4, 6, 7, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	3
8	8	1, 2, 3, 4, 5, 6, 7, 8, 9	8	1
9	2, 3, 4, 6, 7, 9	1, 2, 3, 4, 6, 7, 9	2, 3, 4, 6, 7, 9	3

Notes: AI technologies for sustainable higher education practices are coded using the following:

1 data collection and monitoring systems
2 predictive maintenance
3 occupancy-based resource allocation
4 energy efficiency and conservation measures
5 water conservation techniques
6 resource-saving policies and user education
7 space utilisation optimisation
8 integration of renewable energy sources
9 real-time reporting and feedback.

Figure 1 ISM-based framework of AI technologies for sustainable higher education practices

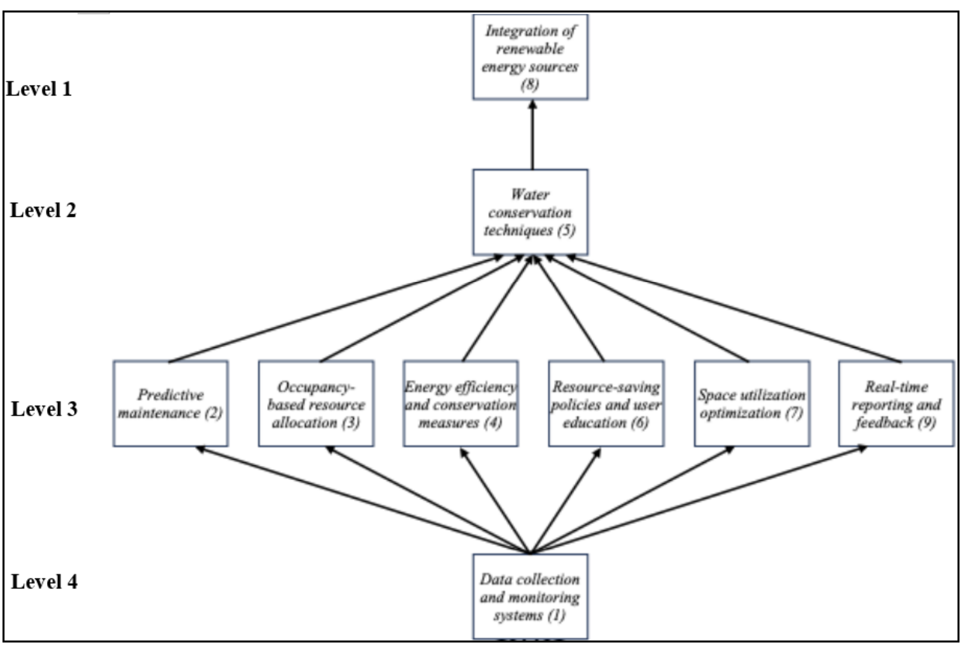
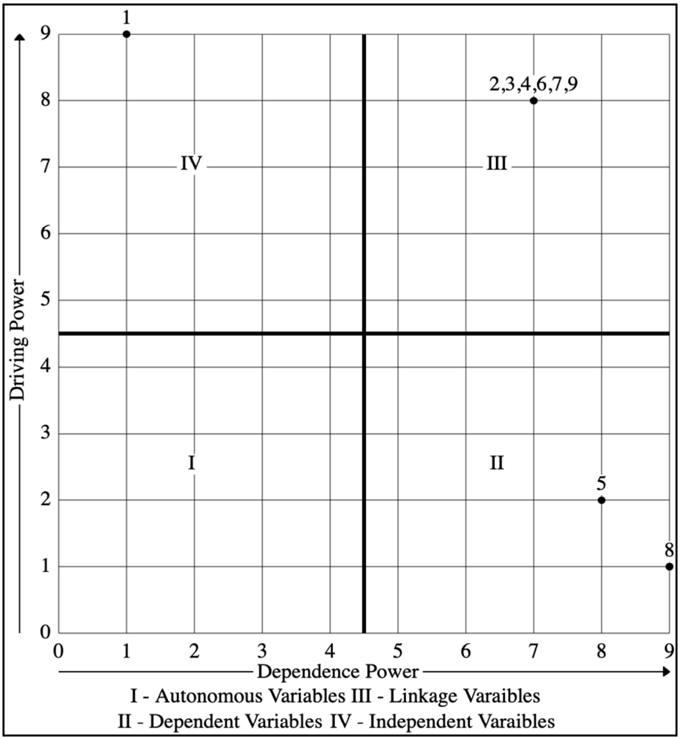


