JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Exploring the Role of Artificial Intelligence for Climate Adaptation in Higher Educational Institutions: A Systematic Literature Review

[1]Banele Mpande, [2]Sibusisiwe Dube

[1]Student, [2]Lecturer
[1]Department of Informatics and Analytics,
[1]National University of Science and Technology, Bulawayo, Zimbabwe

Abstract: Climate change is increasingly impacting infrastructure and operational continuity in higher educational institutions (HEIs) and this is prompting an interest in artificial intelligence (AI) and associated digital technologies as a means of climate adaptation and resilience. Despite the increased interest in AI for climate adaptation, there is still limited reviews of the literature on this field. To fill this gap, the current study conducted a systematic literature review (SLR) to synthesize the existing empirical research on AI-enabled climate adaptation in HEIs. This study was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. The study included 22 peer-reviewed journal articles, conference proceedings, and book chapters written in English, published between 2021 and 2025, and selected from the IEEE Xplore, ScienceDirect, and SpringerLink databases. The results highlighted that Asia is dominating in this area of research, followed by Europe. The most commonly used technologies were AI and machine learning models, then big data analytics and smart campus systems based on the Internet of Things (IoT). Technical and infrastructural preparedness were the major adoption determinants. The reported benefits of AI in climate adaptation included improved energy efficiency, improved forecasting, optimized operations, and substantial carbon reductions. The principal challenges included technical and infrastructural limitations, data and modelling complications, and financial constraints. These findings impact the HEIs' management, researchers and policy-makers who are keen on adapting to climate change, while promoting higher education.

Keywords: Artificial Intelligence, Climate Adaptation, Higher Education Institutions, Climate Resilience

I. Introduction

This paper presents a systematic literature review (SLR) on the adoption of Artificial Intelligence (AI) in climate adaptation in higher Educational Institutions (HEIs). The SLR synthesizes recent empirical evidence on how HEIs are utilizing AI to support climate adaptation, resilience, and sustainability of higher education. The impacts of climate change have accelerated unfavorable climate conditions like heat waves, floods and energy emissions, which are all negatively impacting the HEIS's physical infrastructure and academic operations (Davidson et al., 2024). Artificial intelligence is a promising tool climate adaptation by predicting floods, monitoring droughts, planning and assessing risks (Jain et al., 2023). In response to climate, HEIs are exploring technological solutions for climate adaptation and sustainable campus development such as, AI, machine learning (ML), big data analytics, Internet of Things (IoT), Artificial Intelligence of Things (AIoT), and smart campus systems (Khan et al., 2025; Marimekala et al., 2025; Tabuenca et al., 2024). However, there is a limited literature that consolidates an understanding of the technologies and how they are used to address climate change challenges in the context of HEIs., To address this gap, the SLR answers the following research questions (RQs):

Research Questions

1. What types of technologies are currently used for climate adaptation in higher educational Institutions?
2. What factors influence the adoption of climate adaptation technologies in higher educational institutions?
3. How are AI technologies utilized by higher educational institutions to promote climate adaptation and resilience?
4. In what ways are AI technologies enabling higher education institutions (HEIs) to address climate change complications?
5. What are the challenges associated with the use of AI technologies in addressing climate-related issues within HEIs?

II. Methodology

The review process followed the Preferred Reporting Items for Systematic Review and Meta- Analysis (PRISMA) 2009 model to ensure that there is transparency and replicability of the review process (Page et al., 2021).

2.1 Database Search Strategy

The researcher targeted three major scholarly databases, IEEE Xplore, SpringerLink, and ScienceDirect. The searches were limited to English-Language publications between 2021 and 2025 using a search string. Boolean operators were used in order to refine the search query to get relevant papers. The search strings below were used to explore the databases. ScienceDirect uses fewer Boolean connectors with a maximum of 8 (eight) per field hence a different search string was used on the ScienceDirect database.

On the ScienceDirect database, the following search string was used: (“artificial intelligence" OR “machine learning” OR “energy forecasting”) AND ("climate adaptation" OR “climate resilience”) AND ("higher education" OR "university" OR "tertiary education")

On IEEE Xplore and SpringerLink databases the following search string was used; (“artificial intelligence” OR AI OR “machine learning” OR “deep learning” OR “energy forecasting”) AND (“climate adaptation” OR “climate change adaptation” OR “climate resilience” OR “green campus”) AND (“higher education” OR “university” OR “college” OR “academic institution”)

2.2 Systematic Review Protocol (Search Strategy and Eligibility Criteria)

Table 2.1: Systematic Review Protocol

Protocol Element	Translation in research
Digital libraries	• IEEE Xplore, ScienceDirect and SpringerLink
Time interval	• January 2021 to December 2025
Inclusion criteria	• Peer-reviewed journal articles, conference proceedings, book chapters • Publications written in English • Studies published in the period 2021 to 2025 • Studies focusing on higher educational institutions, climate adaptation, smart campuses, climate resilience, renewable energy, sustainability and environmental management within the context of higher educational institutions.
Exclusion criteria	• Studies not published in English and Studies published before the year 2021 • Non-peer reviewed articles • Studies Addressing AI in Higher education with no explicit climate, sustainability or energy dimension • Studies focusing on climate adaptation with no digital or AI component and Higher educational dimension.

2.3 PRISMA Flow diagram

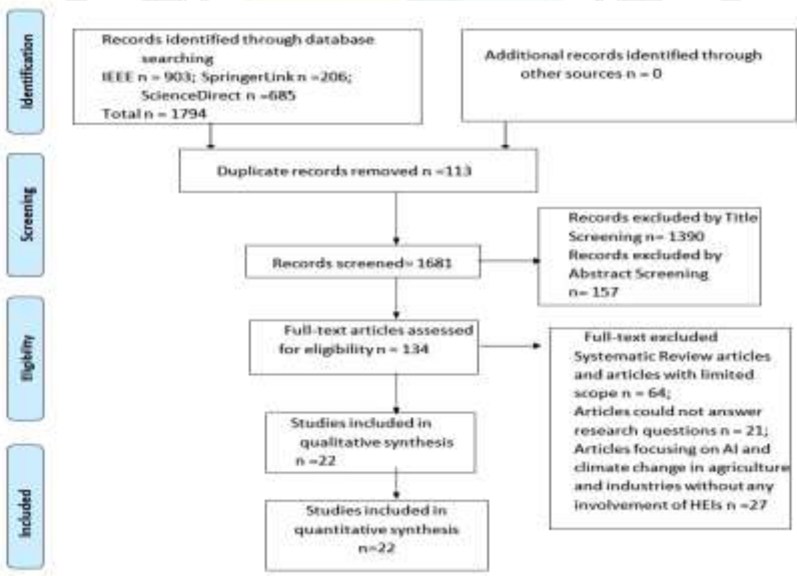

Fig.1 Systematic Prisma flow diagram adopted from (Moher et al., 2009)

III. RESULTS

3.1 Included Studies Grouped by Year

Table 3.1 and Figure 2 below show articles that met the inclusion criteria grouped by Year of publication, with 2025 dominating with 54% of the papers. This also shows that the study is trending.

