Received: 31 December 2022 | Revised: 19 October 2023 | Accepted: 2 January 2024

DOI: 10.1002/bse.3689

RESEARCH ARTICLE

Business Strategy and the Environment WILEY

Artificial intelligence and corporate carbon neutrality: A qualitative exploration

Adeel Luqman[1] | Qingyu Zhang[1] | Shalini Talwar[2] | Meena Bhatia[3] | Amandeep Dhir[4,5,6]

[1]Research Institute of Business Analytics and Supply Chain Management, College of Management, Shenzhen University, Shenzhen, China

[2]Department of Finance and Economics, S P Jain Institute of Management and Research (SPJIMR), Mumbai, India

[3]Birla Institute of Management Technology, Greater Noida, India

[4]Department of Management, School of Business and Law, University of Agder, Kristiansand, Norway

[5]Jaipuria Institute of Management, Noida, India

[6]Optentia Research Focus Area, North-West University, Vanderbijlpark, South Africa

Correspondence
Amandeep Dhir, Department of Management, School of Business and Law, University of Agder, Postboks 422 4604 Kristiansand, Norway.
Email: amandeep.dhir@uia.no

Abstract

Many firms have established formal carbon neutrality (CN) targets in response to the increasing climate risk and related regulatory requirements. Subsequently, they have implemented various measures and adopted multiple approaches to attain these goals. Academic research has given due attention to firms' efforts in this direction. However, past studies have primarily focused on non-digital and process-oriented approaches to achieving CN, with the potential of digital technologies such as artificial intelligence (AI) remaining less explored. Our study aims to address this gap by qualitatively examining the use of AI for pursuing CN, drawing insights from firms with prior experience in the area. We analyzed the collected qualitative data to identify four key dimensions that capture different nuances of applying AI for achieving CN: (a) implementing AI for direct and indirect control of emissions, (b) accepting the strategic trade-offs related to funding, data and systems concerns, and social priorities, (c) overcoming organizational and human-related impediments, and (d) acknowledging the significant impact of AI in terms of gains in business model efficiency and measurable CN target attainment, which ultimately contribute to CN. Based on our findings, we propose a convergence–divergence model encompassing the positive aspects, inhibiting factors, synergies, and offsets necessary for firms to leverage AI to achieve net-zero emissions effectively. Overall, our study contributes to the discourse on the utilization of AI for CN in a comprehensive manner.

KEYWORDS
artificial intelligence, carbon emission, carbon neutrality, digital technologies, energy management, regulatory mandates

Abbreviations: AI, artificial intelligence; CN, carbon neutrality; CO2, carbon dioxide; EV, electric vehicles; GHG, greenhouse gas; PHEVs, plug-in hybrid electric vehicles; TEMC, transport, energy, manufacturing, and construction; WEF, World Economic Forum.

1 | INTRODUCTION

Firms have been actively addressing environmental concerns by restructuring their manufacturing and distribution practices (Cheng et al., 2021). Concurrently, they have sought to raise awareness by launching advertising campaigns promoting the production of eco-friendly products such as recycled plastic toothbrushes, toilet paper, and plastic rugs (Zhao et al., 2022), and solar-powered transportation (Okuyama et al., 2022) in addition to bolstering their green reputation among consumers (Dolge & Blumberga, 2021). Over time, national regulators, the United Nations, and scholars have recognized the progress made by firms across diverse sectors in reducing carbon emissions. However, these endeavors have proven insufficient in enabling firms to fulfill their commitments to carbon neutrality (CN) effectively (Zhang et al., 2022), whereby carbon emissions are balanced with offsetting approaches (IPCC, 2022). Given that the escalating climate risk has become one of the most significant global challenges, the inability to achieve CN poses an issue that cannot be disregarded. Scholars argue that technological innovations, particularly digital advancements, can assist firms grappling with this challenge and facilitate a successful transition toward CN.

Endorsing this view, the World Economic Forum (WEF) acknowledges that adopting digital technologies can enhance resilience to global warming, natural disasters, and emissions control, thereby assisting firms in combating anthropogenic emissions and achieving CN (WEF, 2022). According to recent reports, the automation capabilities of AI can streamline repetitive and time-consuming tasks, enabling businesses to reduce global emissions by up to 4% (WEF, 2022). Notably, scholars contend that specific digital technologies, such as artificial intelligence (AI), can substantially enhance the operational efficiency of firms, make logistic processes resource-efficient, lower emissions, and support the green economy in general (e.g., John et al., 2022; Su & Fan, 2019).