Figure 2 Classification of AI technologies for sustainable higher education practices based on MICMAC analysis



3 Results, discussion, and implementation challenges

As the educational sector continues to innovative given the advances in educational technologies, universities also seek to offer better quality education by implementing sustainable higher education practices through AI. It is a well-known notion that the use of AI in sustainable higher education practices positively fosters scientific reasoning skills that can lead to lasting behavioural changes in students, even in the face of environmental disruptions. Correspondingly, universities aim to achieve sustainable leadership in higher education as a necessity to promote depth learning, justice, communication, and conservation of resources, among others. However, with a big leap of transitioning from traditional teaching and learning process to an innovative approach of integrating AI in sustainable higher education practices calls for a careful analysis to ensure success in its overall implementation, not to mention the number of resources required by universities to support such innovative approaches.

Considering that the full operationalisation of using AI in sustainable higher education practices involve a deep level of commitment among universities, it is essential for stakeholders in higher education institutions to understand the practices and its relations among one another to ensure successful implementation. Therefore, for universities, such as the state university under investigation in this paper, focusing on the most important practice assists in prioritising one that can influence the other practices significantly. To achieve such goal, this paper implemented ISM with MICMAC analysis to assess the practices involved in integrating AI sustainably in higher education. The following sections show the key results obtained from the ISM-MICMAC analysis along with the discussion of implications.

3.1 Key ISM-MICMAC analysis results

First, the ISM approach straightforwardly presents the hierarchical structure of practices according to their driving and dependence powers (as seen in Figure 1). It can be noted that data collection and monitoring systems (1) has the strongest driving power and the weakest dependence power among other practices. This result suggests that by focusing mainly on this practice, the rest of the dependent practices can be significantly achieved at the same time. According to the ISM framework, data collection and monitoring systems (1) drives predictive maintenance (2), occupancy-based resource allocation (3), energy efficiency and conservation measures (4), resource-saving policies and user education (6), space utilisation optimisation (7), and real-time reporting and feedback (9).

Such relationships are further confirmed by empirical evidence from previous works as follows. For example, advanced building management systems (BMS) can collect extensive sensor data to anticipate and prevent failures in data centre infrastructure (Ricci et al., 2020). The integration of sensors, Industry 4.0 technologies, and machine learning algorithms, such as enhanced Naive Bayes artificial neural networks, allows for accurate prediction of machine states and improved reliability (Shrivastava et al., 2023). Distributed agent systems can gather data from globally dispersed manufacturing units, enabling the use of data mining techniques to identify behaviour patterns and detect faults early (Bastos et al., 2009). On the other hand, smart meters and IoT technologies enable comprehensive analysis of energy consumption patterns (Amaxilatis et al., 2017). These systems provide real-time data on energy usage, allowing for the identification of inefficiencies and implementation of energy-saving strategies (Akhtar et al., 2020). In educational settings, such systems can raise awareness among students and staff, promoting behavioural changes towards energy conservation (Amaxilatis et al., 2017). A case study in Spain demonstrated that continuous monitoring of HVAC systems in university buildings can lead to significant energy savings, with potential reductions of 40–70% in HVAC energy consumption (García-Monge et al., 2023). Moreover, these monitoring systems can be scaled to transform entire campuses into smart, energy-efficient environments (García-Monge et al., 2023).

Another interesting result generated from the overall ISM-MICMAC analysis can be seen in Figure 2 involving the classification of AI technologies for sustainable higher education practices based on their driving and dependence powers. According to the results, quadrant I (autonomous variables having low driving and dependence powers) AI technologies for sustainable higher education practices involves no practice. Quadrant II (dependent variables having low driving power and high dependence power) involves water conservation (5) and integration of renewable energy sources (8). Quadrant III (linkage variables having high driving and dependence powers) includes predictive maintenance (2), occupancy-based resource allocation (3), energy efficiency and conservation measures (4), resource-saving policies and user education (6), space utilisation optimisation (7), and real-time reporting and feedback (9). Quadrant IV (independent variables having high driving power and low dependence power) includes data collection and monitoring systems (1). The quadrant assignment of each practice gives stakeholders an idea of which one to prioritise over others. Specifically, Quadrant IV practices must be put into consideration firstly, since these are independent variables which provide the strongest driving power to other practices and are least dependent on others. Furthermore, low driving and low dependence power practices in quadrant I should also be taken cautiously by stakeholders since these do not drive nor depend on other practices.