Table 3.1: Included studies grouped by year

Year	Authors	Count
2023	(García-Monge et al., 2023; Kumar et al., 2023a; Quevedo et al., 2023)	**3**
2024	(Al Salmi et al., 2024; Chou & Nguyen, 2024; Lazaroiu et al., 2024; Leal Filho et al., 2024; Scolobig & Balsiger, 2024a; Silva Lopes, 2024; Tabuenca et al., 2024)	**7**
2025	(Alsamraee & Khanna, 2025a, 2025b; Ayyash & Salah, 2025; Basheer et al., 2025; Chin et al., 2025; Khaerudin et al., 2025; Khan et al., 2025; Leal Filho et al., 2025; Marimekala et al., 2025; Qiao et al., 2025; Retscher, 2025; Sharma et al., 2025)	**12**

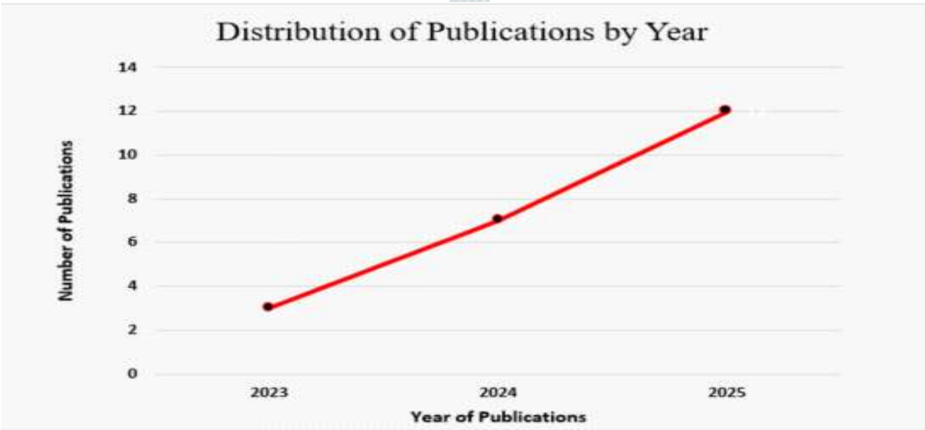

Fig.2 Distribution of Publications by Year

3.2 Methodological Approaches used in the studies

Table 3.2 presents the methodologies adopted by the authors in the studies. The findings reveal that the most adopted methodology in carrying out the research is quantitative and mixed research at par with 9 studies, and the least is qualitative, with 4 studies of the 22 articles.

Table 3.2: Methodology used in the studies

Methodology	Authors	Count
Quantitative	(Alsamraee & Khanna, 2025a, 2025b; Ayyash & Salah, 2025; Chin et al., 2025; Chou & Nguyen, 2024; Khaerudin et al., 2025; Lazaroiu et al., 2024; Qiao et al., 2025; Quevedo et al., 2023)	**9**
Mixed Methods	(Al Salmi et al., 2024; Basheer et al., 2025; García-Monge et al., 2023; Khan et al., 2025; Kumar, Sahani, Rawat, Debele, Tiwari, Mendes Emygdio, et al., 2023a; Leal Filho et al., 2024, 2025; Marimekala et al., 2025; Tabuenca et al., 2024)	**9**
Qualitative	(Retscher, 2025; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Silva Lopes, 2024)	**4**

3.3 Geographical Distribution of Included Studies

Figure 3 below shows the distribution of studies grouped by continents. There are five continents represented by the studies, with one multicontinental study by Leal Filho et al.(2025). The majority of the studies were conducted in Asia (9) and Europe (7), followed by North America (3), Africa (1), and South America (1).

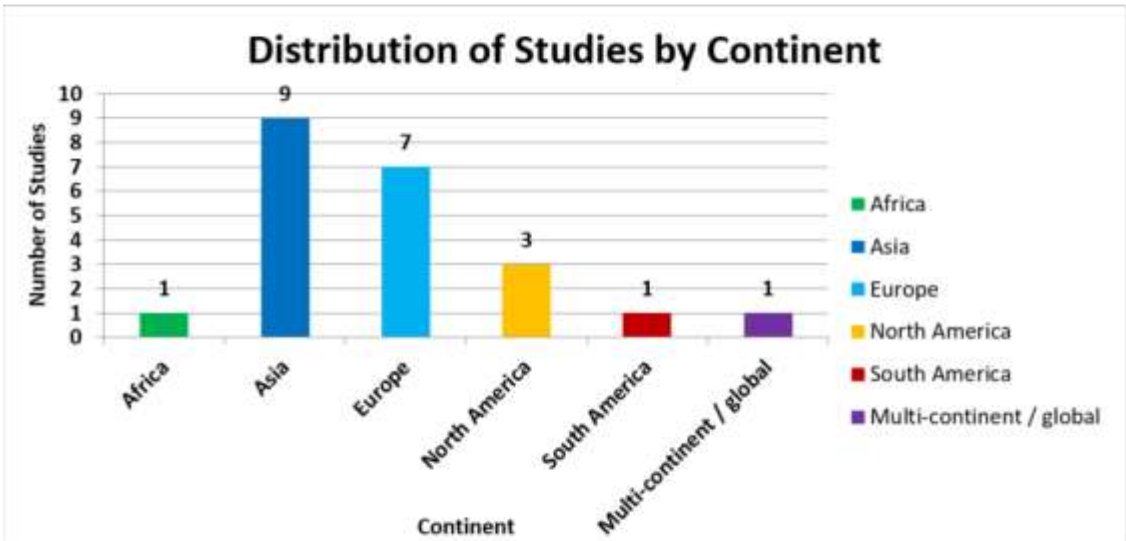

Fig.3 Distribution of Publications by Continent

3.4 Technologies used for climate Adaptation and sustainability in Higher Educational Institutions

Table 3.3 shows a list of technologies in higher educational institutions that were used by the authors in their studies.

Table 3.3: List of technologies used for climate adaptation in HEIs.

Technology category	Author	Count
Generative AI and large language models (LLMs)	(Marimekala et al., 2025)	**1**
AI / machine learning / predictive models (incl. ANN, SVM, RF)	(Al Salmi et al., 2024; Alsamraee & Khanna, 2025b, 2025a; Ayyash & Salah, 2025; Chin et al., 2025; Chou & Nguyen, 2024; García-Monge et al., 2023; Khan et al., 2025; Leal Filho et al., 2025; Marimekala et al., 2025; Qiao et al., 2025; Quevedo et al., 2023; Retscher, 2025; Scolobig & Balsiger, 2024a; Tabuenca et al., 2024)	**15**
Deep learning models (CNN, RNN, LSTM, GRU, hybrid CNN–RNN)	(Alsamraee & Khanna, 2025b; Chin et al., 2025; Chou & Nguyen, 2024; Leal Filho et al., 2025; Qiao et al., 2025)	**5**
Big data, data analytics and learning analytics (incl. predictive analytics, SHAP)	(Ayyash & Salah, 2025; Basheer et al., 2025; Chin et al., 2025; Khaerudin et al., 2025; Khan et al., 2025; Leal Filho et al., 2025; Quevedo et al., 2023; Scolobig & Balsiger, 2024a; Tabuenca et al., 2024)	**9**
IoT/AIoT/sensor networks/ smart campus systems	(Ayyash & Salah, 2025; Basheer et al., 2025; García-Monge et al., 2023; Khaerudin et al., 2025; Khan et al., 2025; Leal Filho et al., 2024; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Tabuenca et al., 2024)	**9**
VR/AR and immersive technologies	(Kumar et al., 2023a; Leal Filho et al., 2025; Sharma et al., 2025)	**3**
Digital learning platforms, LMS, e-learning tools and MOOCs	(Al Salmi et al., 2024; Khaerudin et al., 2025; Khan et al., 2025; Kumar et al., 2023a; Leal Filho et al., 2024, 2025; Retscher, 2025; Sharma et al., 2025; Tabuenca et al., 2024)	**9**
Renewable energy and energy storage systems (incl. hydrogen)	(Basheer et al., 2025; Lazaroiu et al., 2024; Leal Filho et al., 2024)	**3**
GIS, climate and DRR modelling, early warning systems and social media analytics	(Leal Filho et al., 2024; Scolobig & Balsiger, 2024a)	**2**

