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Energy Gen-AI technology framework: A perspective of energy efficiency and business ethics in operation management☆

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ABSTRACT

Considering the mounting request for viable energy solutions emphasising sustainability, this study addresses the context by positioning Generative Artificial Intelligence (Gen-AI) as a pivotal remedy for improved process efficiency. Concerns about its uncontrolled use and ethical implications prompted a thorough examination of problems and gaps in this domain. This study innovates by positioning Gen-AI as a critical solution for improving energy efficiency amidst rising demand for sustainable energy at the operation and supply chain management levels. Based on technological determinism, it introduces an Energy Gen-AI Technology Framework (EnGen-AI) that integrates Gen-AI, energy efficiency, Business Ethics (BE), and Corporate Social Responsibility (CSR) principles for implementing Gen-AI to enhance sustainable energy management. The methodology includes a scoping review, a multi-criteria analysis, and a technology framework. The study harmonises BE-CSR with Gen-AI practices, offering essential guidance for management implementing Gen-AI in sustainable energy solutions whilst observing its impacts on ethical and social aspects.

1. Introduction

Following the exhaustion of fossil fuel reservoirs, the surge in energy costs, and the constraints imposed by governmental regulations (Diaz & Ocampo-Martinez, 2019), the world is increasingly aware of the importance of organisations seeking energy efficiency in their production processes (Fontoura et al., 2023), driven by the effect of economic globalisation (Chen et al., 2019) together with the industrial development of countries, which culminated in significant increases in energy demand and greenhouse gas emissions (X. D. Wu et al., 2019). Enhancing energy effectiveness and curbing emissions of environmental pollutants are pivotal methods to mitigate energy issues (Yan et al., 2019). Therefore, energy consumption and climate change are consolidating each year, inducing nations to promote and encourage sustainable development in their territories, causing energy efficiency programs that address eco-friendly issues to increase worldwide (Safarzadeh & Rasti-Barzoki, 2019), provoking organisations to seek technological solutions to achieve these objectives.

The disruptive technologies of Industry 4.0 (I4.0) can be separated into Artificial Intelligence (AI), Additive Manufacturing (AM), Augmented Reality (AR), Big-Data Analytics (BDA), Blockchain, Cloud Computing (Cloud), Drones, Internet of Things (IoT), Robotics, Nanotechnology, and Simulation (Akpan et al., 2025; S. Kumar & Mallipeddi, 2022; Letaief et al., 2022; Salah et al., 2019), with AI being one of the most disruptive technologies of this century, with great potential to transform many aspects of society (Fosso Wamba et al., 2021), and is directly related to minimising energy consumption (Laskurain-Iturbe et al., 2021). Through continual technological advancements, Generative Artificial Intelligence (Gen-AI) has emerged as a powerful tool across various domains (Ma & Huo, 2023). It leverages algorithms and machine learning to generate innovative solutions or enhance existing processes. (Shumailov et al., 2024; Sætra, 2023). It can certainly be applied to obtain better energy practices.

Owing to elements like swift progress in computing capabilities, technologies linked to Gen-AI have made significant strides in replicating and, occasionally, outperforming human intelligence, acting as a

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powerful disruptive force that has been transforming on a global scale various sectors of society, such as industry, transport, communications, health and finance (Du & Xie, 2021). However, the radical development of Gen-AI has raised questions regarding its moral responsibility, which in the business sphere translates into questions about Business Ethics (BE) and Corporate Social Responsibility (CSR) issues (Hu, 2024; Islam & Greenwood, 2024). To mitigate risks, CSR has increasingly been considered a vital competitive strategy for companies (Godfrey, 2005), serving as a differentiation strategy that helps organisations improve company image and customer loyalty (G. Li et al., 2021).

The rising demand for energy management and the need to reduce carbon emissions place growing pressure on society. While Gen-AI technologies can optimise energy use, they also raise ethical concerns. The governments of several countries worldwide are increasingly concerned about the indiscriminate use of these technologies. Data privacy issues have come to the fore, as large-scale Gen-AI systems often rely on large volumes of consumer data, which can lead to misuse. Algorithm biases can also lead to inequalities in energy access, particularly affecting vulnerable populations. To address these challenges, some countries have initiated AI regulations. For example, Spain's efforts prompted the European Union to establish its first AI regulatory group in 2022. In 2023, the G7 signed an agreement to guide tech companies in AI development, and the US followed with its first executive order to regulate AI. Ethical and environmental concerns, especially in energy management, are now considered crucial research areas, integrating BE and CSR considerations.

A key research challenge is to develop a framework for decision-makers to select Gen-AI technologies that minimise negative impacts on decision-making, balancing innovation with ethical considerations. Although existing studies demonstrate an improvement in the use of Gen-AI in energy efficiency, they lack a concentrated focus, necessitating a deeper analysis of the effectiveness of Gen-AI in improving energy management (Arana-Landín et al., 2023). Organisations and stakeholders are encouraged to prioritise Gen-AI technologies, recognising their fundamental role in achieving significant results and sustaining competitiveness in the dynamic business landscape, bringing new challenges, especially in CSR, requiring greater attention to issues of BE (Ahmad et al., 2021; G. Li et al., 2021). These problems highlight the need to consider how Gen-AI technologies impact society and how they should be used.

The research gap lies in the absence of comprehensive studies exploring the social and ethical implications of using Gen-AI for energy management, especially in contrasting contexts between developed and developing countries. Although technological advancements have shown promise in optimising energy use, existing literature has yet to sufficiently explore how these innovations align with social and ethical principles, especially across diverse socio-economic environments (Ahmad et al., 2022; Pandiyan et al., 2023). This is crucial, as developed countries may have the infrastructure to absorb these technologies more quickly. In contrast, developing countries face challenges related to equity, access, and ethical considerations in their deployment. Current models underperform to address how these technologies impact vulnerable populations or exacerbate existing inequalities. Integrating Gen-AI with BE-CSR frameworks could lead to more responsible energy solutions (Du & Xie, 2021; Luqman et al., 2024). Thus, research is urgently needed to bridge the gap between technical innovation and ethical accountability in energy management across different global contexts. Therefore, considering the challenges discussed, the research question (RQ) is formulated as follows:

RQ: How can decision-makers in developed and developing countries be supported in evaluating the ethical and social implications of implementing Gen-AI technologies for energy management while mitigating organisational risks?

To answer this RQ, this study proposes a technology framework, Energy Gen-AI Technology Framework (EnGen-AI), to empower decision-makers in developed and developing countries by providing a structured approach to evaluating and selecting Gen-AI technologies for energy management. It will identify technologies with the least ethical and social risks while promoting sustainability and efficiency. By integrating BE-CSR considerations, the framework will allow organisations to make informed choices that align with social values and minimise negative impacts, thereby supporting responsible technological adoption across diverse socio-economic contexts.

Theoretical implications affirm Gen-AI's role in driving social change, aligning with technological determinism, particularly its capacity to shape energy management systems. This is especially crucial in both developed and developing countries, where the integration of Gen-AI can significantly impact economic efficiency, environmental sustainability, and social equity. The framework demonstrates how technological innovation can contribute to ethical standards and societal responsibilities by emphasising BE-CSR principles. The proposed EnGen-AI provides practical implications for organisations aiming to improve sustainable energy management through Gen-AI implementation. Identifying specific Gen-AI technologies and their impacts on BE-CSR principles is a valuable tool for decision-makers to align technological choices with ethical and social objectives.

The managerial insights include four key areas: environmental, social, economic, and political. It enhances energy efficiency, reduces CO_2 emissions, fosters inclusive Gen-AI technologies aligned with BE-CSR principles, boosts profits through demand forecasting, and shapes regulations to improve working conditions, all while balancing sustainability, ethics, and profitability. Its implementation in developed countries provides opportunities for refining energy efficiency, while in developing countries, it can address equitable access to resources and help avoid widening social gaps. Adopting the EnGen-AI framework fosters sustainable and ethical energy management across diverse socio-economic landscapes by navigating these distinct contexts.

The study was organised as follows: This section contextualises and presents the research problems and gap, purpose and motivation, and theoretical and practical implications for this research. Section 2 introduces the theoretical settings that form the basis of the study. Section 3 presents the research design, explaining in detail the methodology adopted, which was divided into four stages, the first referring to the scoping review, the second to the questionnaire design and expert panel, the third to Fuzzy DEMATEL (FDEM), and the fourth, the technology framework. Section 4 presents the research results, separated into theoretical and empirical results, and the new EnGen-AI. Section 5 presents the findings' discussions. Section 6 summarises the research and offers some conclusions and contributions.

2. Theoretical settings

Theoretical settings for the EnGen-AI framework are rooted in technological determinism, which posits that technology drives societal change and influences social structures. The proposed framework helps decision-makers evaluate and select optimal Gen-AI technologies for energy management while considering BE-CSR impacts. The theoretical foundation supports the idea that technological advancements in energy management, such as Gen-AI, can bring about substantial shifts in operational efficiency, sustainability, and governance. However, these technologies' unintended consequences could exacerbate energy challenges without a structured approach. This application of technological determinism reinforces the idea that Gen-AI can be a transformative force in energy management, driving both innovation and responsible decision-making.

2.1. Technological determinism theory

In 1964, Marshall McLuhan introduced technological determinism, a theory that examines how technological factors influence human thought and behaviour, questioning their control over human affairs (Dafoe, 2015; de la Cruz Paragas & Lin, 2016). Proponents of technological determinism are influenced and shaped by technological advancements in society, in which the impact of technology on society is significant. However, adverse effects are primarily attributed to human misuse rather than inherent flaws in the technology itself, being recognised as a reductionist approach that overstates the influence of technology on society and understates social influences on the development of technology (Baek & Lee, 2021). Technological determinism can lead to significant analytical problems in work and employment research, asserting a straightforward connection between technology and society, suggesting that technological evolution is linear and independent, influencing society without human intervention (Joyce et al., 2023).

One of the main criticisms of technological determinism is that the model assumes technology can operate autonomously, failing to recognise that humans still possess the ability to control technological development (Leonardi & Barley, 2010). This creates a dilemma where technology dictates societal conditions without human intervention (Šabanović, 2010). Another critique of technological determinism is that it may overlook the significance of social, political, and cultural forces during technological evolution, which can directly influence technological applications. Therefore, presuming that technological impacts on society are always predictable and linear is problematic, as introducing new technologies may lead to unintended consequences, including digital inequality and environmental degradation (Dafoe, 2015).