3.2 Discussion and implications

As a practical implication on the results of MICMAC analysis, the quadrant assignment offers a strategic roadmap for stakeholders in higher education institutions seeking to integrate AI into sustainability practices. First, priority should be given to Quadrant IV practices, such as data collection and monitoring systems, since these constitute independent drivers that exert strong influence over other practices while remaining relatively unaffected by them. By investing in robust data infrastructures, universities can create a foundation that enables evidence-based decision making, supports predictive models, and enhances transparency in resource use (Pesonen et al., 2018; Mylonas et al., 2019; Zhang et al., 2025). Even in contexts with limited funding or digital infrastructure, directing resources to these practices ensures the creation of a scalable base that other initiatives can build upon.

Second, quadrant III linkage practices such as predictive maintenance, occupancy-based resource allocation, or space utilisation optimisation should be approached with deliberate and risk-managed rollouts. Because they simultaneously drive and depend on other factors, they act as both catalysts and potential points of vulnerability. Successful implementation of linkage practices requires phased deployment, pilot testing, and ongoing feedback mechanisms. For instance, launching a predictive maintenance system without sufficient sensor coverage or staff training could lead to systemic inefficiencies rather than improvements (Abdelghany et al., 2024; Da Costa et al., 2024). Administrators should therefore treat linkage practices as high-gain but high-risk initiatives.

Third, quadrant II dependent practices, such as water conservation or renewable energy integration, represent outcome-oriented initiatives that will deliver maximum benefits only after strong drivers (quadrant IV) and stable linkages (quadrant III) are in place. Universities should thus view these as ‘second-wave’ initiatives, focusing on them once the foundational and systemic enablers are operational. This staged approach ensures that sustainability outcomes are not pursued in isolation but are supported by enabling systems. Finally, quadrant I autonomous practices, should they be identified in future studies, would hold limited strategic value because they neither drive nor depend on other practices. While not irrelevant, they should be treated as supplementary enhancements rather than core priorities.

Overall, the results of the ISM-MICMAC analysis are useful for stakeholders in state universities, such as the case tackled in this paper, along the following lines. First, state universities struggle with insufficient funding, government policies, and the need for trained personnel (Leal Filho et al., 2017). To overcome these challenges, institutions can adopt a whole-institution approach, reorient education to address sustainability, and create public awareness. With the understanding that sustainable higher education practices can be prioritised accordingly, then improved planning and problem-based learning approaches can be further promoted thereby enhancing education for sustainable development efforts in universities. Specifically, since the most influential practice identified in this paper points to data collection and monitoring systems, stakeholders of higher education institutions can focus most of their efforts into this practice. Implementing data collection and monitoring systems in education involves automating processes to reduce human dependency and improve quality assessment. The use of an automated system that utilises machine learning, big data analysis, and visualisation techniques for real-time monitoring of educational processes may be put forward (Wang et al., 2024). Furthermore, quality monitoring and evaluation in higher education, incorporating web mining for data collection can also be considered. As a whole, these AI systems can pave the way for an optimised education quality while enhancing teacher performance and providing valuable insights for educational management and decision-making (García-Monge et al., 2025; Zhang et al., 2025).

3.3 Implementation challenges of ISM-MICMAC analysis results

The implementation of the ISM framework in sustainable higher education practices, as demonstrated in the case study conducted in a state university in the Philippines, calls for deliberate planning to address possible institutional, financial, and organisational challenges (Funa and Gabay, 2025). In the context of the AI technologies identified in the analysis, policy tools such as sustainability guidelines, AI governance protocols, and data privacy regulations can provide the necessary institutional foundation for adoption (Barus et al., 2025). Funding mechanisms including dedicated sustainability allocations, collaborations between public and private sectors, and competitive research grants may be utilised to support the acquisition of the prioritised AI tools and the conduct of relevant training programs. Change management approaches such as phased implementation, capacity building initiatives for faculty and staff, and continuous stakeholder engagement are critical to ensure commitment and long-term sustainability. For university administrators, recommended actions include the creation of cross functional sustainability committees, the integration of AI enabled sustainability objectives into institutional plans, and the establishment of partnerships with industry to facilitate the sharing of resources and best practices. These measures can support the effective adoption of the framework in the university setting while keeping it aligned with the broader objectives of the institution and the national agenda for sustainable education.