Climate adaptation toolkits, TIP model resources, field-books and matrices	(Silva Lopes, 2024)	**1**
STEM digital tools, thermography and citizen science apps	(Kumar et al., 2023a)	**1**

3.5 Factors influencing Adoption of Climate Adaptation Technologies

Table 3.4 presents factors influencing the adoption of technologies discussed in the studies. The most popular factor influencing the adoption is technical and infrastructural readiness, addressed by 20 studies of the selected 22.

Table 3.4: Factors influencing the adoption of technologies for climate adaptation.

Factors	Authors	Count
Technical and infrastructural readiness (data availability, computational resources, system integration, infrastructure)	(Al Salmi et al., 2024; Alsamraee & Khanna, 2025b, 2025a; Ayyash & Salah, 2025; Basheer et al., 2025; Chin et al., 2025; Chou & Nguyen, 2024; García-Monge et al., 2023; Khaerudin et al., 2025; Khan et al., 2025; Lazaroiu et al., 2024; Leal Filho et al., 2024, 2025; Marimekala et al., 2025; Qiao et al., 2025; Quevedo et al., 2023; Retscher, 2025; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Tabuenca et al., 2024)	**20**
Financial and organisational constraints (costs, funding, organisational priorities, change management)	(Ayyash & Salah, 2025; Basheer et al., 2025; Chou & Nguyen, 2024; Khan et al., 2025; Lazaroiu et al., 2024; Leal Filho et al., 2024; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Silva Lopes, 2024)	**9**
Human capacity and skills (technical expertise, teacher training, awareness)	(Ayyash & Salah, 2025; Basheer et al., 2025; Khaerudin et al., 2025; Khan et al., 2025; Leal Filho et al., 2024; Retscher, 2025; Scolobig & Balsiger, 2024a; Silva Lopes, 2024)	**8**
Ethical, cultural and governance aspects (bias, fairness, governance, cultural fit)	(Al Salmi et al., 2024; Khan et al., 2025; Leal Filho et al., 2024, 2025; Marimekala et al., 2025; Retscher, 2025; Sharma et al., 2025; Tabuenca et al., 2024)	**8**
Social and contextual factors (digital divide, language, local context)	(Khaerudin et al., 2025; Kumar et al., 2023a; Leal Filho et al., 2024, 2025; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Silva Lopes, 2024)	**7**

3.6 Utilisation of AI and Digital technologies in Higher Educational Institutions (HEIs)

Table 3.5 and Figure 4 below highlight how AI and digital technologies are used by HEIs. The findings of studies show that AI and digital technologies are mostly used by HEIs in operational and infrastructural adaptation.

Table 3.5: How AI and Digital technologies are used in Higher Educational Institutions.

Technology utilization Type	Authors	Count
Operational and infrastructural adaptation (energy management, smart campus operations)	(Alsamraee & Khanna, 2025b, 2025a; Ayyash & Salah, 2025; Basheer et al., 2025; Chin et al., 2025; Chou & Nguyen, 2024; García-Monge et al., 2023; Khan et al., 2025; Lazaroiu et al., 2024; Marimekala et al., 2025; Qiao et al., 2025; Quevedo et al., 2023; Tabuenca et al., 2024)	13
Educational and pedagogical adaptation (teaching, learning, climate literacy)	(Al Salmi et al., 2024; Khaerudin et al., 2025; Khan et al., 2025; Kumar et al., 2023a; Leal Filho et al., 2024, 2025; Retscher, 2025; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Silva Lopes, 2024; Tabuenca et al., 2024)	11
Institutional and community resilience (governance, outreach, co-creation)	(Ayyash & Salah, 2025; Basheer et al., 2025; Khan et al., 2025; Leal Filho et al., 2024, 2025; Marimekala et al., 2025; Scolobig & Balsiger, 2024a; Silva Lopes, 2024)	8

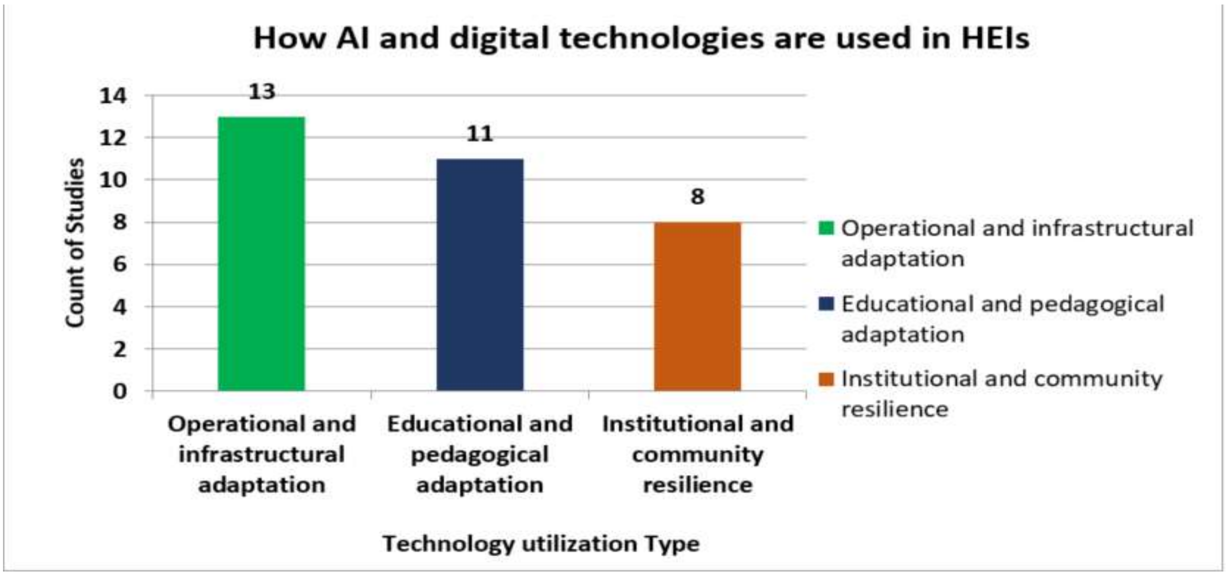

Fig.4 How AI and Digital technologies are used in HEIs

3.7 Benefits of AI and Digital Technologies for Climate-Related Issues in HEIs

Table 3.6 below shows the benefits of AI and Digital Technologies in HEIs discussed in the studies. The most common benefits amongst institutions highlighted by 13 studies in the table are energy and operational efficiency, forecasting accuracy, and carbon reduction.