Motivated by the green potential of AI, existing scholarship has expended considerable effort in examining the role of AI in activities that can inhibit carbon emissions. A comprehensive review of the literature indicates that past studies have examined the application of AI for improving business processes (e.g., Damoah et al., 2021), carbon emission measurement and forecasting (e.g., Scherz et al., 2022), carbon pricing (e.g., Ma et al., 2023), energy management (e.g., Zhao et al., 2021a; Zhou et al., 2022b), energy systems (e.g., Diao et al., 2021; Li & Maréchal, 2023), renewable energy (e.g., Heo et al., 2022; Natgunanathan et al., 2023), transportation scheduling (e.g., Wang et al., 2022), and waste management (e.g., Hai et al., 2022; Li et al., 2022). Proof of the growing use of AI for reducing emissions is Boston Consultancy Group's CO_2 AI, which has helped boost the accuracy of emission measurement and enabled a nearly 40% reduction in emissions of some large corporations (Minevich, 2021). AI is generally being applied to counter several climate change challenges through actions such as optimizing electricity grids (Chasan, 2023). A deeper probing of the literature indicates that despite the documented positive outcomes, the use of AI to achieve CN is not without complexities. It is generally known that its integration into business activities presents various climate-related challenges, including increased energy consumption, increased greenhouse gas (GHG) emissions through e-waste and recycling processes (Gupta et al., 2021), and issues related to the limited lifespan and management of AI waste (M. Fan et al., 2022).

Broadly speaking, scholars caution that adopting AI comes with limitations that should be considered to avoid overestimating its power (Allal-Chérif et al., 2021). Seeking to examine the overtones and connotations in this context, we observe that the debate surrounding the negative consequences of AI, such as economic impacts (Fan & Friedmann, 2021), social implications (Algarvio, 2021), and environmental performance concerns (Lippiatt et al., 2020), is still evolving, with a distinct lack of consensus prevailing in these discussions. This indicates a need for further dissecting the perils of using AI as an apparent panacea for emission-related challenges. Succinctly, the inability of the existing literature to provide conclusive evidence on this aspect represents a gap in research. We contend that, given the transformative power of AI for businesses and the growing criticality of climate risk, such a gap in understanding cannot be left unresolved. In addition to this, a closer investigation of the literature also indicates that while the past studies cover various aspects of the implementation of AI for achieving CN, a significant majority of them have focused on AI-based optimization models. In comparison, the literature is noticeably devoid of empirical evidence elucidating on-the-ground realities of AI implementation and other practical issues from a managerial perspective. As a result, the accumulated knowledge offers limited insights for firms contemplating using AI to achieve CN targets. We argue that this is a serious knowledge gap that reduces the practical takeaway of the extant findings and should thus be remedied expeditiously. Existing scholarship has also taken note of the currently narrow understanding of the long-term effectiveness and potential unintended consequences of AI implementation, calling for further research in this area (Shashi, 2022; Walsh et al., 2020). Putting the preceding discussion in perspective, we reiterate that there is a need to evolve a better understanding of the gains that AI has to offer and the trade-offs involved in its adoption for the achievement of CN targets.

Motivated by this need, we propose to examine and elucidate the actual experiences of firms that have already implemented AI in their businesses to achieve CN targets. Formally, we seek to address the following research question (RQ): How have firms leveraged AI in their businesses to pursue and achieve their CN targets, and what have been the offsets its adoption entailed for these firms?

Consistent with our research question, which aims to explore the less understood aspects of utilizing AI for achieving CN, we have adopted an inductive grounded theory approach introduced by Glasser and Strauss (1967). To operationalize this approach, we collected qualitative data through open-ended essays, allowing us to gain a comprehensive understanding of the experiences and perspectives of firms that have already implemented AI for CN. Analysis of the collected data helped us identify seven dimensions that offer a fine-grained explanation of the intricacies of using AI for pursuing CN: direct emission control measures, indirect emission control measures, strategic trade-offs, organizational impediments, people impediments, achieving CN targets, and business model efficiencies.

The significant contribution of our study comes from the comprehensiveness of insight it offers on various aspects of the use of AI for achieving CN. To elaborate, our findings provide a 360-degree understanding of the topic at hand by explaining the purpose of implementation, the unavoidable trade-offs, the impediments that act as barriers to the effective leveraging of AI for achieving CN, and a wide-ranging explanation of the positive and negative impact on people and processes. By providing such a multi-faceted understanding, our study offers a useful point of reference for managers, clarifying actionable pathways to support their strategic decisions. We further enhance the industry relevance of our study by offering a precise set of factors that make the implementation of AI appealing, and an extensive set of factors that compel managers to take a more cautious view while contemplating the use of AI for achieving CN targets. The comprehensive framework developed inductively also offers a bird's eye view to researchers aiming to advance the research in the area.