On the other hand, it is important to recognise that the adoption of AI-enabled sustainability practices is not without risks. While the analysis emphasises the benefits of AI, potential ethical and equity concerns must be addressed to ensure inclusive and responsible implementation. Universities in developing country contexts, such as the Philippines, often face a persistent digital divide with unequal access to infrastructure, technical expertise, and reliable connectivity across campuses and regions (Ho et al., 2025). Without targeted interventions, this gap may hinder adoption and exacerbate existing inequalities among students and faculty. Furthermore, reliance on AI tools raises the possibility of algorithmic bias, where decision-making systems trained on limited or unrepresentative data may inadvertently reinforce social inequities in resource allocation or student support (Idowu et al., 2024). Concerns about privacy and data security are equally critical, as many AI applications depend on sensitive institutional and personal data, which may be vulnerable in contexts where data governance regulations are still emerging (Pikhart and Al-Obaydi, 2025; Barus et al., 2025).

To mitigate these risks, universities should complement their AI adoption strategies with robust governance mechanisms such as transparent data use policies, ethical review boards, and regular audits of AI tools for fairness and accountability (Barus et al., 2025; Funa and Gabay, 2025). Equally vital are capacity-building initiatives aimed at developing the digital literacy of faculty, staff, and students, ensuring that technological benefits are equitably distributed. By addressing these ethical and social dimensions alongside institutional and financial considerations, administrators can ensure that the integration of AI into sustainable higher education remains not only effective and innovative but also inclusive, equitable, and ethically grounded.

4 Concluding remarks

In this paper, integrating AI technologies into sustainable higher education practices is explored according to the lens of ISM-MICMAC approach. These practices help in attaining sustainability into the education sector in order to improve on the overall quality education offered by institutions. As a demonstration of the approach, a case study is implemented in a state university in the Philippines which also aims to actively implement AI technologies into their own sustainability practices. The key results of the analyses point out to includes data collection and monitoring systems as the core sustainable higher education practice having the strongest driving power and least dependence power to and from other practices. As stakeholders in the educational advancement consider the prowess offered by AI technologies in the field of sustainable higher education, state universities are often in a dilemma on how to go about with the implementation process. The key practice identified in this paper guides stakeholders to focus on data collection and monitoring systems over other practices since this significantly influences others. For example, implementation strategies must consider systematic data collection and analysis to assess goal achievement and identify student challenges. Aside from this, automated monitoring systems can be developed to reduce dependence on human factors, incorporating machine learning, big data analysis, and visualisation techniques. Further, these systems is able to collect data from various sources, including educational websites and open data repositories, to provide a comprehensive view of educational processes at different levels. More specifically, framework designs for student performance monitoring systems are being explored, considering factors such as assignment points and quiz results to reduce course retakes, particularly among freshmen.

Furthermore, it is important to acknowledge some limitations that exist in the paper. First, the case study is limited to a single state university in Cebu, Philippines. Although this institution offers a relevant context for examining AI-enabled sustainability in higher education, findings should be interpreted with caution when considering broader generalisability. The insights are more aligned with analytic generalisation which builds theoretical understanding rather than statistical representativeness across institutions. Second, the sample of eight experts, though consistent with ISM practices and sufficient for generating structured relationships, narrows the diversity of perspectives that might emerge from a larger or more varied panel. To mitigate this, expert judgments were complemented by reference to institutional documents, policy guidelines, and sustainability reports where available; however, systematic triangulation with large-scale secondary data was not feasible in the present study. Future research may expand the scope by including multiple universities across different regions, engaging a broader expert pool, and integrating longitudinal data to strengthen both robustness and generalisability of results.

As an extension to this paper, the following areas can be accounted for. First, aside from the structural relationship among practices, their priority weights can also be explored using other expert-based analytical approaches such as fuzzy analytic hierarchy process (ANP), coupled with Decision-Making Trial and Evaluation Laboratory (DEMATEL) to further uncover the classification of practices. These approaches can also provide another perspective of prioritising the practices so that state universities can effectively point out which one to implement first over others. Finally, future research works and policymakers must take into consideration that the results in this paper can only be applied directly to state universities. Other categories of higher educational institutions such as private institutions, colleges, and technical schools may have different perspectives with respect to the integration of AI technologies in sustainable higher education.

Declarations

Funding: No funding was received to assist with the preparation of this manuscript.

Conflicts of interest: The authors have no relevant financial or non-financial interests to disclose.

References

Abdelghany, K., Ibrahim, M. and Abdelkader, M. (2024) 'Improve predictive maintenance through artificial intelligence: a systematic review', *Results in Engineering*, Vol. 21, p.101234, https://doi.org/10.1016/j.rineng.2023.101234.