Table 3.6: Benefits of AI and Digital Technologies in HEIs.

Benefits	Authors	Count
Energy and operational efficiency, forecasting accuracy and carbon reduction	(Alsamraee & Khanna, 2025a, 2025b; Ayyash & Salah, 2025; Basheer et al., 2025; Chin et al., 2025; Chou & Nguyen, 2024; García-Monge et al., 2023; Khan et al., 2025; Lazaroiu et al., 2024; Marimekala et al., 2025; Qiao et al., 2025; Quevedo et al., 2023; Tabuenca et al., 2024)	**13**
Teaching, learning and student outcomes (personalisation, engagement, literacy, skills)	(Al Salmi et al., 2024; Khaerudin et al., 2025; Khan et al., 2025; Kumar et al., 2023a; Leal Filho et al., 2024, 2025; Retscher, 2025; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Silva Lopes, 2024; Tabuenca et al., 2024)	**11**
Institutional sustainability and strategy (SDG alignment, reporting, indicators)	(Ayyash & Salah, 2025; Basheer et al., 2025; Khan et al., 2025; Lazaroiu et al., 2024; Leal Filho et al., 2024, 2025; Marimekala et al., 2025; Silva Lopes, 2024)	**8**
Community and societal resilience, partnerships and outreach	(Kumar et al., 2023a; Leal Filho et al., 2024, 2025; Scolobig & Balsiger, 2024a; Silva Lopes, 2024)	**5**

3.8 Challenges of AI and Digital Technologies for Climate-Related Issues in HEIs

Table 3.7 below shows the challenges of AI and Digital Technologies in HEIs discussed in the studies, with the authors supporting the benefits.

Table 3.7: Challenges of AI and Digital Technologies in HEIs.

Challenge Category	Studies	Count
Data and modelling challenges (bias, data quality, generalisation, concept drift)	(Alsamraee & Khanna, 2025b, 2025a; Chin et al., 2025; Chou & Nguyen, 2024; García-Monge et al., 2023; Kumar et al., 2023a; Marimekala et al., 2025; Qiao et al., 2025; Quevedo et al., 2023; Tabuenca et al., 2024)	**10**
Technical and infrastructure limitations (system complexity, integration, hardware, connectivity)	(Al Salmi et al., 2024; Alsamraee & Khanna, 2025b, 2025a; Ayyash & Salah, 2025; Chin et al., 2025; Chou & Nguyen, 2024; García-Monge et al., 2023; Khaerudin et al., 2025; Khan et al., 2025; Lazaroiu et al., 2024; Leal Filho et al., 2025; Marimekala et al., 2025; Qiao et al., 2025; Quevedo et al., 2023; Retscher, 2025; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Tabuenca et al., 2024)	**18**
Financial and resource constraints (high costs, limited funding, competing priorities)	(Al Salmi et al., 2024; Ayyash & Salah, 2025; Basheer et al., 2025; Chou & Nguyen, 2024; Khaerudin et al., 2025; Khan et al., 2025; Lazaroiu et al.,	**10**

	2024; Leal Filho et al., 2024; Scolobig & Balsiger, 2024a; Sharma et al., 2025)	
Human capacity and organisational challenges (skills, training, resistance, institutional support)	(Ayyash & Salah, 2025; Basheer et al., 2025; Khaerudin et al., 2025; Khan et al., 2025; Leal Filho et al., 2024; Retscher, 2025; Scolobig & Balsiger, 2024a; Silva Lopes, 2024)	**8**
Ethical, privacy and trust issues (bias, fairness, surveillance, environmental impact of AI)	(Al Salmi et al., 2024; Khan et al., 2025; Leal Filho et al., 2024, 2025; Marimekala et al., 2025; Retscher, 2025; Sharma et al., 2025; Tabuenca et al., 2024)	**8**
Equity, digital divide and contextual limitations	(Khaerudin et al., 2025; Kumar et al., 2023a; Leal Filho et al., 2024, 2025; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Silva Lopes, 2024)	**7**

IV. DISCUSSION

The discussion below interprets the findings in relation to the four research questions and explicitly considers the frameworks used across the 22 included studies

4.1 Technologies for climate adaptation in Higher Educational Institutions

The review shows that climate adaptation and sustainability in HEIs are supported by a broad ecosystem of technologies, rather than a single class of tools. On the operational side, AI and machine learning models are widely used for energy forecasting, optimization, and benchmarking in campus buildings, power plants and accommodation facilities (Alsamraee & Khanna, 2025a, 2025b; Chin et al., 2025; Chou & Nguyen, 2024; Qiao et al., 2025; Quevedo et al., 2023). This pattern is consistent with broader work on smart campuses and smart buildings, where AI-based forecasting and optimization are positioned as key enablers of energy efficiency and decarbonization. This is supported by (Kourgiozou et al., 2021), highlighting that smart energy systems in UK university campuses increasingly rely on data-driven control and prediction to support net-zero strategies.

Technologies include machine learning algorithms such as SVM and ANN, as well as more advanced deep learning architectures such as CNN-RNN hybrids, RNN models, and spatial-temporal graph convolutional networks (Chou & Nguyen, 2024; Qiao et al., 2025). Similar studies by (Elhabyb et al., 2024; Salem et al., 2025; Tariq et al., 2024) on AI-based building energy prediction highlight the dominance of deep learning and hybrid ML models for improving accuracy and supporting operational decisions in educational and other buildings. This external evidence supports the findings that AI is currently used as a technical instrument for energy management in HEIs, with climate adaptation often treated indirectly through efficiency and emissions reduction.

Internet of Things (IoT) and Advanced Internet of Things support smart campus sensing, and monitoring, energy usage, environmental conditions, and smart learning environment (García-Monge et al., 2023; Khaerudin et al., 2025; Sharma et al., 2025; Tabuenca et al., 2024). These architectures typically integrate sensors, communication protocols, dashboards, and analytics platforms. This is aligned with international literature on smart campuses, which emphasises IoT-enabled environmental monitoring, energy management, and comfort optimisation as central features of intelligent campus technology (Cavus et al., 2022). In addition, renewable energy, and storage systems are deployed to enhance energy self-sufficiency and resilience (Ayyash & Salah, 2025; Lazaroiu et al., 2024), supporting studies that frame AI and IoT as part of integrated smart-energy and resilience strategies in buildings and districts (Das, 2025).

In education and the social side, AI is used for sustainability in teaching and climate literacy through intelligent tutoring systems, virtual reality, and augmented reality (Kumar et al., 2023; Leal Filho et al., 2025; Retscher, 2025; Sharma et al., 2025). Other digital tools such as thermography apps, climate adaptation toolkits, and GIS/DRR systems are used to enhance climate awareness among students and communities (Kumar et al., 2023b; Leal Filho et al., 2024; Scolobig & Balsiger, 2024b; Silva Lopes, 2024). These studies are evident in confirming trends showing that AI can enable personalized instructions, interactive simulations, and data-driven insights that deepen the understanding of complex environmental issues

4.2 Technologies Adoption factors: Socio-technical and constraints

The results indicate that adoption of AI-based climate adaptation technologies in higher educational institutions is driven and constrained by a combination of technical, financial, organizational, human, and ethical factors. The results also highlight that adoption is not simply a technical choice but a socio-technical process that requires governance, capacity building, and ethical frameworks.