Technological Determinism has two versions: a soft view, which maintains that technological change drives social change but at the same time responds in a discriminatory way to social pressures, and a complex view, which perceives technological development as an autonomous force, utterly independent of social restrictions, that is, the relationship between technology and society; the analysis attribute that can be extracted from technological determinism is that it is a technology that affects and society that is affected (Baek & Lee, 2021). In this way, the present study uses technological determinism to investigate the impact of Gen-AI-related technologies on BE-CSR principles.

2.2. *Gen-AI-related technologies*

Data has emerged as a new valuable asset, wherein obtaining pertinent data remains a hurdle for decision-making, impacting the efficacy of AI algorithms (Patel et al., 2024). Modern AI technologies are widely employed for automating processes and enhancing learning within the digital service provisions of cloud computing giants like Google, Facebook, and Amazon (Castañé et al., 2023). AI aims to create intelligent entities capable of learning and performing tasks that usually require human intelligence on devices or computerised systems with the ability to acquire knowledge for executing tasks (Fosso Wamba et al., 2021). AI has developed rapidly due to the need for technologies capable of interpreting large amounts of data and learning and adapting as needed (Kaplan & Haenlein, 2019). AI methodologies have two main classifications: (i) reasoning and decision-making and (ii) learning. The first set focuses on decision-making, searching for solutions, and optimising processes, while the second set concerns learning, communication, and perception (Colchester et al., 2017).

The swift advancement of AI-related technologies is evident in innovations like ChatGPT, GitHub Copilot, and DALL-E, exemplifying progress in Gen-AI technologies (Jackson, Jesus Saenz, & Ivanov, 2024). Recently, Gen-AI has become a representative technological advancement in deep learning research, as classical methods present difficulties in data learning and design efficiency, opening new possibilities in different areas of society (Liao et al., 2024). Therefore, Gen-AI models seek to comprehend and replicate the inherent patterns within a dataset, facilitating the creation of new content that closely mirrors the original data distribution (Jackson, Ivanov, et al., 2024). Presently, forecasts suggest that Gen-AI will contribute trillions of dollars in annual value to the worldwide economy (Fosso Wamba et al., 2023), with the global market for Gen-AI technologies and services projected to attract investment amounting to billions of dollars in the coming years.

Generative learning is an intelligent design method dominated by Gen-AI, which has powerful design data learning and new efficient design generation capabilities and has been continuously developing and advancing in recent years with Convolutional Neural Networks (CNNs) (Chougale et al., 2022), Graph Neural Networks (GNNs) (Tan et al., 2022), and Variational Autoencoders (VAEs) (Ba-Alawi et al., 2022) being the most utilised techniques (Liao et al., 2024). Other Gen-AI-related technologies are also highlighted, such as Recurrent Neural Networks (RNNs) (Cabello-López et al., 2023), Transformers or Generative Language Models (GLMs) (Saheb et al., 2022), Generative Adversarial Networks (GANs) (Prabha et al., 2023), and diffusion models. Table 1 displays, with the support of the scoping review, six Gen-AI-related technologies applied to promote better energy practices, maintaining concerns inherent to the principles of BE-CSR in their practices.

2.3. *BE-CSR principles*

With the increasing use of technologies based on Gen-AI in everyday life, more developments appear promising for use in areas related to operation management, especially for energy management, but simultaneously, there are growing concerns inherent to their use in ethical and social responsibility issues (Tseng & Lin, 2024). However, the great challenge is understanding how these issues affect operational management and how they are linked to society's well-being (Saheb et al., 2022). To better understand these impacts, the research categorised the principles related to BE-CSR based on the literature as follows: (i) integrity, (ii) transparency and accountability, (iii) fairness and bias mitigation, (iv) privacy and data protection, (v) compliance with laws and regulations, (vi) sustainability and environmental responsibility, and (vii) employment and workforce.

Integrity is paramount in addressing ethical issues. This ensures that Gen-AI technologies are developed, distributed, and utilised according to moral and ethical standards, aligning with human values to reach justifiable conclusions and embody machine ethics' essence (Han et al., 2023). Transparency and accountability are essential for upholding human values and privacy in companies. In addition to preventing bias or inaccurate conclusions, this principle promotes accurate assessment for management decision-making (Dansana et al., 2023). Fairness and bias mitigation are vital to avoid biased data in training Gen-AI models, which can lead to discriminatory behaviour and unfair outcomes (C. H. Liu et al., 2021). Privacy and data protection were trending as essential themes to safeguard user privacy, which is constantly developing in Gen-AI to avoid forbidden access to personal and sensitive information (Asha et al., 2023).

Compliance with laws and regulations is critically important, and organisations that adhere to its use can guarantee the protection of human values and minimise adverse consequences, building public trust that Gen-AI is safe and ensuring their rights and interests are protected (W. Liu et al., 2023). Sustainability and environmental responsibility significantly impact social and environmental issues when using Gen-AI models to identify sustainable product features, which can mitigate energy use and carbon emissions (Cabello-López et al., 2023). The advance of Gen-AI technologies can affect employment and the workforce, raising concerns about job displacement and the need to adapt to changes in the workforce, which impacts ethical and social principles in society (R. Kumar et al., 2021).

3. Research design

The epistemological foundation of this research is post-positivist with mixed methods, which entails the pursuit of an objective understanding of reality while acknowledging the inherent limitations of human knowledge and the uncertainty associated with the phenomena under investigation (Aghimien et al., 2022; Baskerville & Wood-Harper, 1996). The scoping review aligns with a post-positivist epistemology by

Table 1
Gen-AI-related to improve energy efficiency.

Gen-AI	Authors	Objectives	Findings
GANs	Prabha et al. (2023)	To address security vulnerabilities and attacks in wireless ad hoc networks (WANs) by proposing a novel routing protocol called CH-SR-DDCGAN-NBOA-WAN (Cluster Head-based Secure Routing using Dual-Discriminator Conditional GAN Optimized with Namib beetle optimisation algorithm).	The proposed protocol approach performs better in reducing packet drop, increasing network lifetime, and decreasing average delay time than previously proposed methods, thereby demonstrating its potential to enhance security and efficiency in wireless ad hoc networks.
	Wang et al. (2023)	To develop a generation and forecasting approach using Wasserstein GAN (WGAN) for modelling inherent operational uncertainties in Integrated Energy Systems.	The well-trained WGAN facilitates scenario forecasting across forecast look-ahead horizons when integrated into constrained optimisation.
GLMs	Purbey et al. (2023)	To introduce a novel approach to address the challenges in analysing and reporting medical events accurately from numerical and textual data present in medical reports, aiming to mitigate multiple attacks and maintain low communication delay, low energy consumption, and high throughput levels	Compared with standard alerting models under clinical scenarios, the proposed model achieved 8.5% higher alert identification accuracy, 3.9% higher alert precision, and 4.5% higher alert recall.
	Saheb et al. (2022)	To propose an innovative contextual topic modelling approach combining Latent Dirichlet Allocation, BERT, and clustering to analyse scholarly work on sustainable AI in energy.	Eight key topics were identified: climate AI, sustainable buildings, and AI-driven water management. Fourteen research directions were proposed to address theoretical gaps.
RNNs	Cabello-López et al. (2023)	To tackle the issues linked with the considerable fluctuations in renewable energy generation and their effects on grid reliability. This will be accomplished by enhancing the precision of current forecasting methods.	The leading models, employing Convolutional Networks and Convolutional + Recurrent Neural Networks, surpass ESIOS (the Spanish System Operator) by decreasing the mean absolute error by 41% and 47.58%, respectively.
	Asha et al. (2023)	To achieve optimum network performance by amalgamating diverse renewable energy sources and leveraging advanced technologies.	The output from each network serves as input for the Optimized Recurrent Neural Network, which anticipates the final superiority of the IoT network. Empirical results validated that the devised approach accurately forecasted and improved the overall excellence of a simulated IoT system.

Table 1 (*continued*)

Gen-AI	Authors	Objectives	Findings
CNNs	Abdelaziz et al. (2023)	To unveil scientific rules (If-Then rules) that can assist decision-makers in determining the appropriate energy consumption levels for each building.	Employing a genetic algorithm, CNN achieves a 99.01% accuracy on the training dataset and a 97.74% accuracy on the validation dataset, showcasing an accuracy of 0.02 and 0.09 errors correspondingly. Additionally, the CNN delivers a 98.03% accuracy with a 0.05 standard error on the training dataset and records a 94.91% accuracy alongside a 0.26 standard error on the validation dataset.
	Chougale et al. (2022)	To propose a flexible memristor device for data storage and neuromorphic computing optimized using CNN for pattern recognition accuracy.	Demonstrate the memristor's stable synaptic behaviour, improving CNN pattern recognition accuracy on CIFAR-10 and highlighting its potential for AI electronics.
VAEs	Ba-Alawi et al. (2022)	To suggest a comprehensive structure for addressing missing data and sensor self-validation by integrating VAEs within a deep residual network framework.	The envisioned framework aims to enhance the dependability of malfunctioning sensors by filling in missing data, spotting irregularities, pinpointing the origins of failures, and restoring flawed data to its standard state.
GNNs	Tan et al. (2022)	To develop an energy-conserving cell switching approach for highly dense HetNets employing GNNs to alleviate escalating energy usage.	The proposed GNN-based solution showcases a 10.41% energy efficiency gain compared to the baseline, achieving 75.76% of optimal performance.
	Xue et al. (2023)	To improve the forecast accuracy of distributed photovoltaic energy generation for the following electrical grid, given the intermittency of renewable sources	The proposed model utilised GNNs to handle distributed generation time series data, enhancing prediction accuracy by capturing spatiotemporal relationships based on data similarity. This is crucial for maintaining a secure power grid despite intermittent renewable energy sources.

systematically mapping and synthesising existing knowledge (Fontoura et al., 2023; Nascimento et al., 2022). The scoping review was chosen to gather Gen-AI technologies for energy management and BE-CSR principles because it enables a broad mapping of the research field, identifies gaps in existing literature, and establishes potential criteria analysis (Levac et al., 2010).