Aggarwal, D., Sharma, D. and Saxena, A.B. (2023) 'Exploring the role of artificial intelligence for augmentation of adaptable sustainable education', *Asian Journal of Advanced Research and Reports*, Vol. 17, No. 11, pp.179–184, https://doi.org/10.9734/ajarr/2023/v17i11563.

Ahmad, N. and Qahmash, A. (2021) 'Smartism: implementation and assessment of interpretive structural modeling', *Sustainability*, Vol. 13, No. 16, p.8801, https://doi.org/10.3390/su13168801.

Akhtar, T., Rehman, A.U., Jamil, M. and Gilani, S.O. (2020) 'Impact of an energy monitoring system on the energy efficiency of an automobile factory: a case study', *Energies*, Vol. 13, No. 10, p.2577, https://doi.org/10.3390/en13102577.

Almasri, R.A., Abu-Hamdeh, N.H. and Al-Tamimi, N. (2024) 'A state-of-the-art review of energy-efficient and renewable energy systems in higher education facilities', *Frontiers in Energy Research*, Vol. 11, p.1344216, https://doi.org/10.3389/fenrg.2023.1344216.

Amaxilatis, D., Akrivopoulos, O., Mylonas, G. and Chatzigiannakis, I. (2017) 'An IoT-based solution for monitoring a fleet of educational buildings focusing on energy efficiency', *Sensors*, Vol. 17, No. 10, p.2296, https://doi.org/10.3390/s17102296.

Attri, R., Dev, N. and Sharma, V. (2013) 'Interpretive structural modelling (ISM) approach: an overview', *Research Journal of Management Sciences*, Vol. 2, pp.3–8.

Atymtayeva, L., Kozhakhmet, K. and Savchenko, A. (2020) 'Automated system for monitoring of educational processes: collection, management, and modeling of data', in Shishkov, B. (Ed.): *Business Modeling and Software Design*, Vol. 391, pp.341–351, Springer International Publishing, https://doi.org/10.1007/978-3-030-52306-0_24.

Ayyash, M.M. and Salah, O.H. (2025) 'AI adoption in higher education: advancing sustainable energy management in Palestinian universities', *Journal of Open Innovation: Technology, Markets, and Complexity*, Vol. 11, Article 100534, https://doi.org/10.1016/j.joitmc.2025.100534.

Azizi, S., Rabiee, R., Nair, G. and Olofsson, T. (2020) 'Application of occupancy and booking information to optimize space and energy use in higher education institutions', *E3S Web of Conferences*, Vol. 172, p.25010, https://doi.org/10.1051/e3sconf/202017225010.

Barus, O.P., Hidayanto, A.N., Handri, E.Y., Sensuse, D.I. and Yaiprasert, C. (2025) 'Shaping generative AI governance in higher education: Insights from student perception', *International Journal of Educational Research Open*, Vol. 8, p.100452, https://doi.org/10.1016/j.ijedro.2025.100452.

Bastos, P., Lopes, R., Pires, L. and Pedrosa, T. (2009) 'A maintenance prediction system using data mining techniques', in *2012 Proceedings of the World Congress on Engineering*, IEEE, pp.2487–2491, https://doi.org/10.1109/IEEM.2009.5373535.

Behl, A., Sheorey, P., Pal, A., Veetil, A. K.V. and Singh, S.R. (2020) 'Gamification in e-commerce: a comprehensive review of literature', *Journal of Electronic Commerce in Organizations (JECO)*, Vol. 18, No. 2, pp.1–16.

Bhole, G.P. and Deshmukh, T. (2018) 'Multi-criteria decision making (MCDM) methods and its applications', *International Journal for Research in Applied Science & Engineering Technology (IJRA-SET)*, Vol. 6, No. 5, pp.899–915.

Bonini, P. (2020) 'When tomorrow comes: technology and the future of sustainability learning in higher education', *Environment: Science and Policy for Sustainable Development*, Vol. 62, No. 4, pp.39–48, https://doi.org/10.1080/00139157.2020.1764300.

Carless, D., Salter, D., Yang, M. and Lam, J. (2011) 'Developing sustainable feedback practices', *Studies in Higher Education*, Vol. 36, No. 4, pp.395–407, https://doi.org/10.1080/03075071003642449.