Several studies by Alsamraee & Khanna (2025a, 2025b); Chin et al. (2025); Qiao et al. (2025), highlighted the dependency on high-quality, continuous, and multi-dimensional data essential for robust forecasting and benchmarking but often difficult to secure in a real-world campus context. Limited generalizability raises concerns in AI-based energy models, particularly when trained on single-campus datasets (Chin et al., 2025; Chou & Nguyen, 2024). IoT-based smart campus architectures also face integration and data-management challenges, especially when combining legacy systems with new sensors, communication protocols and visualisation tools (García-Monge et al., 2023).

Financial and organizational constraints play a crucial role in the adoption of technologies. High investment costs and ongoing maintenance costs for AI, IoT and renewable energy systems hinders the large scale deployment of technologies (Chou & Nguyen, 2024; Lazaroiu et al., 2024; Sharma et al., 2025). Sustainability initiatives must often compete with other institutional priorities (Basheer et al., 2025; Scolobig & Balsiger, 2024b). There is a need to change management and coherent institutional strategies when implementing AI and big data for sustainable university development (Ayyash & Salah, 2025; Khan et al., 2025). The lack of trained technical staff, teacher training and low digital literacy among students and communities also hinders the adoption of technologies, particularly in resource- constrained or rural areas (Khaerudin et al., 2025; Leal Filho et al., 2024; Retscher, 2025; Silva Lopes, 2024).

Ethical and cultural concerns such as privacy, surveillance, fairness and algorithmic bias also play a central role, mostly when AI systems collect sensitive behavioral data for decision making.(Al Salmi et al., 2024; Leal Filho et al., 2025; Marimekala et al., 2025; Tabuenca et al., 2024)

4.3 Artificial Intelligence in Climate adaptation and resilience

The findings from the studies suggest that AI and digital technologies support climate adaptation and resilience at three related levels, which are;

- Campus infrastructure and operations
- Teaching, learning and climate literacy
- Institutional and community resilience

4.3.1 Campus infrastructure and Operations

Artificial intelligence and machine learning models are deployed for energy forecasting, optimization, and management. Forecasting frameworks developed by Alsamraee & Khanna (2025b, 2025a); Chou & Nguyen (2024); Qiao et al. (2025) support short-term and long term planning of energy demand, budgeting and maintenance in campus power plants and buildings. Generative AI and LLMs are combined with sensor optimization and automation to create smart energy systems that adapt to changing conditions (Marimekala et al., 2025). IoT and smart campus architectures provide real-time data streams for monitoring energy use, comfort and system performance (García-Monge et al., 2023; Quevedo et al., 2023). Renewable energy and storage frameworks help campuses in having independent, self-sufficient energy (Lazaroiu et al., 2024). These applications contribute to physical and operational resilience, enabling campuses to better cope with climate-induced stresses on energy and infrastructure.

4.3.2 Teaching, learning and climate literacy

Artificial intelligence is also used for teaching and learning by embedding climate adaptation and sustainability within pedagogical practices. Smart educational campus framework integrates AI, augmented reality, virtual reality, cloud and edge computing to support personalized, accessible, and sustainability-oriented learning environments (Sharma et al., 2025). AI-integrated geomatics education frameworks combine problem-based e-learning, Bloom's taxonomy, and adaptive systems to modernise curricula in data-intensive, environment-related disciplines (Retscher, 2025). AI-enabled sustainability teaching, under SDGs, and sustainability education frameworks, provides immersive simulations, intelligent tutoring, and global collaboration opportunities (Leal Filho et al., 2025). Tools such as the Heat–Cool Initiative and Play–Observe–Ask models leverage digital thermography and citizen science to enhance climate literacy and critical thinking (Kumar et al., 2023b). Internet of Things and big data-based sustainability learning improves digital literacy and climate awareness (Khaerudin et al., 2025).

4.3.3 Institutional and community resilience

Studies by (Leal Filho et al., 2024; Scolobig & Balsiger, 2024b), emphasizes on the universities roles as climate action hubs, using ICT tools, climate modelling, DRR systems and online platforms to strengthen institutional and community resilience. University climate action frameworks highlight multi-stakeholder alliances, policy engagement, and research-driven solutions that address both adaptation and mitigation (Leal Filho et al., 2024). The Territory–Intervention–Proposal (TIP) model and associated climate adaptation toolkits empower students to co-create solutions with local communities, building practical adaptation skills and strengthening local resilience (Silva Lopes, 2024). These studies show the importance of higher educational institutions in sustainability and climate action, in view of universities acting as living labs, community partners, and knowledge brokers in the transition to climate-resilient societies

4.4 Benefits and Challenges of AI-enabled Climate Adaptation

4.4.1 Benefits of AI-Enabled Climate Adaptation

In energy and operational benefits, there is improved forecasting accuracy, energy saving, cost reduction, enhanced operational efficiency, support for carbon emission reduction and sustainable reporting (Alsamraee & Khanna, 2025a, 2025b; Ayyash & Salah, 2025; Basheer et al., 2025; Chin et al., 2025; Chou & Nguyen, 2024; García-Monge et al., 2023; Khan et al., 2025; Lazaroiu et al., 2024; Marimekala et al., 2025; Qiao et al., 2025; Quevedo et al., 2023;Tabuenca et al., 2024). Additional studies by (Das, 2025; Elhabyb et al., 2024; Salem et al., 2025), also highlight AI and ML as powerful tools for improving energy and enabling more efficient and sustainable operation of educational institutions. Benefits of AI enabled climate adaptation on educational institutions include personalized learning, improved accessibility, increased climate literacy, stronger motivation and engagement, development of digital and green competences (Al Salmi et al., 2024; Khaerudin et al., 2025; Khan et al., 2025; Kumar et al., 2023a; Leal Filho et al., 2024, 2025; Retscher, 2025; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Silva Lopes, 2024; Tabuenca et al., 2024). Benefits of AI-enabled climate adaptation on institutional and social benefits includes, alignment with SDGs, comprehensive sustainability indicators, multi-stakeholder partnerships and strengthened institutional capacity for climate action and community resilience (Ayyash & Salah, 2025; Basheer et al., 2025; Khan et al., 2025; Lazaroiu et al., 2024; Leal Filho et al., 2024, 2025; Marimekala et al., 2025; Silva Lopes, 2024).