This proposed framework endorses applying quantitative methods, including Likert-scale questionnaires (Garcia-Buendia et al., 2022), to identify participants' demographic information and collect data on the interrelationships between identified Gen-AI technologies and BE-CSR principles and FDEM, which aim to objectively structure complex issues while acknowledging potential biases and uncertainties in data interpretation (Swarnakar et al., 2022). The FDEM in this study was used to classify the impact forces between the identified Gen-AI technologies on BE-CSR principles. The main advantages of using FDEM are overcoming the inevitable uncertainty, reducing the number of searches, and enabling the semantic structure of the prediction items to be explained, along with the individual attributes of the expert (Fontoura et al., 2023).

Additionally, the framework grounded in technological determinism underscores the notion that technology profoundly influences social structures (Salehan et al., 2018). Building upon this foundation, we propose a novel technology framework that integrates Gen-AI technologies to enhance energy efficiency while concurrently aligning with BE-CSR principles. This framework differentiates between developed and developing countries, acknowledging their distinct technological capacities, regulatory landscapes, and socio-economic contexts to ensure a more tailored and effective implementation. This epistemological stance validates the selection of methods, blending quantitative approaches with solid theoretical foundations to offer a comprehensive yet adaptable understanding of the phenomena under investigation. The research design was separated into four stages, as shown in Fig. 1.

3.1. Scoping review

The scoping review was selected to combine Gen-AI technologies for energy management and BE-CSR principles due to its ability to comprehensively map critical concepts across a broad research panorama. This approach facilitates the identification of gaps in the literature, aiming to systematically determine which criteria best represent the nature of the research (Levac et al., 2010). Moreover, scoping reviews enable the inclusion of various study designs, which is crucial when tackling complex interdisciplinary subjects such as energy management, Gen-AI, and BE-CSR. The iterative nature of the scoping review process allows researchers to refine the scope and adjust the review as new evidence emerges, ensuring a thorough analysis of these emerging fields (Nascimento et al., 2022).

The scoping review facilitates a comprehensive mapping of the literature, enabling a broad and practical evaluation while summarising diverse and heterogeneous themes (Di Pasquale et al., 2020). In this study, the scoping review was separated into six stages: (i) identify the research questions, (ii) identify relevant studies, (iii) study selection, (iv) chart the data, (v) validation and data coding, and (vi) collating, summarising, and reporting (Danese et al., 2018; Fontoura et al., 2023). Recently, the scoping review methodology has been applied across various fields relevant to this study, such as AI technologies (De Wilde et al., 2025), energy efficiency (Maani et al., 2021), and ethical and social principles (Chu et al., 2023), among others.

For transparency, the scoping review was conducted considering a rigorous interdisciplinary discussion between authors to activate the research questions, which focused on Gen-AI, energy efficiency, and BE-CSR principles. A reasonable review provided the theoretical basis and identified research gaps; in this way, to identify relevant studies, the search string was built using the word tree technique, containing relevant keywords found in the literature on the topic studied, improving the quality of research (Saieg et al., 2018). This technique helped find precisely what authors were looking for in the literature, reducing the number of documents in the initial collection, as shown in Fig. 2. The compilation was assembled utilising literature from the Scopus and Web of Science (WoS) databases, configured to execute the search by title, abstract, and keywords.

The process of selecting studies was detailed to establish and implement criteria for inclusion and exclusion, as shown in Table 2, discarding any study that does not fit the established criteria. This objective is achieved through criteria that allow the inclusion of studies in the review (inclusion criteria) and those that should be discarded in a thorough reading (exclusion criteria) (Núñez-Merino et al., 2020). The inclusion and exclusion criteria must be implemented objectively, explicitly and consistently, providing clarity in the selection (Saieg et al., 2018). Only peer-reviewed papers from journals and conference proceedings were used, as they are more reliable documents for carrying out a literature review (Fontoura et al., 2023; Nascimento et al., 2022).

The collection contains 209 documents, resulting in a final portfolio with 79 documents after applying the inclusion and exclusion criteria, as shown in Fig. 3 and outlined in the supplementary documentation (https://data.mendeley.com/datasets/wrjgynvthf). The documents were analysed in two stages: reading the titles, abstracts, and keywords, followed by the second stage, where the full reading was accomplished.

The data was charted using content analysis techniques (Garza-Reyes, 2015), in which all Gen-AI-related technologies used to improve energy efficiency were listed with objectives, findings, and application areas. In addition, BE-CSR principles were identified in the scenario of using Gen-AI practices. The validation and data code stage enabled the comparison of all data between the authors, allowing discussions to solve possible differences, guaranteeing reliability, and eliminating bias of the evaluators (Danese et al., 2018). The last stage is Collating, summarising, and reporting, in which all the scoping review results are grouped into a table to support authors in continuing their research.

3.2. Questionnaire design and expert panel

The questionnaire design and the expert panel selection for data collection in the FDEM study followed a structured approach to ensure rigour and reliability, guided by the principles outlined by Okoli and Pawlowski (2004). The objective was to verify, through a Likert scale, the impact of Gen-AI technologies used for energy management on BE-CSR principles, derived from a comprehensive scoping review. The selection of experts followed the criteria outlined by Fontoura et al. (2023), which required the inclusion of academics and practitioners actively engaged in research and professional activities relevant to the subject matter. Experts were required to meet three critical criteria: (i) extensive knowledge and experience in the area under investigation, with a minimum of five years of relevant professional engagement; (ii) current employment within the focal firm or organisation; and (iii) willingness and availability to actively contribute to the study, as recommended by Bokrantz et al. (2017).

To recruit participants, 82 experts were initially contacted and identified through recommendations from higher authorities within the focal firm, with all expressing willingness to participate. These experts occupied roles such as electronic engineers, production engineers, technology analysts, university professors, production and industrial managers, production heads, and directors in manufacturing. After profile reviews, the final panel included 23 experts, yielding a response rate of approximately 28%. The panel consisted of 10 practitioners and 13 academics, all with at least five years of experience in engineering, computing and information technology, business management systems, or finance, as summarised in Table 3. Although there are no rules regarding the minimum number of participants for FDEM (Moktadir et al., 2020), a minimum of 10 participants is recommended to reach a consensus (Okoli & Pawlowski, 2004).

The panel's expertise covered a range of specialisations within engineering, including software development, electrical and energy projects, digital transformation, data analysis, project management, automation, and I4.0 technologies. Participants from computing and IT had in-depth knowledge of AI, including machine learning, image analysis, and deep learning. At the same time, those in business and management systems contributed expertise in digital technologies, operations, logistics, supply chains, and ethical and social audits. The finance experts brought insights into technology management and neural networks. Furthermore, the expert panel was designed to ensure diversity in technical, social, and cultural perspectives, with participants representing developed and developing countries. The geographical distribution of experts was represented using a colour scale, with Brazil having the highest number of specialists, followed by Spain.

The questionnaire was administered in two phases via Google Forms, with all responses securely stored online in the Mendeley cloud-based

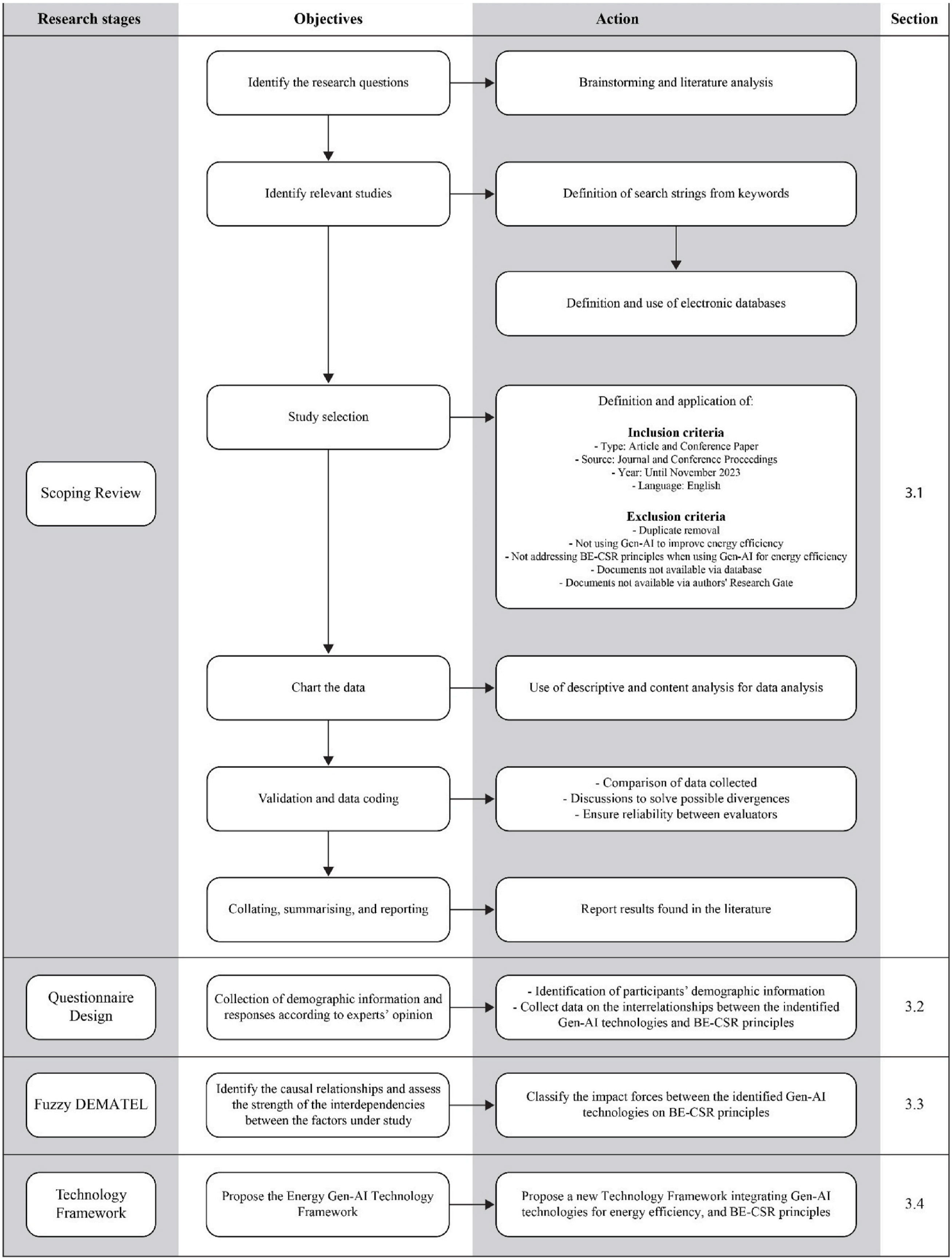

Fig. 1. Research design of the study.