Da Costa, R., Albuquerque, D. and Pinto, A. (2024) 'Towards maintenance as a sustainability tool in high-risk industries: a review', *Journal of Loss Prevention in the Process Industries*, Vol. 87, p.105789, https://doi.org/10.1016/j.jlp.2024.105789.

Fernandes, R.M., Nagata, V.D.M.N., Melo, A.C.S. and Martins, V.W.B. (2024) 'Artificial intelligence and sustainability in higher education: a bibliometric analysis and its relations with the UN SDGs: inteligência artificial e sustentabilidade no ensino superior: uma análise bibliométrica e suas relações com os ODS da ONU', *Concilium*, Vol. 24, No. 3, pp.229–248, https://doi.org/10.53660/CLM-2872-24C47.

Filho, W. (2015) 'Education for sustainable development in higher education: reviewing needs', in Leal Filho, W. (Ed.): *Transformative Approaches to Sustainable Development at Universities*, pp.3–12, Springer International Publishing, https://doi.org/10.1007/978-3-319-08837-2_1.

Frank, M. and Ricci, E. (2023) 'Education for sustainability: transforming school curricula', *Southern Perspective/Perspectiva Austral*, Vol. 1, p.3, https://doi.org/10.56294/pa20233.

Funa, A.A. and Gabay, R.A.E. (2025) 'Policy guidelines and recommendations on AI use in teaching and learning: a meta-synthesis study', *Social Sciences & Humanities Open*, Vol. 11, p.101221, https://doi.org/10.1016/j.ssaho.2024.101221.

García-Monge, Á., García, S. and López, R. (2025) 'Smart energy monitoring in higher education institutions: a systematic review', *Sustainability*, Vol. 17, No. 2, p.607, https://doi.org/10.3390/su17020607.

García-Monge, M., Zalba, B., Casas, R., Cano, E., Guillén-Lambea, S., López-Mesa, B. and Martínez, I. (2023) 'Is IoT monitoring key to improve building energy efficiency? Case study of a smart campus in Spain', *Energy and Buildings*, Vol. 285, p.112882, https://doi.org/10.1016/j.enbuild.2023.112882.

Gardas, B.B., Raut, R.D. and Narkhede, B. (2017) 'Modeling causal factors of post-harvesting losses in vegetable and fruit supply chain: an Indian perspective', *Renewable and Sustainable Energy Reviews*, Vol. 80, pp.1355–1371, https://doi.org/10.1016/j.rser.2017.05.259.

Garrido-Yserte, R. and Gallo-Rivera, M-T. (2020) 'The potential role of stakeholders in the energy efficiency of higher education institutions', *Sustainability*, Vol. 12, No. 21, p.8908, https://doi.org/10.3390/su12218908.

Gholami, H., Bachok, M.F., Mat Saman, M.Z., Streimikiene, D., Sharif, S. and Zakuan, N. (2020) 'An ISM approach for the barrier analysis in implementing green campus operations: towards higher education sustainability', *Sustainability*, Vol. 12, No. 1, Article 363, https://doi.org/10.3390/su12010363.

Gras-Velazquez, A. and Fronza, V. (2020) 'Sustainability in formal education: ways to integrate it now', *IUL Research*, Vol. 1, No. 2, pp.154–175, https://doi.org/10.57568/iulres.v1i2.84.

Gupta, A., Dwivedi, A. and Paul, S.K. (2025) 'Developing a sustainability index for implementing big data analytics in the logistics sector', *Sustainable Development*, p.sd.70024, https://doi.org/10.1002/sd.70024.

Hasan, M.K., Lei, X., Hlali, A. and Bian, Z. (2024) 'Modelling capability factors of logistics industry based on ISM-MICMAC', *Heliyon*, Vol. 10, No. 22, p.e40539, https://doi.org/10.1016/j.heliyon.2024.e40539.

Ho, T.L., Ngoc, L.H. and Ho, T.H. (2025) 'Digital inclusion or exclusion? Exploring the moderating role of governance in digitalization's impact on income inequality in developing countries', *Research in Globalization*, Vol. 10, p.100283, https://doi.org/10.1016/j.resglo.2025.100283.

Hughes, L., Malik, T., Dettmer, S., Al-Busaidi, A.S. and Dwivedi, Y.K. (2025) 'Reimagining higher education: navigating the challenges of generative AI adoption', *Information Systems Frontiers*, https://doi.org/10.1007/s10796-025-10582-6.