In sum, our study contributes to both research and practice by systematically revealing the convergences and divergences inherent in the application of AI for achieving CN. At the same time, by analyzing the qualitative responses collected from 22 firms that have already implemented AI-based solutions for pursuing their CN targets, we present a detailed and nuanced view of the synergies and offsets that need to be fully appreciated for the successful implementation of AI for CN.

2 | AI AND CN

Climate change and risk are the most debated topics in scholarly literature, popular press, industry forums, and policy circles. A large part of the conversation has now swung from identifying the climate risks to discussing how to best combat the issues. CN has taken a central role in this discourse, and the approaches that can help to achieve it have become the focal point of concern. The resultant literature has been focused largely on several process-based approaches, such as carbon capture and storage, with a comparatively narrow focus on digital technologies to achieve CN. Nevertheless, the limited literature that has evolved, particularly around the use of AI for CN, is quite informative and promising.

A review of the literature on the role of AI in climate change reveals that existing scholarship has acknowledged the effectiveness of AI in achieving CN goals in sectors such as energy, transportation, construction-building, and manufacturing (e.g., Shi et al., 2021; Xi et al., 2021; Zhou et al., 2022b) (see Table 1). In sum, the research on the use of AI in these and other sectors, such as health care, can be categorized under the following clusters, which are distinct but not all voluminous in terms of the number of studies: (a) business processes, (b) carbon emissions and measurement, (c) carbon pricing, (d) energy management, (e) energy systems, (f) renewable energy, (g) transportation scheduling, and (h) waste management. The key findings under each of the clusters are summarized below.

In discussing the use of AI for some or other business activities/processes, a set of studies has noted its contribution to improved decision-making and reduced environmental consequences. For instance, Allal-Chérif et al. (2021) discussed how AI was being used effectively in the purchasing departments of firms by taking procurement activities beyond just operational decisions to make them more strategic, and Su and Fan (2019) discussed the efficacy of AI in green logistics. Providing evidence to further support the positive impact of AI as a key enabling technology for business processes, John et al. (2022) noted its capability to reduce barriers impeding sustainability-related innovations, and Damoah et al. (2021) showcased its effectiveness in healthcare supply chains.

A notable number of recent studies on using AI to achieve some or the other CN objectives have discussed three aspects: carbon emissions, emission measurement, and carbon pricing. Most studies conforming to the two clusters—carbon emissions and measurement—have either emphasized the need for better forecasting of emissions to support policymaking or suggested ways to measure emissions in different sectors. Studies aimed at addressing the need for improved forecasting have suggested models such as new information-based gray model (Ding & Zhang, 2023), ensemble prediction system with both point and interval estimates of future emissions (Liu et al., 2022), and predictive model for estimating global warming (Babatunde et al., 2020). In addition, some studies also proposed models for determining fuel combinations and building designs to lower emissions. For example, Bhowmik et al. (2018) developed a model to determine the optimal operating parameters for varying fuel combinations and Scherz et al. (2022) presented decision support systems that could be useful in designing carbon-neutral buildings.

Coming to research on carbon pricing, studies have made specific contributions, such as assessment of carbon markets as a solution to offset the costs of emissions efficiently (Cao et al., 2022), the use of optimization techniques for purchasing carbon emission rights in carbon spot and future markets (Ma et al., 2023), and the development of a multi-factor decomposition and integration carbon price forecasting model (Zhao et al., 2021b).

As expected, the largest number of studies on the application of AI for CN focused on one or more aspects of energy. We divided them into three clusters: energy management, energy systems, and renewable energy. The studies categorized under energy management discussed aspects such as consumption, efficiency, and optimization. Of these, the emphasis on the development of predictive and other models was quite apparent, with studies proposing models such as a fuzzy logic-based model for predicting the concentration of harmful emissions in flue gases arising from combustion of coal and biomass (Krzywanski et al., 2022), a theoretical intelligent strategic bidding simulation model for the electricity market (Wu et al., 2022), and a transfer learning routine to support real-time energy management for plug-in hybrid electric vehicles (PHEVs; Zhou et al., 2022b). Several other studies developed AI-based models for energy management in different contexts, such as smart homes (Rocha et al., 2021), manufacturing (Huang et al., 2019; Xi et al., 2021), PHEVs (Zhao et al., 2021a), residential buildings (Tien et al., 2020), and off-grid microgrid (Kumar et al., 2019).