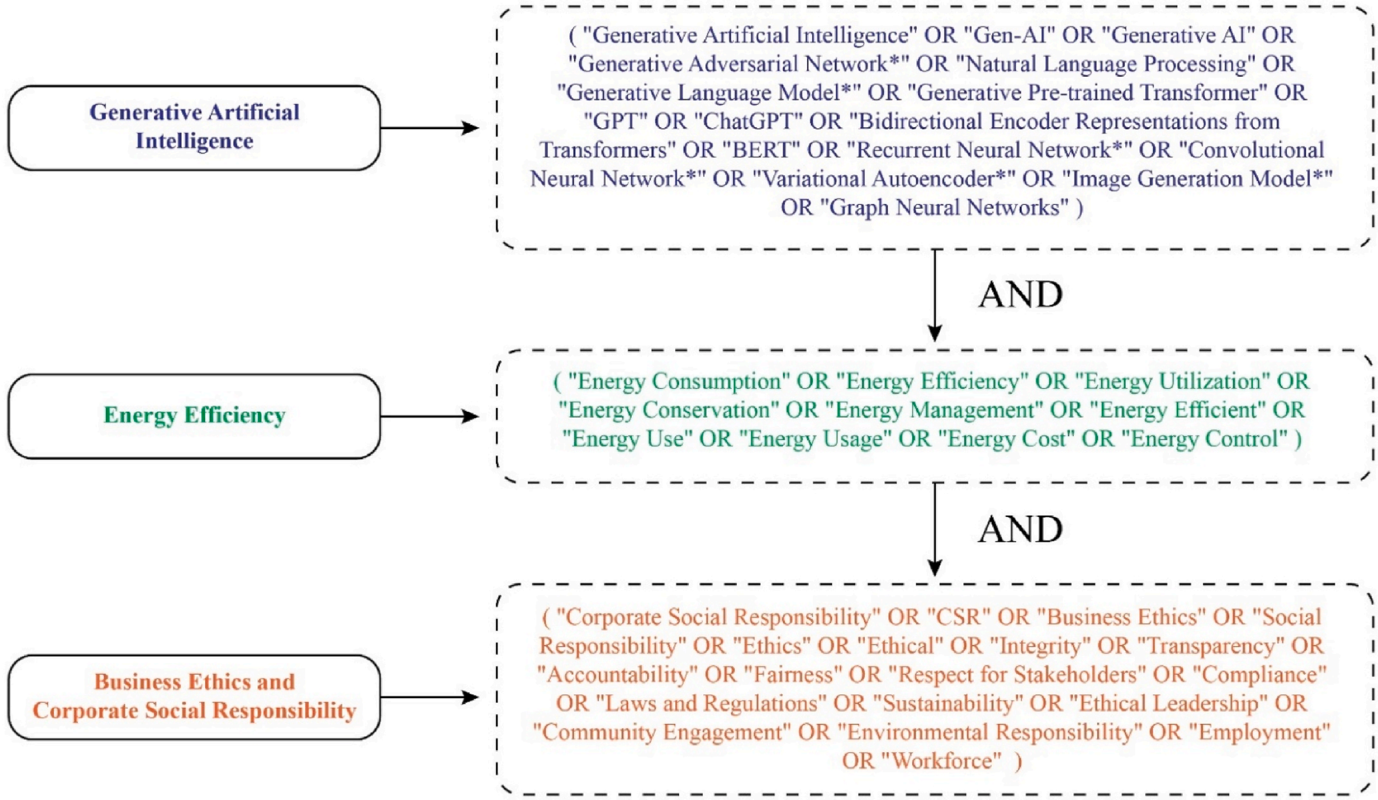

Fig. 2. Search string word tree.

Table 2
Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
Document Type: Article and Conference Paper	Duplicate removal
Document Source: Journal and Conference Proceedings	Not using Gen-AI to improve energy efficiency
Year: Until November 2023	Not addressing BE-CSR principles when using Gen-AI for energy efficiency
Language: English	Documents not available via the databases Documents not available via authors' Research Gate

platform (https://data.mendeley.com/datasets/wrjgynvthf). The first phase collected demographic information, including participants' academic qualifications, professional background, current roles, total years of experience, and country of residence. The second phase aimed to gather data on the perceived impact of Gen-AI technologies on BE-CSR principles, focusing on improving energy efficiency. To ensure the questionnaire's clarity and accuracy, a pre-test was conducted by the authors to identify and correct any potential errors or ambiguities. Before completing the form, all participants were provided with a brief overview of the study's objectives and the topics' relevance. Each participant was asked to evaluate the impact of Gen-AI technologies on the identified BE-CSR principles using a 5-point Likert scale. Responses ranged from 'very low impact' (VLI) to 'very high impact' (VHI), reflecting the experts' assessment of how these technologies influence ethical and social principles.

3.3. Fuzzy DEMATEL (FDEM)

The FDEM method combines fuzzy set theory and the traditional DEMATEL technique to improve expert judgment proficiency (Fontoura et al., 2023), converting cause-effect relationships into an intelligible structural model and identifying the most critical elements that affect other elements (Garcia-Buendia et al., 2022; Keskin, 2015; D. Kumar et al., 2023). The fuzzy set theory introduced the notion of a membership function to address issues related to various linguistic variables (B. Chang et al., 2011), converting highly uncertain linguistic preferences into quantitative values while maintaining human choices and their qualitative characteristics (P.-T. Chang et al., 2000). The defuzzification process reduces a series of conclusions of varying relevance to a single exit point (Cheung et al., 2005).

This method is helpful for visualising complex causal relationship structures with matrices and can convert the relationship between the criteria causes and effects into a comprehensible structural model of system (B. Chang et al., 2011). The fuzzy membership functions $f_{ij}^{k} = \left(f_{l_{ij}}^{k}, f_{m_{ij}}^{k}, f_{r_{ij}}^{k}\right)$ are used to generate the total weighted values, assuming that k experts participated in the evaluation process, which f_{ij}^{k} signifies the fuzzy weight of the i^{th} attribute's effect on the j^{th} attribute as assessed by the expert k^{th} (Fontoura et al., 2023). The cause-and-effect groups containing specific attributes represent the structured interrelationships and essential effects. A set of attributes is proposed (F), and specific pairwise interrelationships are used to create the mathematical relations (Tsai et al., 2020).

FDEM was used in different types and areas of research, such as management, to segment the necessary skills to promote better the development of global managers' skills (W.-W. Wu & Lee, 2007), business, to evaluate Lean Supply Chain Management performance (Garcia-Buendia et al., 2022), manufacture, to discover better energy metrics, production and environmental processes (Fontoura et al., 2023), healthcare, evaluating the universal health coverage in emerging seven economies, highlighting economic conditions and population challenges (Shi et al., 2019), financial market, to identify and prioritise the key criteria that influence the performance of wealth management

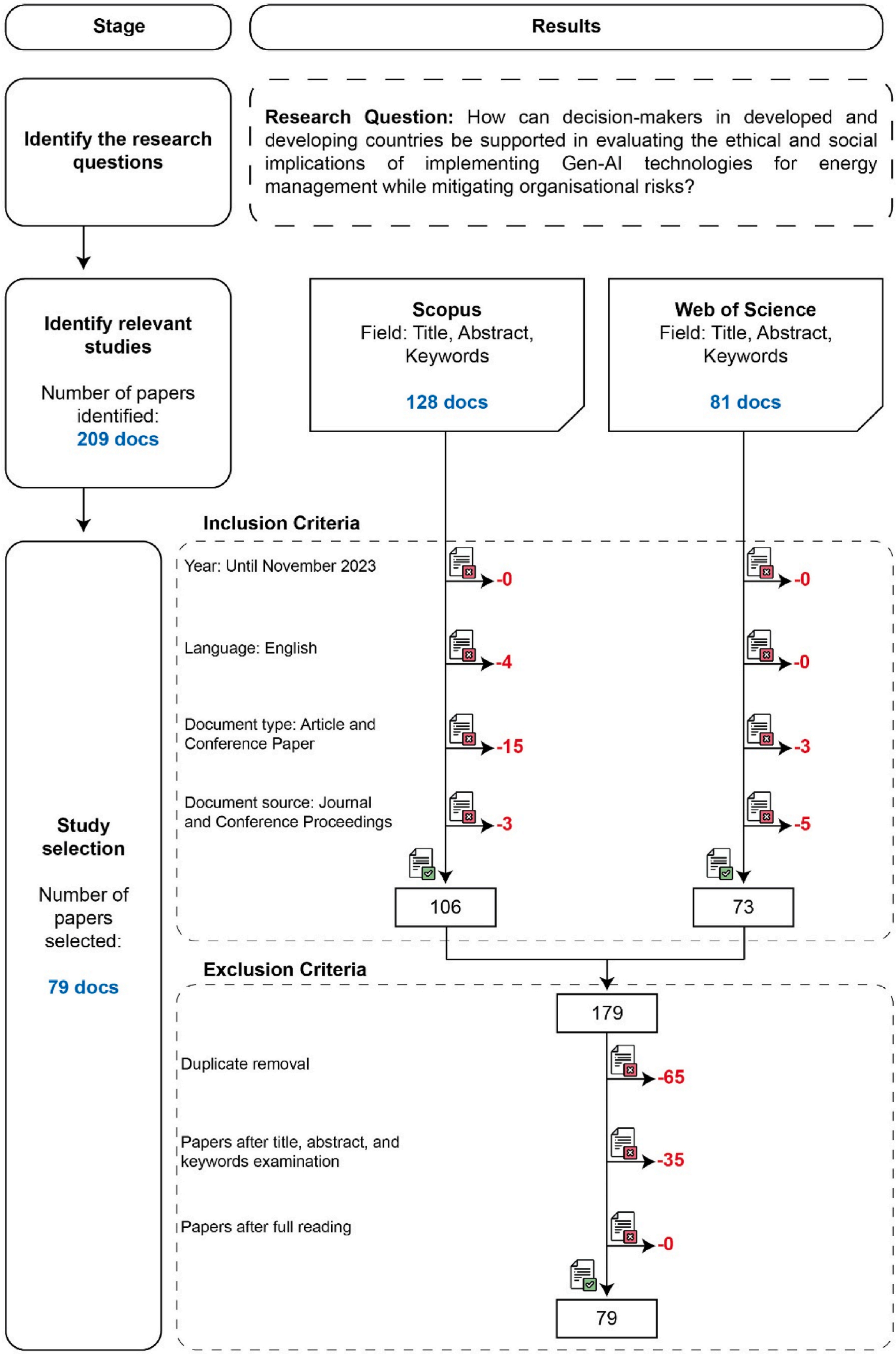

Fig. 3. Study selection.