Idowu, J.A., Koshiyama, A.S. and Treleaven, P. (2024) 'Investigating algorithmic bias in student progress monitoring', *Computers and Education: Artificial Intelligence*, Vol. 7, p.100267, https://doi.org/10.1016/j.caeai.2024.100267.

Kotomina, O.V. and Sazhina, A.I. (2020) 'Higher education for sustainable development: stakeholders' benefits', *Management and Business Administration*, Vol. 1, pp.121–136, https://doi.org/10.33983/2075-1826-2020-1-121-136.

Leal Filho, W., Kim, E., Borsatto, J.M.L. and Marcolin, C.B. (2025) 'Using artificial intelligence in sustainability teaching and learning', *Environmental Sciences Europe*, Vol. 37, Article 124, https://doi.org/10.1186/s12302-025-01159-w.

Leal Filho, W., Shiel, C., Paço, A., Mifsud, M., Avila, L.V., Brandli, L.L. and Molthan-Hill, P. (2017) 'Sustainable development goals and sustainability teaching at universities: falling behind or getting ahead of the pack?', *Journal of Cleaner Production*, Vol. 232, pp.285–294, https://doi.org/10.1016/j.jclepro.2017.01.112.

Lee, D., Arnold, M., Srivastava, A., Plastow, K., Strelan, P., Ploeckl, F., Lekkas, D. and Palmer, E. (2024) 'The impact of generative AI on higher education learning and teaching: a study of educators' perspectives', *Computers and Education: Artificial Intelligence*, Vol. 6, p.100221, https://doi.org/10.1016/j.caeai.2024.100221.

Lertprapai, S. (2013) 'Review: multiple criteria decision making method with applications', *International Mathematical Forum*, Vol. 8, pp.347–355, https://doi.org/10.12988/imf.2013.13033.

Lin, C-C., Huang, A.Y.Q. and Lu, O.H.T. (2023) 'Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review', *Smart Learning Environments*, Vol. 10, No. 1, p.41, https://doi.org/10.1186/s40561-023-00260-y.

Liz-Domínguez, M., Caeiro-Rodríguez, M., Llamas-Nistal, M. and Mikic-Fonte, F.A. (2019) 'Systematic literature review of predictive analysis tools in higher education', *Applied Sciences*, Vol. 9, No. 24, p.5569, https://doi.org/10.3390/app9245569.

Majumder, M. and Saha, A.K. (2016) 'Multi criteria decision making', in Majumder, M. and Saha, A.K. (Eds.): *Feasibility Model of Solar Energy Plants by ANN and MCDM Techniques*, pp.9–12, Springer, https://doi.org/10.1007/978-981-287-308-8_3.

Mylonas, G., Athanasiou, A. and Amaxilatis, D. (2019) 'An open-source IoT platform for smart energy management in buildings', *Computer Communications*, Vols. 140–141, pp.10–21, https://doi.org/10.1016/j.comcom.2019.04.012.

Nagpal, R., Mehrotra, D., Bhatia, P.K. and Bhatia, A. (2015) 'FAHP approach to rank educational websites on usability', *International Journal of Computing and Digital Systems*, Vol. 4, No. 4, pp.251–260, https://doi.org/10.12785/ijcds/040404.

Nazipov, F., Tokbolat, S., Khussainova, D., Mustafa, M. and Almahadin, A. (2021) 'Integration of renewable energy technologies in university campuses: a case study', *IOP Conference Series: Materials Science and Engineering*, Vol. 1044, No. 1, p.12015, https://doi.org/10.1088/1757-899X/1044/1/012015.

Noaman, A.Y., Gad-Elrab, A.A.A. and Baabdullah, A.M. (2024) 'Towards scientists and Researchers classification model (SRCM)-based machine learning and data mining methods: an ISM-MICMAC approach', *Journal of Innovation & Knowledge*, Vol. 9, No. 3, p.100516, https://doi.org/10.1016/j.jik.2024.100516.

Okulich-Kazarin, V., Artyukhov, A., Skowron, Ł., Artyukhova, N. and Wołowiec, T. (2024) 'Will AI become a threat to higher education sustainability? A study of students' views', *Sustainability*, Vol. 16, No. 11, p.4596, https://doi.org/10.3390/su16114596.

Pavlova, I. and Kavčič, A. (2020) 'Resource saving technologies in education: a step towards a green society', *Uporabna Informatika*, Vol. 28, No. 1, https://doi.org/10.31449/upinf.vol28.num1.75.