Continuing the discussion on energy, but shifting focus to energy systems, we find that the congruent studies in this cluster also focused on developing AI-based models. For example, X. Li and Maréchal (2023) developed a model for quantifying the impact of uncertainty on national-level energy systems, and Diao et al. (2021) proposed a deep learning architecture for energy system design and predicting power cycle performance.

TABLE 1 Literature review.

Study	Data and Method	Country	Main variables
Ding and Zhang (2023)	New-information-based gray model/Monte-Carlo simulation/probability density analysis/ experiments	China	Forecasting provincial carbon emissions
Ma et al. (2023)	Lyapunov optimization technique/theoretical analysis and simulation/modeling	China	Carbon-aware ML task offloading/green edge AI/purchasing carbon emission rights in carbon spot and future markets
Li and Maréchal (2023)	Optimization/Monte Carlo simulation/AI/case study	Switzerland	Energy autonomy/carbon neutrality/negative emissions/uncertainty impacts on the energy system
Natgunanathan et al. (2023)	ML-based prediction models/computational experiments/real-world data generated from Deakin Microgrid	Australia	Prediction of generated power from the Deakin solar farm
John et al. (2022)	Systems thinking/multi-level perspective/review of technical scientific articles/semi-structured interviews	Netherlands	Socio-technical impact of AI as a key enabling technology
Scherz et al. (2022)	Hierarchical decision modeling (HDM)/systems thinking methodology/life-cycle perspective/ modeling	UK	Integration of sustainability requirements inthe early design phase of buildings/carbon-neutral buildings
Cao et al. (2022)	Metrics for evaluating the carbon efficiency of a data center	China	Carbon neutral data centers/carbon market
Krzywanski et al. (2022)	Fuzzy logic/simulation/experimental studies	Poland	Prediction of polluting gaseous emissions from advanced combustion
Wu et al. (2022)	Multi-agent transfer learning (MATL)/multi-agent reinforcement learning (MARL)/simulation experiment/open source data	China	Electricity market/MATL algorithm comparison
Zhou et al. (2022b)	Modeling/adaptive neural fuzzy inference system/Gaussian process regression/ experimental evaluations	UK and China	Reduce the development workload for the energy management controller
Heo et al. (2022)	Data processing techniques/variational autoencoder (VAE)/explainable artificial intelligence (XAI)/deep learning-based generative modeling/stochastic scenarios/ offshore wind speed datasets and energy data obtained from petrochemical industrial parks	South Korea	Forecasting model for offshore wind farms (OWFs)/techno-economic and environmental assessments
Wang et al. (2022)	Optimization/modeling/hybrid algorithm based on PSO and gray wolf/sensitivity and robustness analysis	China	EV charging stations
Hai et al. (2022)	Genetic algorithm/simulation/sensitivity analysis	China	Waste heat recovery/GHG emission reduction/ integrated energy system
Huseien et al. (2022)	Metaheuristic shuffled frog leaping algorithm/ experiment	Singapore	Construction material/waste recycling/reduction in energy consumption
Li et al. (2022)	ML algorithms	China	Predicting CO_2 production from green waste composting
Liu et al. (2022)	Time-varying filter-based empirical mode decomposition (TVF-EMD)/statistics/ANNs/ deep learning predictors	China	Ensemble prediction system for forecasting emissions
Zhou et al. (2022a)	Review of learning mechanisms of AI-based applications/review of AI applications for renewable energy utilization and intelligent buildings	China	AI in buildings and renewable energy systems/ carbon-neutrality transition in building sector
Zhou (2022b)	Review of advanced ocean energy converters/ power supply characteristics of ocean energy resources/hybrid ocean energy storages with synergies/application of diversified ocean energy systems/application of AI	China	Ocean energy/reducing carbon emissions/carbon neutrality/application of AI

TABLE 1 (Continued)