Table 3
Composition of the expert panels for Fuzzy DEMATEL.

Characteristics	n (%) total Developing countries	n (%) total Developed countries	n (%) total
Experience			
From 5 to 15 years	6 (40.00)	4 (50.00)	10 (43.48)
From 15 to 25 years	4 (26.67)	4 (50.00)	8 (34.78)
Over 25 years	5 (33.33)	0 (0.00)	5 (21.74)
Background			
Engineering	9 (60.00)	3 (37.50)	12 (52.17)
Computing and Information Technology	2 (13.33)	0 (0.00)	2 (8.70)
Business and Management Systems	2 (13.33)	5 (62.50)	7 (30.43)
Finances and Quantitative Methods	2 (13.33)	0 (0.00)	2 (8.70)
Role			
Practitioners	8 (53.33)	2 (25.00)	10 (43.48)
Academics	7 (46.67)	6 (75.00)	13 (56.52)
Qualification			
Bachelor	5 (33.33)	0 (0.00)	5 (21.74)
Master of Science (MSc)	3 (20.00)	1 (12.50)	4 (17.39)
Doctor (PhD or DSc)	7 (46.67)	7 (87.50)	14 (60.87)
Country			
Brazil	15 (100.00)	–	15 (65.21)
Spain	–	4 (50.00)	4 (17.39)
France	–	1 (12.50)	1 (4.35)
Ireland	–	1 (12.50)	1 (4.35)
Portugal	–	1 (12.50)	1 (4.35)
United Kingdom	–	1 (12.50)	1 (4.35)

banks (Lin et al., 2021), and information technology to explore the essential components for constructing a resilient AI cloud system (Alshahrani et al., 2024). This study classified the strength level of the impacts between the resulting Gen-AI-related technologies on BE-CSR principles. Table 4, adapted from Garcia-Buendia et al. (2022), gives the Triangular Fuzzy Numbers (TFN) corresponding to the linguistic terms used in this study.

The proposed FDEM method is divided into six steps, as shown below.

Step 1 Normalise the Fuzzy numbers:

$$F^k_{ij} = \left(f^k_{l_{ij}}, f^k_{m_{ij}}, f^k_{r_{ij}}\right) = \left[\frac{l^k_{ij} - min\left(l^k_{ij}\right)}{\Delta}, \frac{m^k_{ij} - min\left(m^k_{ij}\right)}{\Delta}, \frac{r^k_{ij} - min\left(r^k_{ij}\right)}{\Delta}\right] \tag{1}$$

$$\Delta = max\left(r^k_{ij}\right) - min\left(l^k_{ij}, m^k_{ij}, r^k_{ij}\right) \tag{2}$$

Where:

l^k_{ij} = Left TFN values

m^k_{ij} = Mean TFN values

r^k_{ij} = Right TFN values

Step 2 Compute right (rv) and left (lv) normalised values:

Table 4
Corresponding Triangular Fuzzy Numbers adapted from Garcia-Buendia et al. (2022).

Scale	Linguistic terms	TFN
VLI	Very low impact	(0; 0.1; 0.3)
LI	Low impact	(0.1; 0.3; 0.5)
MI	Moderate impact	(0.3; 0.5; 0.7)
HI	High impact	(0.5; 0.7; 0.9)
VHI	Very high impact	(0.7; 0.9; 1.0)

$$\left(lv^k_{ij}, rv^k_{ij}\right) = \left[\frac{f^k_{m_{ij}}}{1 + f^k_{m_{ij}} - f^k_{l_{ij}}}, \frac{f^k_{r_{ij}}}{1 + f^k_{r_{ij}} - f^k_{m_{ij}}}\right] \tag{3}$$

Where:

$f^k_{l_{ij}}$ = Minimum normalised Fuzzy number

$f^k_{m_{ij}}$ = Mean normalised Fuzzy number

$f^k_{r_{ij}}$ = Maximum normalised Fuzzy number

Step 3 Compute the normalised crisp values (x):

$$x^k_{ij} = \frac{\left[lv^k_{ij}\left(1 - lv^k_{ij}\right) + \left(rv^k_{ij}\right)^2\right]}{\left(1 - lv^k_{ij} + rv^k_{ij}\right)} \tag{4}$$

Where:

lv^k_{ij} = Left normalised value computed

rv^k_{ij} = Right normalised value computed

Step 4 Integrate the crisp values ($\widetilde{x}$):

$$\widetilde{x}_{ij} = \frac{x^1_{ij} + x^2_{ij} + \ldots + x^k_{ij}}{K} \tag{5}$$

Where.

x^k_{ij} = Normalised crisp value computed

K = Total number of respondents

Step 5. Arrange the generalised direct relation matrix (G):

$$G = \left[\widetilde{x}_{ij}\right]_{I \times J} \tag{6}$$

Where:

$\widetilde{x}_{ij}$ = Integrated crisp values

Step 6 Compute the normalised total direct relation matrix (T):

$$T = \tau \otimes G \tag{7}$$

$$\tau = \frac{1}{\max\left(\sum_{i=1}^{I} \widetilde{x}_{ij}\right)} \tag{8}$$

Where:

G = Generalised direct relation matrix

$\widetilde{x}_{ij}$ = Integrated crisp values

3.4. Technology framework

A technology framework was developed using technological determinism, emphasising that technological changes directly cause changes in social structures, institutions and cultural practices (Baek & Lee, 2021) to improve the decision-making regarding Gen-AI for better energy practices, addressing BE-CSR principles. This technology framework was built based on a flowchart using the Business Process Model and Notation (BPMN), which provides a notation system that can be easily grasped by a diverse range of users, including business analysts, technical developers, and business personnel engaged in the implementation and oversight of processes (Chinosi & Trombetta, 2012).

EnGen-AI integrates Gen-AI-related technologies, prioritises energy efficiency, and incorporates BE-CSR principles. This convergence forms a novel technology framework geared towards enhancing sustainable energy management. The framework operates on multiple layers, offering a comprehensive perspective. This holistic view facilitates a better understanding of these technologies' ethical and social implications. It also enables the identification of optimal pathways to achieve managerial objectives. Developed to empower managers and stakeholders, the framework aids in selecting Gen-AI technologies tailored to specific challenges. It considers the country's developmental stage, revealing the varying impacts on BE-CSR principles in response to social, cultural, and technological dynamics.

4. Results

The following section provides a comprehensive analysis of the study's results, focusing on the impacts of Gen-AI technologies. The findings detail how these technologies influence ethical and socially responsible practices. This analysis informed the creation of the EnGen-AI framework, which outlines critical problem statements related to energy management, identifies the most suitable Gen-AI technologies, and links their impact to BE-CSR principles. The framework is a strategic guide for organisations aiming to enhance their ethical standards and operational efficiency through advanced AI solutions. These results form the foundation for the EnGen-AI framework, underscoring its potential to shape future developments in technology and ethics.

4.1. BE-CSR principles have been addressed using Gen-AI to improve energy efficiency

Despite the proliferation of AI technology over the last decade, public perception of its use raises several ethical, legal and social questions, making it necessary to go beyond addressing issues related to algorithms to analyse the translation of legislation and guidelines into practice to ensure BE and CSR principles (Y. Huang et al., 2023). In this way, essential questions arise about integrity (Prabha et al., 2023), transparency and accountability (Dansana et al., 2023), fairness and bias mitigation (C. H. Liu et al., 2019), privacy and data protection (Asha et al., 2023), compliance with laws and regulations (Abdelaziz et al., 2023), sustainability and environmental responsibility (Cabello-López et al., 2023), and employment and workforce (R. Kumar et al., 2021), which are considered essential principles in using AI. Table 5 shows the Gen-AI-related technologies used to improve energy efficiency and BE-CSR principles discussed in the literature.

Among all Gen-AI-related technologies for energy efficiency found in data analysis, which addressed BE-CSR principles, CNNs are highlighted as the most cited technologies to improve energy management, with 45.12% of citations, followed by RNNs with 25.61%. GNNs were the worst cited technologies, with only 1.22%. Regarding BE-CSR principles, sustainability and environmental responsibility stand out as the most cited principle, with 48.86% of citations, followed by integrity, with 18.18%.

4.2. Impacts of Gen-AI-related technologies on BE and CSR principles

A study was conducted to determine the Gen-AI-related technologies for energy efficiency that have the most impact on BE-CSR principles. For this, the FDEM technique was applied to evaluate these influences. The analysis was separated into two clusters: developing countries and developed countries. An analysis to shape the initial direct relation matrices I was applied using all responses collected from experts of each cluster, in which the linguistic scales VLI, LI, MI, HI, VHI ("very low impact", "low impact", "moderate impact", "high impact", and "very high impact") were used. The next step was to convert the initial direct relation matrix I into a Triangular Fuzzy Number (TFN), using the data in Table 4, replacing each linguistic variable with its corresponding number. The defuzzification process uses Equations (1) and (3). Equation (4) used the resulting crisp values to generate the direct relation matrices D. Equation (5) was used to calculate the average values of the direct relation matrices D, followed by the generalised direct relation matrix G, built with Equation (6). The total direct relation matrix T was acquired using Equations (7) and (8), presented in detail in Table 6.

Table 6 shows the impact forces between Gen-AI-related

Table 5
Gen-AI-related technologies and BE-CSR principles.