4.4.2 Challenges of AI-enabled Climate Adaptation

The most frequently reported challenge, dominating with 18 studies, is the technical and infrastructure limitation. This includes system complexity, integration problems, hardware and connectivity constraints (Al Salmi et al., 2024; Alsamraee & Khanna, 2025b, 2025a; Ayyash & Salah, 2025; Chin et al., 2025; Chou & Nguyen, 2024; García-Monge et al., 2023; Khaerudin et al., 2025; Khan et al., 2025; Lazaroiu et al., 2024; Leal Filho et al., 2025; Marimekala et al., 2025; Qiao et al., 2025; Quevedo et al., 2023; Retscher, 2025; Scolobig & Balsiger, 2024a; Sharma et al., 2025; Tabuenca et al., 2024). These conditions are not yet in place in many higher educational institutions and the technical readiness emerges as the most widespread constraint. Ten studies reported data and modelling challenges, this involves data bias, poor data quality, limited generalizability and concept drift (Alsamraee & Khanna, 2025b, 2025a; Chin et al., 2025; Chou & Nguyen, 2024; García-Monge et al., 2023; Kumar et al., 2023a; Marimekala et al., 2025; Qiao et al., 2025; Quevedo et al., 2023; Tabuenca et al., 2024). Campus energy models depend on continuous, high quality historical data, hence missing or inconsistent records undermine forecasting performance (Alsamraee & Khanna, 2025a; Chin et al., 2025). Financial and resource constraints were reported by 10 studies reflecting the high cost of AI, Internet of things and renewable energy infrastructure (Al Salmi et al., 2024; Ayyash & Salah, 2025; Basheer et al., 2025; Chou & Nguyen, 2024; Khaerudin et al., 2025; Khan et al., 2025; Lazaroiu et al., 2024; Leal Filho et al., 2024; Scolobig & Balsiger, 2024a; Sharma et al., 2025).

Human capacity and organisational challenges were highlighted in 8 studies focusing on skills gaps, limited training, resistance to change and, weak institutional support (Ayyash & Salah, 2025; Basheer et al., 2025; Khaerudin et al., 2025; Khan et al., 2025; Leal Filho et al., 2024; Retscher, 2025; Scolobig & Balsiger, 2024a; Silva Lopes, 2024). AI adoption for green energy management is mediated by staff awareness, perceived usefulness, and organisational culture (Ayyash & Salah, 2025). Institutional staff need preparation to use AI tools responsibly in geomatics and sustainability education (Retscher, 2025; Silva Lopes, 2024). These show that resources and people are also critical; without funding, skills, and supportive leadership, it is difficult to adopt new technologies for climate adaptation.

Eight studies highlight ethical, privacy, and trust issues such as the concerns about data protection, surveillance, algorithmic bias, fairness, and even the environmental footprint of AI systems (Al Salmi et al., 2024; Khan et al., 2025; Leal Filho et al., 2024, 2025; Marimekala et al., 2025; Retscher, 2025; Sharma et al., 2025; Tabuenca et al., 2024). Generative AI and black box models raise questions about transparency and fairness in decision-making (Marimekala et al., 2025). Internet of Things learning environments involve intense data collection on human behavior, prompting concerns about surveillance and informed consent (Tabuenca et al., 2024)

4.5 Frameworks Used

Several studies adopted different frameworks for energy forecasting and optimisation that shape how AI and climate adaptation are conceptualized in higher educational institutions. Data-driven ML frameworks, five-step ANN-based forecasting models, STGCN architectures, and metaheuristic-optimised AI frameworks provide structured approaches to modelling campus energy use and planning (Alsamraee & Khanna, 2025b; Chin et al., 2025; Chou & Nguyen, 2024; Qiao et al., 2025). These frameworks emphasizes performance metrics, computational optimization, and the capacity to capture complex temporal and spatial patterns but they have limited attention to organizational, ethical, or pedagogical dimensions. Other studies use sustainability and governance frameworks. Sustainability indicator frameworks for higher educational institutions connect digital and smart campus tools to governance, environmental impact , economic viability, academic integrity, and social responsibility(Basheer et al., 2025; Khan et al., 2025). The university climate action framework situates AT and ICT tools within broader institutional roles in research, policy, and community engagement(Leal Filho et al., 2024).

Studies by (Retscher, 2025; Sharma et al., 2025; Silva Lopes, 2024; Tabuenca et al., 2024), used frameworks that integrate teaching, learning, and adaption practices. These frameworks include the Smart Educational Campus Framework, AI-integrated geomatics education framework, IoT Smart Learning Environment Framework and TIP model connect AI and digital technologies to curriculum design, pedagogies, student engagement and community-based adaptation. These frameworks highlight how AI can underpin transformative learning, and participatory adaptation. Finally, the integrated AI adoption model that combines TRA, TAM, DOI and RBV explicitly theorises adoption processes for AI in green campus energy management(Ayyash & Salah, 2025). This is one of the few studies to systematically link technical innovation with behavioral and organisational theories, emphasising perceived usefulness, subjective norms, diffusion dynamics and resource-based capabilities.

4.6 Research Gaps in Literature

The systematic review revealed a significant gap in methodology, theory and practice in the literature on AI for climate adaptation in higher educational Institutions (HEIs). Few studies employed a structured Information systems framework to explain how AI is adopted and embedded within an institutional context. Most studies focused narrowly on technical performance or individual behavioural factors. A gap in practice was also identified as the studies are geographically concentrated in developed regions, with limited context-specific evidence from African universities. Many universities in Africa face challenges such as digital limitations, poor infrastructure, and insufficient energy, which directly influence the feasibility, design, and effective use of AI-based solutions. Most of the ideas and evidence about AI and climate adaptation in HEIs are based on experiences from Asia, Europe, and North America, which differ substantially from African institutional realities. Methodologically, the dominance of quantitative and mixed methods emphasises modelling and forecasting outcomes, but there are not enough qualitative studies to explore an in-depth in understanding and deployment of AI-based technologies for climate adaptation and resilience in the particular institutional and cultural context.

4.7 Potential Contributions of the Study

This study delivers theoretical and contextual value to the developing body of research in addressing the potential of artificial intelligence (AI) for climate adaptation within higher educational institutions (HEIs). This study contributes in covering the research gaps in theory and practice. The gap in practice by producing empirical literature about the implementation of artificial intelligence in climate adaptation in institutions of higher learning in Africa, which is an area that has not been significantly covered in the existing literature. In reference to the African universities, the study outlines the practical factors that guide the use of AI, including infrastructures, scarce digital and energy infrastructures, economic demands, and institutional readiness by explaining the influence of the local contextual factors on the viability, design, and effectiveness of AI-based climate adaptation programs. The conceptual framework proposed in this study seeks to address the gaps identified in the study by providing a theoretically grounded and practically applicable model for understanding how AI can be systematically integrated into climate resilience planning within HEIs.