Study	Data and Method	Country	Main variables
Zhao et al. (2021b)	Hodrick–Prescott filter/meta-analysis/partial correlation function (PACF)/least absolute shrinkage and selection operator (LASSO)/modeling	China	Carbon price forecasting model
Zhao et al. (2021a)	A variety of battery sizes and innovations for EV and PHEVs/modeling	China	Environmental carbon pollution and management/AI assisted V2G for a plug-in hybrid vehicle
Allal-Chérif et al., 2021)	Exploratory, inductive, and qualitative approach based on a multiple case studies	France	Purchasing and the performance of purchasing departments
Damoah et al. (2021)	Documentary and in-depth semi-structured interviews	Ghana	AI-enhanced medical drone application in health-care supply chain
Rocha et al. (2021)	Elitist non-dominated sorting genetic algorithm II/support vector regression technique/numerical simulations/real data from a smart home/K-means clustering technique	Brazil	Energy demand planning in smart homes/forecast of a distributed generation
Xi et al. (2021)	Gradient boosted regression trees with Bayesian optimization/particle swarm optimization (PSO) algorithm/case studies/sensitivity analyses/real-world weather data	China	Efficient utilization of gases in steel mills for power supply/deployment of carbon capture technologies, use of renewable power/carbon neutrality
Diao et al. (2021)	Convolutional neural networks (DL-CNN)	China	Performance prediction of power cycle
Liu et al. (2021)	Machine learning algorithms	China	New energy materials/data-driven materials/global carbon neutrality/application of AI & ML
Shukhobodskiy et al. (2021).	RED WoLF hybrid storage system/simulation/progressive threshold approach	UK	Energy consumption in residential dwellings/reducing load from the electrical grid/savings in emissions
Sadoudi et al. (2021)	Elephant herding optimization/scenario analysis	Algeria	Interconnected microgrid/renewable energy sources/power management
Babatunde et al. (2020)	Case study/predictive modeling/fuel flowrates and air–fuel mass ratios (AFRs)/Aspen HYSYS 8.8/GaBi 8.0/GMDH Shell DS 3.8.9/Microsoft Excel software	Nigeria	Global warming potential/carbon tax
Tien et al. (2020)	Convolutional neural network/modeling/building energy simulation (BES) tool	UK	Building energy management systems/vision-based deep learning approach
Kempitiya et al. (2020)	AI-based bidding optimization/case study	Finland	Frequency reserves of renewable energy/frequency reserves market
Kumar et al. (2020)	Simulation-optimization approach	India	Energy consumption of electric-powered bus system
Zhang et al. (2020)	AI and metaheuristic algorithms	Australia	Optimizing mixtures of recycled aggregate concrete (RAC)
Su and Fan (2019)	Optimization/modeling/computational experiments with simulation data	China	Intelligent logistics/green logistics/green vehiclerouting problem
Pulselli et al. (2019)	Carbon accounting methodology	Italy	Assess GHG emissions in urban environments/carbon footprint of urban neighborhoods/spatial visualization of forestland
Huang et al. (2019)	Optimization/modeling/case study	South Korea	Industrial energy management
Kumar et al. (2019)	Optimization/modeling/economic analysis	India	Multi-energy off-grid microgrid
Bhowmik et al. (2018)	Multi-objective response surface methodology (MORSM)/modeling/artificial neural network/AI	India	Performance and exhaust emissions of diesel engines fueled by Diesosenol blends

Another prominent cluster of studies found in the congruent literature focused on the role of AI in the management of renewable energy. This is as expected since one of the prominent ways of lowering emissions that is considered feasible the world over is the substitution of fossil fuels with renewable energy sources. In some of the recent studies in this regard, Natgunanathan et al. (2023) discussed the digital twin of the Deakin Microgrid, a facility for researching solar energy data, and Zhou (2022b) reviewed the use of AI to understand its role in promoting sustainable ocean energy systems.

Notably, several studies grouped under this cluster also developed and discussed AI-based models such as an explainable AI-based generative model producing stochastic scenarios for renewable energy (Heo et al., 2022); an AI-based optimization and control strategy for an interconnected microgrid of wind turbines, solar power, and photovoltaic generators (Sadoudi et al., 2021); a generalized model for the operation of frequency reserve markets for renewable energy (Kempitiya et al., 2020); and AI applications for renewable energy utilization (Y. Zhou, 2022a).

The remaining relevant studies either discussed transportation scheduling or waste management since these two activities can substantially impact emissions and their reduction. In these two clusters too, the previously observed emphasis on AI-based model development was noted. The studies related to transportation proposed models such as optimal and economic EV charging stations (Wang et al., 2022) and a simulation-optimization approach to manage energy consumption in electric-powered bus systems (Kumar et al., 2020).