BE-CSR principles	How Gen-AI-related technologies were approached	Area of impact	Authors
Integrity	Neural networks were employed to safeguard the integrity of information, accomplishing this by skipping links within the network's internal residual blocks.	Data analysis	Han et al. (2023)
	GNNs were applied to optimise cell switching, enhance network data integrity, reduce computational complexity, and ensure adaptive performance in ultra-dense HetNet environments.	Communication Networks	Tan et al. (2022)
Transparency and Accountability	A CNN was employed for real-time traffic analysis, significantly reducing communication delay and power consumption while enhancing attack detection accuracy and throughput. This approach also contributed to increased transparency and security.	Communication Networks	Dansana et al. (2023)
	A bioinspired blockchain-based medical event analysis model was presented. It integrates LSTM, Gated Recurrent Unit, and CNN for disease probability estimation, ensuring high transparency and accountability of alerts.	Healthcare	Purbey et al. (2023)
Fairness and Bias Mitigation	CNN extracted features, aiding mobile terminals in ensuring geographical fairness during data collection across points of interest.	Smart City	Liu et al. (2019)
	The proposed e-Divert framework optimises energy efficiency, data collection, and fairness by leveraging DRL, CNN, LSTM, and bias mitigation strategies.	Autonomous Vehicles	Liu et al. (2021)
Privacy and Data Protection	RNN optimises IoT network performance in smart cities, enhancing prediction accuracy while addressing energy	Smart City	Asha et al. (2023)

(continued on next page)

Table 5 (*continued*)

BE-CSR principles	How Gen-AI-related technologies were approached	Area of impact	Authors
	consumption, privacy, and data protection challenges in WSN systems.		
	A combined approach of deep learning and distributed tracking control is applied to autonomous decision-making in high-speed train systems, utilising GANs to optimise data security, punctuality, and energy efficiency.	Autonomous Vehicles	Wang et al. (2022)
Compliance with Laws and Regulations	A forecasting framework integrating feature selection with a hybrid deep learning model (CNN-LSTM-TCN) was introduced to enable accurate multivariate time series forecasting and ensure compliance with existing standards and norms.	Wastewater treatment plants	Liu et al. (2023)
	GAN is integrated into a constrained optimisation problem to predict scenarios based on specific data inputs and guidelines.	Power Systems	Wang et al. (2023)
Sustainability and Environmental Responsibility	Regression techniques, combined with CNN and RNN models, were employed to enhance the accuracy of sustainable energy management. This approach supports political decision-making, improves network stability, and boosts the precision of national solar energy forecasting.	Power Systems	Cabello-López et al. (2023)
	Incorporating deep learning, the proposed power dispatch model significantly reduces system costs by leveraging an advanced, efficient algorithm to optimise Smart Island grid operations and lower energy expenses.	Power Systems	Gao and Gao (2023)
Employment and Workforce	CNN enabled real-time defect identification and process analysis in manufacturing, integrated with a cyber-physical production system. This approach supports learning factories in training employees to adapt to the challenges of I4.0.	Manufacturing	Kumar et al. (2021)

technologies to improve energy efficiency on BE-CSR principles, based on expert opinions, in which high values represent a stronger impact. Percentage analysis was used to help and facilitate the interpretation of the results, in which for developing countries and developed countries, the percentiles 80 and 60 were computed as limits, representing strong and moderate impacts on the interrelationship (Garcia-Buendia et al., 2022). In other words, values above 0.1622 (developing countries) and 0.1567 (developed countries) were considered to have a moderate impact (yellow), and values above 0.1688 (developing countries) and 0.1715 (developed countries) were considered to have a strong impact (green). Any impact values below percentile 25 (0.1541 for developing countries and 0.1428 for developed countries) were considered insufficient (Fontoura et al., 2023).

4.3. EnGen-AI for better energy management and BE-CSR through Gen-AI practices

EnGen-AI integrates Gen-AI technologies, energy efficiency strategies, and BE-CSR principles to develop an innovative approach for improving sustainable energy management through Gen-AI implementation. Built on technological determinism, EnGen-AI highlights how technological advancements drive changes in social structures, institutions, and cultural practices (Baek & Lee, 2021). It can be used as a guideline for implementing Gen-AI-related technologies in favour of energy efficiency. It allows managers and stakeholders a macro view of which technologies would best apply to the desired project, including observing which impacts would be caused on BE-CSR principles and providing better decision-making. As portrayed in Figs. 4 and 5, the context of development level and area of activity, as well as the nature of the Gen-AI problem at hand, introduces contingencies that significantly influence the selection and impact of Gen-AI technologies on BE-CSR principles in energy efficiency. The disparities between developing and developed countries, marked by variations in technological infrastructure, resource availability, and regulatory frameworks, contribute to the need for tailored solutions.

To effectively utilise the EnGen-AI framework, the manager or stakeholder must first select the context in which they operate, explicitly determining whether the country is classified as developed or developing. This classification is based on the criteria set by the Organisation for Economic Co-operation and Development (OECD). Following this, the manager should define the problem statement, identifying the organisation's specific energy requirements to inform the scope of the study. Once these foundational steps are completed, EnGen-AI will recommend the most suitable Gen-AI technology to address the identified needs. Subsequently, the BE-CSR principles will be identified and assessed based on their level of impact. A colour-coded scale is applied, where green indicates a strong impact and yellow signifies a moderate impact.

In developing countries, as shown in Fig. 4, where challenges such as security vulnerabilities in wireless networks and energy forecasting approaches are prevalent, the emphasis on technologies like GANs reflects a pragmatic response to specific contextual needs. In developed countries, as shown in Fig. 5, where the challenges are to improve renewable energy generation, RNN can enhance forecasting and energy demand methods. The level of impact on BE-CSR principles varies depending on the technologies applied, with privacy and data protection playing a pivotal role in addressing pressing concerns in developing countries. On the other hand, fairness and bias mitigation are among the main concerns in developed countries.

Furthermore, the type of Gen-AI problem and the complexity of the energy efficiency challenge further accentuate the need for diverse Gen-AI tools. For instance, CNNs and RNNs are highlighted for their role in categorising energy consumption levels in buildings and improving the accuracy of renewable energy forecasting. The choice of these technologies underscores their efficacy in addressing specific complexities within the energy efficiency domain. In more complex scenarios, such as

Table 6
Total direct relation matrix T.

Developing countries	E1	E2	E3	E4	E5	E6	E7
T1	0,1740	0,1770	0,1615	0,1799	0,1872	0,1266	0,1556
T2	0,1579	0,1538	0,1428	0,1798	0,1692	0,1359	0,1788
T3	0,1669	0,1431	0,1639	0,1614	0,1643	0,1432	0,1549
T4	0,1554	0,1620	0,1318	0,1580	0,1548	0,1426	0,1550
T5	0,1648	0,1552	0,1779	0,1645	0,1607	0,1410	0,1609
T6	0,1651	0,1656	0,1695	0,1563	0,1624	0,1306	0,1528
Developed countries	E1	E2	E3	E4	E5	E6	E7
T1	0,1426	0,1812	0,1663	0,1346	0,1367	0,1200	0,1851
T2	0,1653	0,1653	0,1629	0,1582	0,1828	0,1145	0,1718
T3	0,1558	0,1868	0,1801	0,1829	0,1160	0,1413	0,1705
T4	0,1491	0,1435	0,1562	0,1732	0,1504	0,1514	0,1327
T5	0,1363	0,1496	0,1905	0,1569	0,1333	0,1324	0,1468
T6	0,1529	0,1453	0,1440	0,1457	0,1440	0,1453	0,1645

Strong impact (percentile 80)
Moderate impact (percentile 60)

T1: Generative Adversarial Networks (GANs); T2: Generative Language Models (GLMs); T3: Recurrent Neural Networks (RNNs); T4: Convolutional Neural Networks (CNNs); T5: Variational Autoencoders (VAEs); T6: Graph Neural Network (GNNs); E1: Integrity; E2: Transparency and Accountability; E3: Fairness and Bias Mitigation, E4: Privacy and Data Protection; E5: Compliance with Laws and Regulations, E6: Sustainability and Environmental Responsibility; E7: Employment and Workforce.

those involving distributed energy generation or innovative city applications, integrating multiple Gen-AI technologies, including GNNs, becomes essential. The contingencies embedded in the energy efficiency landscape thus necessitate a nuanced approach, wherein the selection of Gen-AI tools aligns with the intricacies of the problem, subsequently influencing companies' BE-CSR outcomes. Organisations must recognise these contingencies and strategically adopt technologies that align with their operational needs and contribute positively to ethical and social responsibilities, acknowledging the unique challenges presented by their specific contexts.

5. Discussion

The intersection of Gen-AI technologies and BE-CSR principles, as discussed in the context of energy efficiency, unveils a nuanced landscape that can be analysed through technological determinism. Technological determinism, as a theoretical framework, posits that technological innovation plays a pivotal role in steering societal change. In our exploration, we observe how various Gen-AI technologies influence BE-CSR principles, thereby contributing to the broader discourse on technological determinism. The results underscore the significant impact of Gen-AI technologies on BE-CSR principles, both in developing and developed countries.

5.1. Contributions and impacts of Gen-AI on ethical and social principles

For instance, GANs and GLMs are identified as critical contributors to privacy and data protection in developing countries. The highlights of these technologies include addressing security vulnerabilities in wireless networks and improving accuracy in medical event analysis. This aligns with the technological determinist notion that technological progress equals social progress, as advancements in AI-driven security protocols directly enhance information systems' privacy and data protection. Moreover, the prominence of these technologies also addresses compliance with laws and regulations, resonating with societal concerns about the ethical use of Gen-AI. This alignment fosters public confidence and acceptance of these technologies, influencing organisational behaviour and shaping broader social outcomes. CNNs used for improved energy control have minimal impact on ethical and social aspects, as their primary focus is image processing.

Gen-AI technologies' strong impact on fairness and bias mitigation in developed countries reinforces the technological determinist perspective. RNNs and VAEs are identified as critical players, aligning with the belief that technology can drive positive changes in governance and organisational practices. Additionally, RNNs can analyse historical energy consumption data and help forecast energy demand, optimising load management in manufacturing processes. VAEs, in turn, can detect faults by analysing real-time energy consumption data, reducing systems downtime. All these benefits promote better sustainability and align with the technological determinist assertion that technological progress is inseparable from societal progress. The discussion also sheds light on the varying degrees of impact among Gen-AI technologies on different BE-CSR principles. For instance, GNNs are recognised for their relatively lower impact, mainly because these technologies are system-centred, highlighting the nuanced aspects of technological determinism.