Pesonen, J., Kurhila, J. and Vihavainen, A. (2018) 'Data science infrastructure for education: predicting student graduation', *Procedia Computer Science*, Vol. 145, pp.62–71, https://doi.org/10.1016/j.procs.2018.11.024.

Pikhart, M. and Al-Obaydi, L.H. (2025) 'Reporting the potential risk of using AI in higher education: subjective perspectives of educators', *Computers in Human Behavior Reports*, Vol. 18, p.100693, https://doi.org/10.1016/j.chbr.2025.100693.

Ricci, P.P., Donatelli, M., Onofri, M., Scarponi, L.B. and Velardo, A. (2020) 'An innovative monitoring and maintenance model for the INFN CNAF Tier-1 data center infrastructure', *Journal of Physics: Conference Series*, Vol. 1525, No. 1, p.12039, https://doi.org/10.1088/1742-6596/1525/1/012039.

Seatter, C.S. and Ceulemans, K. (2017) 'Teaching sustainability in higher education: pedagogical styles that make a difference', *Canadian Journal of Higher Education*, Vol. 47, No. 2, pp.47–70, https://doi.org/10.47678/cjhe.v47i2.186284.

Sebire, R.H. and Isabeles-Flores, S. (2023) 'Sustainable development in higher education practices', *Revista Lengua y Cultura*, Vol. 5, No. 9, pp.89–96, https://doi.org/10.29057/lc.v5i9.10971.

Shrivastava, M., Singhal, P. and J., B. (2023) 'Integrating sensor data and machine learning for predictive maintenance in Industry 4.0', *Proceedings on Engineering Sciences*, Vol. 5, No. S1, pp.55–62, https://doi.org/10.24874/PES.SI.01.007.

Siddiqui, A., Siddiqui, M. and Kulkarni, N. (2022) 'Artificial intelligence in water conservation: a meta-analysis study', *Prabandhan: Indian Journal of Management*, Vol. 15, No. 3, p.24, https://doi.org/10.17010/pijom/2022/v15i3/160407.

Sihombing, D.I., Sinambela, L. and Nababan, L. (2020) 'A resource allocation problem in higher education with integrated multicriteria decision making', *Sepren*, Vol. 1, No. 2, pp.34–45, https://doi.org/10.36655/sepren.v1i02.219.

Soares, A.E.P., Silva, J.K.D., Nunes, L.G.C.F., Rios Ribeiro, M.M. and Silva, S.R.D. (2023) 'Water conservation potential within higher education institutions: lessons from a Brazilian university', *Urban Water Journal*, Vol. 20, No. 10, pp.1429–1437, https://doi.org/10.1080/1573062X.2021.2013903.

Sorour, A. and Atkins, A.S. (2024) 'Big data challenge for monitoring quality in higher education institutions using business intelligence dashboards', *Journal of Electronic Science and Technology*, Vol. 22, No. 1, p.100233, https://doi.org/10.1016/j.jnlest.2024.100233.

Suryanarayana, K.S., Kandi, V.S.P., Pavani, G., Rao, A.S., Rout, S. and Siva Rama Krishna, T. (2024) 'Artificial intelligence enhanced digital learning for the sustainability of education management system', *The Journal of High Technology Management Research*, Vol. 35, No. 2, p.100495, https://doi.org/10.1016/j.hitech.2024.100495.

Tanveer, M., Hassan, S. and Bhaumik, A. (2020) 'Academic policy regarding sustainability and artificial intelligence (AI)', *Sustainability*, Vol. 12, No. 22, p.9435, https://doi.org/10.3390/su12229435.

Vidrevich, M. and Pervukhina, I. (2023) 'Higher education for sustainable environment: from theory to practice', *E3S Web of Conferences*, Vol. 451, p.06009, https://doi.org/10.1051/e3sconf/202345106009.

Wang, X., Li, M. and Chen, J. (2024) 'AI-enhanced digital learning for sustainable education management', *Journal of High Technology Management Research*, Vol. 35, No. 1, p.100456, https://doi.org/10.1016/j.hitech.2024.100456.

Zeleny, M. (2011) 'Multiple criteria decision making (MCDM): from paradigm lost to paradigm regained?', *Journal of Multi-Criteria Decision Analysis*, Vol. 18, Nos. 1–2, pp.77–89, https://doi.org/10.1002/mcda.473.

Zhang, Y., Zhao, J. and Wang, H. (2025) 'Explainable AI for sustainable energy management in smart buildings', *Journal of Environmental Management*, Vol. 350, p.120451, https://doi.org/10.1016/j.jenvman.2024.120451.