4.8 Conceptual Framework

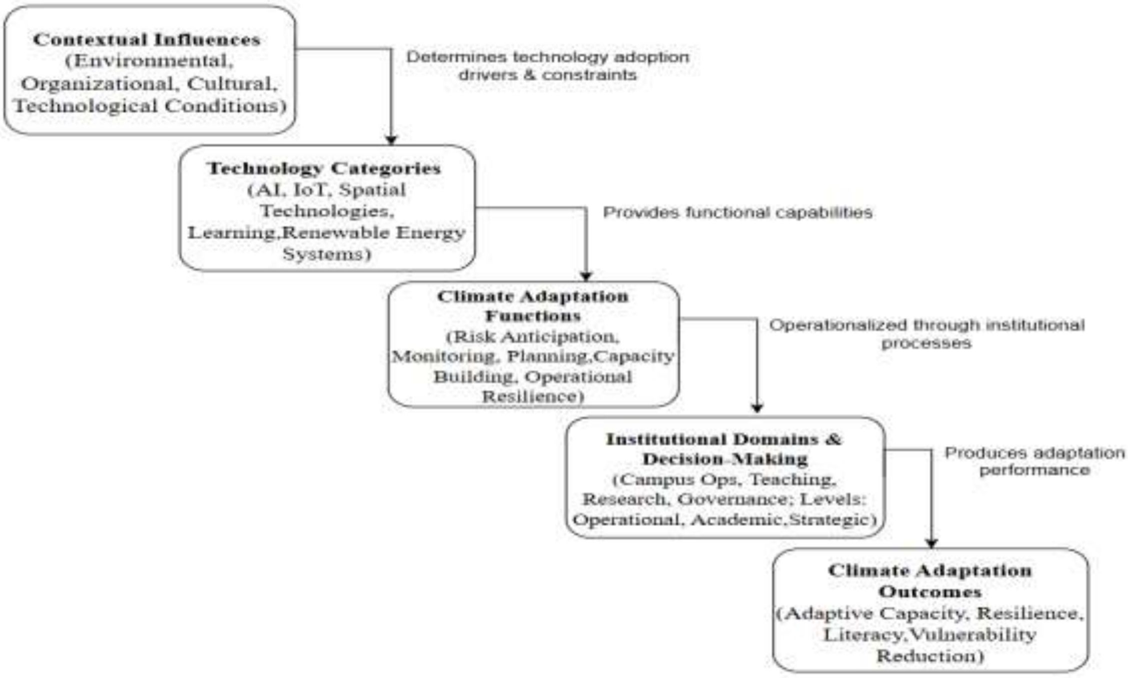

Fig. 5 Conceptual framework

The conceptual framework in figure 5 above, shows a sequence of processes by which contextual factors, including environmental, organizational, cultural and technological factors influence drivers and barriers of technology adoption in institutions, establishing how and which types of technology categories of artificial intelligence (AI), Internet of Things (IoT), spatial technologies, learning systems and renewable energy systems will be adopted. The technologies have functionalities that facilitate fundamental climate adaptation processes of the risk's anticipation, monitoring, planning, and capacity building, as well as operational resilience. Technological tools are then operationalized in the form of the adaptation functions by institutional domains and processes of decision making, like the university operations, teaching, research, and governance in the operational, academic, and strategic levels, where policies, resource allocation, and strategic plans merge with the application of the tools. This systematic process results in quantifiable performance of adaptation by institutions, which eventually results in better climate adaptation performance, such as better adaptive capacity, resilience, climate literacy, and vulnerability

4.9 Conclusion

This paper presented a systematic literature review guided by the PRISMA model to systematically review 22 recent articles on AI and other digital technologies in climate adaptation, resilience, sustainability, and energy management within higher educational institutions. Three digital databases, IEEE Xplore, SpringerLink, and ScienceDirect, were used to yield the research articles using a search string. The results show a diverse range of technologies, such as AI/ML energy models and IoT-based smart campuses that are used by HEI in response to climate challenges. Factors of technology adoption were discussed and grouped into technical, financial, organizational, human, and ethical drivers. The significant benefits and challenges of AI-enabled climate adaptation in higher educational institutions were discussed as well. The discussions highlighted the key gaps around integrating AI in climate adaptation within the higher educational institutions' context. The insights informed the conceptual framework of the study, linking adoption factors, technologies, utilization domains, adaptation outcomes, and feedback loops to guide the empirical study

4.10 Limitations of the study

The study was restricted to three databases (IEEE Xplore, ScienceDirect, and SpringerLink), English language publications between 2021 and 2025, Peer-reviewed journal articles, conference proceedings, and book chapters, which may have excluded relevant studies indexed in other sources or languages. The geographical concentration of studies in Asia and Europe, with minimal representation from Africa and other resource- constrained regions, constrains global applicability.

4.11 Recommendations for Future Research

Research studies should adopt stronger Information Systems (IS) theoretical frameworks to help in explaining how AI technologies are adopted and integrated into institutional systems. There is a need for more theory-driven empirical research that integrates technology, organization, and the environmental dimensions rather than just technical dimensions. The future research should incorporate more qualitative approaches to better the understanding of institutional culture, stakeholder perceptions, governance, and ethical considerations surrounding AI use in climate adaptations.

REFERENCES

[1] Al Salmi, H. M., DivyaJyothi, M. G., Jopate, R., Al Ghafri, R. M., & Al Abri, M. S. 2024. Exploring the Integration of Artificial Intelligence in Education and Smart Transport Technology in Oman; Perceptions, Challenges and Ethical Considerations. *2024 2nd International Conference on Computing and Data Analytics, ICCDA 2024 - Proceedings*, 1–5. https://doi.org/10.1109/ICCDA64887.2024.10867343

[2] Alsamraee, S. A., & Khanna, S. 2025a. High-resolution energy consumption forecasting of a university campus power plant based on advanced machine learning techniques. *Energy Strategy Reviews*, *60*(August 2024), 101769. https://doi.org/10.1016/j.esr.2025.101769

[3] Alsamraee, S. A., & Khanna, S. 2025b. Long-term electricity demand forecasting of a university campus based on advanced deep learning artificial neural network algorithms. *Results in Engineering*, *27*(August), 106683. https://doi.org/10.1016/j.rineng.2025.106683

[4] Ayyash, M. M., & Salah, O. H. 2025. AI adoption in higher education: Advancing sustainable energy management in palestinian universities. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(2), 100534. https://doi.org/10.1016/j.joitmc.2025.100534

[5] Basheer, N., Ahmed, V., Bahroun, Z., & Anane, C. 2025. Sustainability assessment in higher education institutions : exploring indicators , stakeholder perceptions , and implementation challenges. *Discover Sustainability*. https://doi.org/10.1007/s43621-025-01116-w

[6] Cavus, N., Mrwebi, S. E., Ibrahim, I., Modupeola, T., & Reeves, A. Y. 2022. Internet of Things and Its Applications to Smart Campus: A Systematic Literature Review. *International Journal of Interactive Mobile Technologies*, *16*(23), 17–35. https://doi.org/10.3991/ijim.v16i23.36215

[7] Chin, S. Y., Hasikin, K., Mohamed Zaid, N. S., & Jamaludin, A. A. 2025. Integrating behavioural and environmental data for energy forecasting in tropical campus buildings using machine learning techniques. *Journal of Building Engineering*, *113*(September), 114134. https://doi.org/10.1016/j.jobe.2025.114134

[8] Chou, J. S., & Nguyen, H. M. 2024. Simulating long-term energy consumption prediction in campus buildings through enhanced data augmentation and metaheuristic-optimized artificial intelligence. *Energy and Buildings*, *312*(January), 114191. https://doi.org/10.1016/j.enbuild.2024.114191

[9] Das, D. K. 2025. Integrating IoT and AI for Sustainable Energy-Efficient Smart Building: Potential, Barriers and Strategic Pathways. *Sustainability (Switzerland)*, *17*(22). https://doi.org/10.3390/su172210313

[10] Davidson, E., Schwartz, Y., Williams, J., & Mumovic, D. 2024. Resilience of the higher education sector to future climates: A systematic review of predicted building energy performance and modelling approaches. *Renewable and Sustainable Energy Reviews*, *191*(April 2023), 114040. https://doi.org/10.1016/j.rser.2023.114040

[11] Elhabyb, K., Baina, A., Bellafkih, M., & Deifalla, A. F. 2024. Machine Learning Algorithms for Predicting Energy Consumption in Educational Buildings. *International Journal of Energy Research*, *2024*(Ml). https://doi.org/10.1155/2024/6812425