Divergent perspectives exist regarding how technologies influence ethical and social principles, and these perspectives vary based on a country's level of development. Developing countries experience a significant impact of Gen-AI on matters related to privacy and data protection, while in developed countries, the primary impact is on fairness and bias mitigation. For developing countries, these findings regarding privacy and data protection concerns are consistent with existing studies that underscore apprehensions regarding the ethical use of Gen-AI. In this context, data protection is essential due to the sensitive nature of certain information, and inadequate safeguards can lead to unauthorised access, data breaches, and potential data theft, underscoring the need for robust security protocols (Kaissis et al., 2020; Vlačić et al., 2021).

Regarding developed countries, these findings align with society's ongoing anxieties regarding fairness and bias mitigation, which studies caution against the unscrupulous and irresponsible design of Gen-AI technologies, as such practices may perpetuate systemic prejudices and disparities, particularly affecting marginalised groups and potentially exacerbating existing biases (Meyer et al., 2023). In the literature, one of the major concerns with using Gen-AI is the potential for bias and fairness issues stemming from the training data, which reflects the values of its creators and users, resulting in inaccuracies in the model's output (Y. Li & Goel, 2025). As Gen-AI and related technologies advance and become more pervasive in everyday processes, addressing algorithmic bias emerges as a substantial challenge, necessitating the utilisation of diverse datasets and ongoing monitoring to safeguard more accurate decisions (Barredo Arrieta et al., 2020; Ntoutsi et al., 2020).

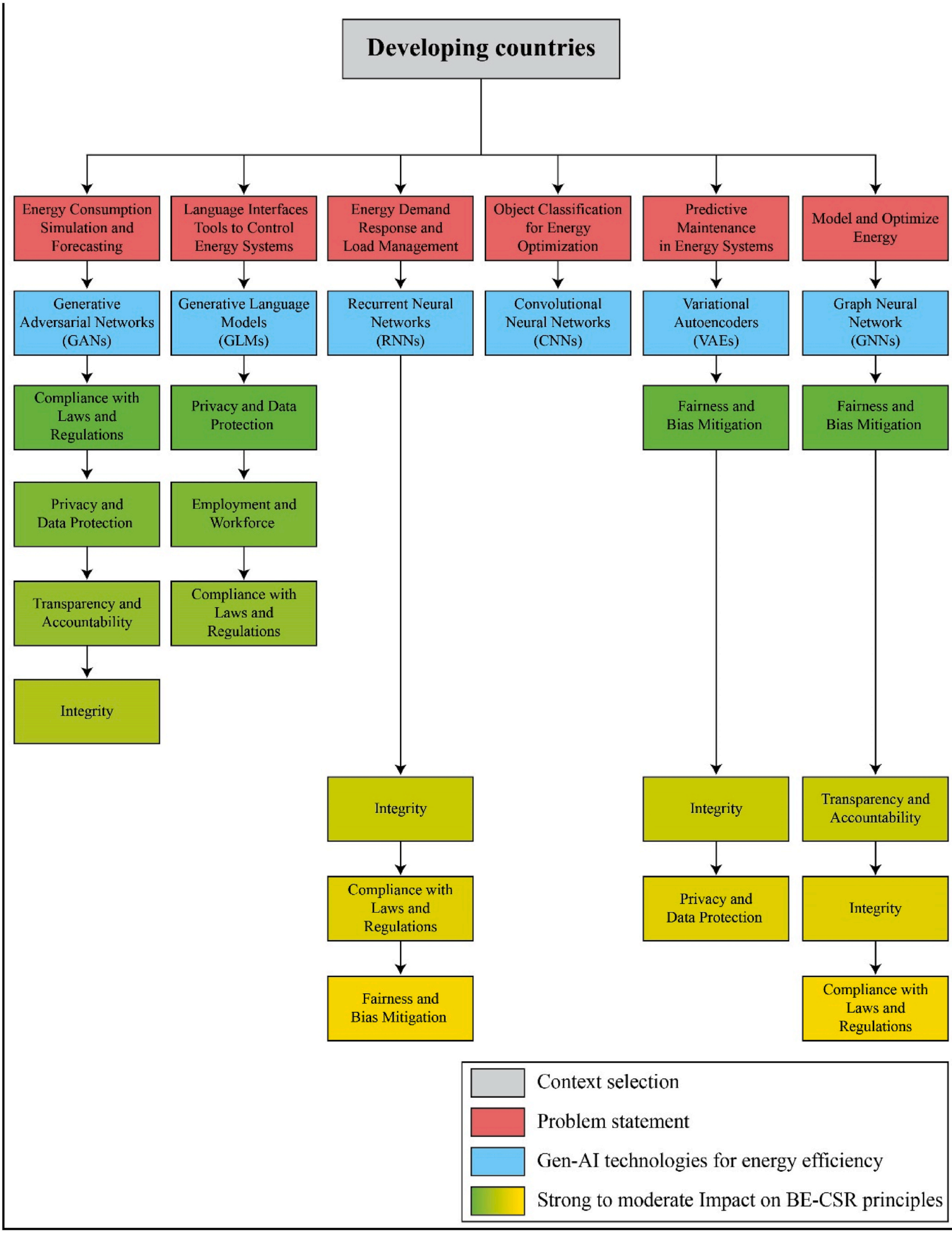

Fig. 4. Energy Gen-AI technology framework in developing countries.

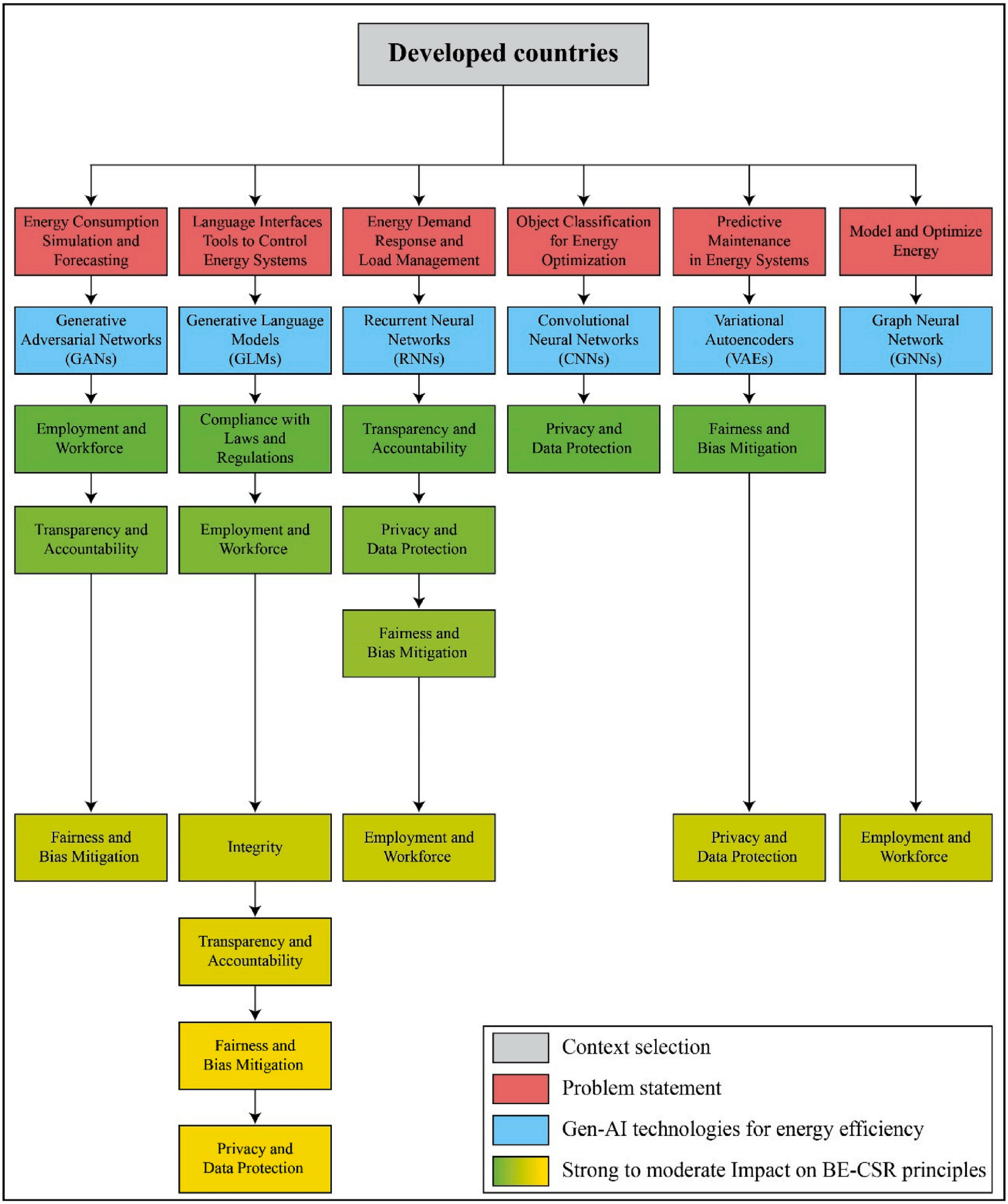

Fig. 5. Energy Gen-AI technology framework in developed countries.

One of the notable research findings reveals that, despite concerns in the literature and public perception about the potential impact of indiscriminate Gen-AI technologies use on employment and the workforce (M.-Huang & Rust, 2018). Experts from developed and developing countries do not regard this issue as among the most significant or pressing. However, it will be a perennial issue requiring close monitoring by the authorities involved since approximately 47% of jobs in the US will face a significant risk in the forthcoming decades (Frey & Osborne, 2017).

Social and economic inequalities often serve as catalysts, amplifying data protection concerns in developing countries where these issues are prevalent. Regarding fairness and bias mitigation, developed countries, with their superior access to advanced technologies, are more concerned about the quality of the data available for training these technologies and how to avoid introducing bias, thus avoiding inaccurate or unfair decision-making. The theory acknowledges that not all technological innovations hold equal influence, and the societal impact is contingent on the nature and design of the technology. Therefore, the findings of the Gen-AI and BE-CSR principles analysis, viewed through technological determinism, provide valuable insights into the intricate relationship between technological advancements and societal progress. The results affirm that Gen-AI technologies are not just tools but active agents shaping ethical considerations and corporate social responsibility, supporting the broader concept that technology is central in influencing and driving social change.

5.2. Theoretical implications

The theoretical implications of the study are to promote innovation by integrating Gen-AI with ethical and social responsibility principles for enhanced energy management control (Thomas et al., 2024). This approach offers a technological perspective and a holistic view of BE-CSR issues, enabling researchers and those interested in the topic to understand the opportunities and impacts of the indiscriminate use of Gen-AI (Wael AL-khatib, 2023). Aligning with technological determinism, the findings affirm the theory's assertion that technological progress drives social change (Sætra, 2023). The role of Gen-AI technologies in shaping BE-CSR principles highlights how technological advancements can actively contribute to ethical considerations and societal responsibilities, emphasising the inseparable link between technological innovation and social progress (Sætra, 2023; Thomas et al., 2024).

Another theoretical advantage of the EnGen-AI framework is its capacity to differentiate its effects between developed and developing countries by considering the varying levels of technological sophistication, regulatory landscapes, and societal needs in these regions. In developed countries, Gen-AI technologies can enhance energy efficiency by leveraging advanced infrastructure and established ethical frameworks, offering valuable insights into how these innovations can further optimise existing systems. In contrast, these technologies may accelerate technological and societal progress in developing countries, addressing specific challenges such as infrastructural deficiencies or regulatory shortcomings. Consequently, the framework offers a more nuanced understanding of Gen-AI technologies' ethical and societal impacts in energy management across diverse global contexts, enabling more tailored and context-specific strategies for each environment.

The study extends the current understanding by demonstrating that human-centred design and technological determinism converge in acknowledging this dynamic interaction, where technology evolves through user feedback, and society continually adapts to new technological advancements. The theory of technological determinism posits that technology plays a dominant role in shaping societal behaviours and structures (Carlisle & Manning, 1999; Herrera-Vega, 2015). In contrast, the principles of human-centred design advocate for technology to be tailored to users' needs and abilities, placing human experience at the core of the design process (Contreras-Cruz et al., 2023). Despite these foundational differences, both paradigms align in certain vital areas. Technological determinism and human-centred design agree that technology aims to enhance the quality of life. Significantly, technology influences society and is shaped by it, indicating a reciprocal relationship between human behaviour and technological innovation.

This study also delineates seven unprecedented aspects of ethical and social issues when examined in the context of Gen-AI technologies most utilised to promote energy efficiency. These aspects are integrity, transparency and accountability, fairness and bias mitigation, privacy and data protection, compliance with laws and regulations, sustainability and environmental responsibility, and employment and workforce. The Gen-AI technologies were categorised and identified for their optimal use in improving energy management, indicating that the proposed framework, EnGen-AI, can serve as a guideline for researchers and those interested in the topic to delve deeper into the impact of these technologies.

5.3. Methodological implications

The study employed mixed methods, including scoping reviews, expert surveys using questionnaires, FDEM, and a technological framework, resulting in significant methodological advancements. This integration enabled a robust and multidimensional analysis. The scoping review comprehensively mapped existing literature, identifying gaps and consolidating evidence to form a solid theoretical foundation. From this, a questionnaire was created to capture expert insights, ensuring the collection of relevant data reflecting current trends. Using FDEM was crucial for examining the connections and the relative significance of different variables, helping to resolve complex and unstructured problems. Finally, integrating this information into a technological framework facilitated the transformation of theoretical and empirical knowledge into actionable recommendations, leading to effective and innovative implementation strategies.

Combining these methods offers multiple advantages for future research. This approach provides a comprehensive, multidimensional perspective, expert insights, and advanced analytical tools. It enables researchers to explore complex and less-studied topics, map knowledge gaps, and understand relationships between critical factors. Additionally, it helps bridge theory and practice, turning academic insights into real-world solutions. The flexibility and rigour of this methodology make it suitable across different fields, allowing for more accurate, insightful, and practical outcomes in future studies.

5.4. Practical implications

The proposed EnGen-AI offer actionable guidance for organisations seeking to enhance their sustainable energy management practices through Gen-AI implementation. Identifying specific Gen-AI technologies and their impacts on BE-CSR principles is a practical tool for decision-makers, helping them align technological choices with ethical and social objectives. The EnGen-AI model provides distinct advantages to developed and developing countries by addressing their unique energy challenges. In developed countries, where energy infrastructure is more advanced, Gen-AI implementation can precisely optimise energy consumption, further reducing CO2 emissions and enhancing efficiency across production chains. Additionally, these countries can leverage the model to comply with stringent environmental regulations, fostering innovation and maintaining global competitiveness. EnGen-AI is a vital tool for improving energy management in developing countries, enabling local businesses to utilise their energy resources more effectively, minimise waste, and boost economic efficiency. Moreover, the model supports social inclusion by advocating for an ethical and sustainable adoption of Gen-AI technologies, assisting these economies in balancing economic growth with social and environmental responsibilities.

EnGen-AI distinctly impacts various actors within the energy industry and other sectors. Industrial companies in the energy sector stand to benefit significantly from Gen-AI by optimising production processes and leveraging time-series data to identify energy consumption patterns. This enables them to implement improvements that lower operational costs and reduce carbon emissions, all while ensuring that the chosen technologies align with ethical and social considerations. For industries outside the energy sector, EnGen-AI can be adapted to enhance energy management, leading to more intelligent resource utilisation and increased efficiency. The framework influence also extends to end consumers, who reap the benefits of more sustainable and responsible business practices, including potential cost savings and a reduced environmental footprint. Ultimately, EnGen-AI catalyses creating a more sustainable and ethical equilibrium among the diverse actors in the economy. The managerial insights were divided into four types: environmental, social, economic, and political.

Regarding environmental insights, using Gen-AI in energy management could allow for more effective use of energy in production processes, identifying patterns in consumption through energy modelling, signalling possible energy improvements to managers, and, through these actions, reducing CO2 emissions. Concerning social insights, thanks to the EnGen-AI as a new driver, organisations could be more aware of implementing Gen-AI-related technologies for energy management, always observing aspects related to BE and CSR, and maintaining the inclusion and development of humans as the centre of activities. Regarding economic insights, the EnGen-AI could promote more efficient energy use in production processes, support demand forecasting, eliminate waste, and thus increase the company's profits. Regarding political insights, the EnGen-AI can guide changes in political regulations for using Gen-AI, ensuring better worker conditions.

6. Conclusions

In addressing the comprehensive research goals, this study has offered valuable insights into integrating Gen-AI technologies for energy efficiency on BE-CSR principles, highlighting how Gen-AI influences BE-CSR principles to enhance energy management practices. The results demonstrate that different Gen-AI technologies play distinct roles in influencing specific BE-CSR principles, offering a comprehensive insight into the diverse effects of Gen-AI on ethical and societal energy management practices. Also, the study delved into identifying which Gen-AI-related technologies impact BE and CSR principles, elucidating the nuanced relationships between technologies such as GANs, GLMs, RNNs, CNNs, VAEs, and GNNs and different facets of BE-CSR principles. The research aimed to identify critical priority areas for improving functional energy management performance through Gen-AI practices, offering a strategic framework for organisations to implement these technologies. In addition to differentiating strategies based on the development level of the countries, the framework also provides a classification of the ethical and social impacts associated with these technologies.

This study significantly contributes to the literature by introducing the EnGen-AI framework, a novel tool for integrating Gen-AI technologies into energy management in alignment with BE-CSR principles. It deepens understanding of how technologies like GANs, GLMs, RNNs, CNNs, VAEs, and GNNs impact BE-CSR, offering a structured impact scale to improve energy management practices. Additionally, the research highlights regional differences in Gen-AI's influence, linking them to cultural and economic factors and offering valuable insights into how Gen-AI is applied across developed and developing countries. On a societal level, the study addresses crucial ethical issues, including Privacy and Fairness, when adopting Gen-AI technologies in energy management. It offers practical, tailored solutions to enhance energy efficiency according to different countries' developmental levels. Furthermore, by addressing concerns over AI-driven job displacement, the research shows that these fears are overstated, helping policymakers and the public develop a more balanced understanding of Gen-AI's role in the workforce.

The focus on Gen-AI technologies and BE-CSR principles within energy efficiency may limit the generalizability of findings to other domains. Additionally, the study assumes a certain level of technological infrastructure and expertise, which may not be universally applicable. To prevent the EnGen-AI framework from becoming inflexible under the influence of technological determinism, it is recommended that managers and users be emphasised in selecting and implementing technologies, as well as ensure that technologies are adapted to the specific needs of each organisation. Encouraging interdisciplinarity, with the active involvement of stakeholders, including experts in ethics, social sciences, and technology, should ensure that all perspectives are considered during the process. An essential consideration in Gen-AI studies is the potential for political bias within its underlying data. Recent research has highlighted that tools like ChatGPT may exhibit a predominant political bias, which can distort outcomes and compromise the objectivity of the recommendations provided (Fujimoto & Takemoto, 2023; Rutinowski et al., 2024). This bias can distort analyses, leading to certain technologies being either favoured or overlooked rather than allowing for an impartial assessment of their ethical and social impacts. To mitigate these biases, it is crucial to incorporate regular human reviews and periodic audits to identify and address potential biases.

Within technological determinism, a potentially overlooked trade-off in adopting Gen-AI for energy efficiency lies in the environmental impact of the expanding technological infrastructure, since with the rapid growth in demand for data centres, driven by the need for massive data processing, storage, and cooling, has led to a significant increase in energy consumption (Baek & Lee, 2021). In some instances, this heightened energy demand can offset the efficiency gains that Gen-AI seeks to achieve. In other words, it is crucial to incorporate a human——and social-centred approach to promote the continuous development of the EnGen-AI framework, adapting it transparently to new technologies and ethical and social challenges so that everyone understands the evaluation criteria. Future research should explore the broader implications of Gen-AI technologies in diverse industries and consider contextual variations to provide a more comprehensive understanding of their impact on BE-CSR principles. In parallel, future research can further investigate various areas to examine the environmental impact of Gen-AI adoption, particularly concerning technological infrastructure and energy consumption.

CRediT authorship contribution statement

Leonardo Fontoura: Writing – review & editing, Writing – original draft, Investigation. **Daniel Luiz de Mattos Nascimento:** Writing – review & editing, Validation, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Julio Vieira Neto:** Validation. **Rodrigo Goyannes Gusmão Caiado:** Conceptualization.

Data availability

Data will be made available on request.

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