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

[13] Jain, H., Dhupper, R., Shrivastava, A., Kumar, D., & Kumari, M. 2023. AI-enabled strategies for climate change adaptation: protecting communities, infrastructure, and businesses from the impacts of climate change. *Computational Urban Science*, *3*(1). https://doi.org/10.1007/s43762-023-00100-2

[14] Khaerudin, Arita, M., Saputro, R. H., & Marfu, A. 2025. Smart education for a sustainable future: Integrating IoT and big data in sustainability-based learning. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(4), 100638. https://doi.org/10.1016/j.joitmc.2025.100638

[15] Khan, M. A., Rehman, A., Ali, A., Sagheer, S., & Meshal, A. 2025. Navigating the future of higher education in Saudi Arabia : implementing AI , machine learning , and big data for sustainable university development. *Discover Sustainability*. https://doi.org/10.1007/s43621-025-01388-2

[16] Kourgiozou, V., Commin, A., Dowson, M., Rovas, D., & Mumovic, D. 2021. Scalable pathways to net zero carbon in the UK higher education sector: A systematic review of smart energy systems in university campuses. *Renewable and Sustainable Energy Reviews*, *147*(May), 111234. https://doi.org/10.1016/j.rser.2021.111234

[17] Kumar, P., Sahani, J., Rawat, N., Debele, S., Tiwari, A., Mendes Emygdio, A. P., Abhijith, K. V., Kukadia, V., Holmes, K., & Pfautsch, S. 2023a. Using empirical science education in schools to improve climate change literacy. *Renewable and Sustainable Energy Reviews*, *178*(May 2022), 113232. https://doi.org/10.1016/j.rser.2023.113232

[18] Kumar, P., Sahani, J., Rawat, N., Debele, S., Tiwari, A., Mendes Emygdio, A. P., Abhijith, K. V., Kukadia, V., Holmes, K., & Pfautsch, S. 2023b. Using empirical science education in schools to improve climate change literacy. *Renewable and Sustainable Energy Reviews*, *178*(November 2022), 113232. https://doi.org/10.1016/j.rser.2023.113232

[19] Kumar, P., Sahani, J., Rawat, N., Debele, S., Tiwari, A., Paula, A., Emygdio, M., Abhijith, K. V, Kukadia, V., Holmes, K., & Pfautsch, S. 2023. Using empirical science education in schools to improve climate change literacy. *Renewable and*

Sustainable Energy Reviews, *178*(November 2022), 113232. https://doi.org/10.1016/j.rser.2023.113232

[20] Lazaroiu, A. C., Panait, C., Serițan, G., Popescu, C. L., & Roscia, M. 2024. Maximizing renewable energy and storage integration in university campuses. *Renewable Energy*, *230*(June), 120871. https://doi.org/10.1016/j.renene.2024.120871

[21] Leal Filho, W., Kim, E., Borsatto, J. M. L. S., & Marcolin, C. B. 2025. Using artificial intelligence in sustainability teaching and learning. *Environmental Sciences Europe*, *37*(1). https://doi.org/10.1186/s12302-025-01159-w

[22] Leal Filho, W., Sierra, J., Kalembo, F., Ayal, D. Y., Matandirotya, N., de Victoria Pereira Amaro da Costa, C. I., Sow, B. L., Aabeyir, R., Mawanda, J., Zhou, L., & Baldeh, D. 2024. The role of African universities in handling climate change. *Environmental Sciences Europe*, *36*(1). https://doi.org/10.1186/s12302-024-00933-6

[23] Marimekala, D., Krishnan, S., & Lamb, J. 2025. Harnessing AI to Optimize Energy Consumption in Academic Institutions to Combat Climate Change. *2025 15th IEEE Integrated STEM Education Conference, ISEC 2025*, 1–7. https://doi.org/10.1109/ISEC64801.2025.11147246

[24] Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., Antes, G., Atkins, D., Barbour, V., Barrowman, N., Berlin, J. A., Clark, J., Clarke, M., Cook, D., D'Amico, R., Deeks, J. J., Devereaux, P. J., Dickersin, K., Egger, M., Ernst, E., Gøtzsche, P. C., … Tugwell, P. 2009. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine*, *6*(7), 873–880. https://doi.org/10.1371/journal.pmed.1000097

[25] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. 2021. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Bmj*, *372*. https://doi.org/10.1136/bmj.n71

[26] Qiao, Q., Xu, Z., Ren, C., Yunusa-Kaltungo, A., & Cheung, C. 2025. Building energy consumption prediction for campus accommodation buildings based on spatial temporal graph convolution networks. *Procedia CIRP*, *135*, 498–502. https://doi.org/10.1016/j.procir.2025.01.060

[27] Quevedo, T. C., Geraldi, M. S., & Melo, A. P. 2023. Applying machine learning to develop energy benchmarking for university buildings in Brazil. *Journal of Building Engineering*, *63*(PA), 105468. https://doi.org/10.1016/j.jobe.2022.105468

[28] Retscher, G. 2025. Exploring the intersection of artificial intelligence and higher education: opportunities and challenges in the context of geomatics education. *Applied Geomatics*, *17*(1), 49–61. https://doi.org/10.1007/s12518-024-00602-6

[29] Salem, K. M., Rey-Martínez, F. J., Elgharib, A. O., & Rey-Hernández, J. M. 2025. Energy Demand Forecasting Scenarios for Buildings Using Six AI Models. *Applied Sciences (Switzerland)*, *15*(15), 1–24. https://doi.org/10.3390/app15158238

[30] Scolobig, A., & Balsiger, J. 2024a. Emerging trends in disaster risk reduction and climate change adaptation higher education. *International Journal of Disaster Risk Reduction*, *105*(December 2023), 104383. https://doi.org/10.1016/j.ijdrr.2024.104383

[31] Scolobig, A., & Balsiger, J. 2024b. Emerging trends in disaster risk reduction and climate change adaptation higher education. *International Journal of Disaster Risk Reduction*, *105*(March), 104383. https://doi.org/10.1016/j.ijdrr.2024.104383

[32] Sharma, H., Sengupta, E., & Saini, M. 2025. Smart Educational Campuses: Leveraging AI and Emerging Technologies for Sustainable Development. *2025 Global Conference in Emerging Technology, GINOTECH 2025*, 1–6. https://doi.org/10.1109/GINOTECH63460.2025.11076726

[33] Silva Lopes, H. 2024. Educational sustainability initiatives in higher education: An integrative approach to urban areas in northwestern Portugal. *Societal Impacts*, *4*(August), 100093. https://doi.org/10.1016/j.socimp.2024.100093

[34] Tabuenca, B., Uche-Soria, M., Greller, W., Hernández-Leo, D., Balcells-Falgueras, P., Gloor, P., & Garbajosa, J. 2024. Greening smart learning environments with Artificial Intelligence of Things. *Internet of Things (Netherlands)*, *25*(August 2023), 101051. https://doi.org/10.1016/j.iot.2023.101051

[35] Tariq, R., Mohammed, A., Alshibani, A., & Ramírez-Montoya, M. S.2024. Complex artificial intelligence models for energy sustainability in educational buildings. *Scientific Reports*, *14*(1), 1–17. https://doi.org/10.1038/s41598-024-65727-5

0