In the case of the final cluster, waste management, the models proposed include an AI-based genetic algorithm to reduce emissions and environmental costs of a hybrid energy system based on fuel from a wastewater treatment plant (Hai et al., 2022), an informational algorithm-based model to assess high-strength alkali-activated mortars made from waste bottle glass nanoparticles with ground blast furnace slag and fly ash (Huseien et al., 2022), a hybrid intelligent system to determine optimal mixtures of recycled coarse aggregate (Zhang et al., 2020), and an ML-based model to predict CO_2 release during green waste composting (Li et al., 2022).

The preceding discussion underscores the notion that past studies are skewed towards optimization models and design issues. As a result, empirical insights on the implementational aspects and the firm-level experiences related to the use of AI for pursuing CN targets are practically non-existent. This gap in understanding severely limits the usefulness of the accumulated findings, making it imperative for researchers to suitably address the deficit.

Furthermore, although the literature around the use of AI is heavily skewed towards acknowledging its multiple benefits, some studies in different settings have raised a word of caution that the integration of AI in businesses might itself pose climate-related challenges arising from energy consumption, e-waste management, and related environmental issues (M. Fan et al., 2022; Gupta et al., 2021). At the same time, scholars are still debating whether AI brings with it certain economic, social, and other issues (Algarvio, 2021; Fan & Friedmann, 2021). The debate is far from settled and remains too coarse-grained at the moment. Overall, the understanding of adverse outcomes of using AI for pursuing CN, various barriers encountered by firms trying to implement AI for this purpose, and the tangible outcomes of such an implementation are limited.

3 | METHODOLOGY

3.1 | Research context

The research context of our study is situated in the broad socio-economic landscape characterized by escalating climate risk, rising debate on the responsibility of firms to control polluting emissions, global calls for pursuing CN targets, and strict regulatory mandates imposed by governments. Within this context, our study aims to investigate the on-the-ground realities and real-life experiences of firms that have taken the initiative to implement AI in pursuit of their CN targets. Furthermore, our study focuses on firms operating in the transport, energy, manufacturing, and construction (TEMC) sectors, since these are known to be among the highest emissions contributors.

3.2 | Research design

Although climate change has been a widely discussed topic, the debate around corporate CN and the use of AI for achieving it is still in an evolutionary state. As discussed in the preceding sections, our understanding of various aspects of leveraging AI for CN is not as refined as it could be. As a result, to better elucidate the intricacies involved, we opted to undertake an exploratory qualitative examination of the topic. Our decision to employ a qualitative research design is motivated by scholarly recommendations based on its inherent emphasis on exploring intricate phenomena, capturing rich descriptions, and generating comprehensive insights (Maxwell, 2000). Using a qualitative approach facilitated an in-depth exploration of the intricacies and varied dimensions of implementing AI for achieving CN.

Specifically, we used open-ended essays to collect written responses from participants through a set of questions. This method has been gaining popularity in the academic literature (e.g., Dhir et al., 2017; Talwar et al., 2021a). The essay-type survey method enabled us to seek detailed textual responses from the study respondents, providing extensive input for a comprehensive exploration of firms' experiences. We derived the set of open-ended questions for the study by comprehensively reviewing the available literature and seeking expert input to refine them. Through these questions, we tried to understand how firms currently use AI to achieve CN, how effective those initiatives are, what the different implementation-related challenges and problems are, and what major gains, if any, have emerged.

3.3 | Data collection and sampling

We solicited participation from employees of firms that had already implemented AI to achieve CN. The participants were recruited through an online platform, and participation was kept voluntary. Since we wanted participation among employees who could be considered key informants based on their knowledge and experience using of AI for CN, we executed the data collection process in multiple phases *or* waves, followed by data analysis. The entire process is illustrated in Figure 1.

In the first and the second phases, we conducted two screening surveys, inviting participation from full-time employees of firms operating in the TEMC sectors. The purpose of screening surveys was to identify key informants who work at managerial levels and are closely associated with the AI-CN project in their firms. In the third phase, we collected qualitative responses to our main study's open-ended questions. We kept the study open, checking the data continuously, and closed it when theoretical saturation was reached. As a result, we ended up with 22 complete responses from respondents working in full-time managerial roles in firms in the TEMC sectors.

Of the 22 respondents, the majority were male (86%). The age distribution of respondents fell into the following ranges: 26–30 years (18%), 31–35 years (36%), 36–40 years (9%), 41–45 years (23%), and 51 years or above (23%). In terms of employment, manufacturing had the highest representation (55%), followed by construction (27%). The transportation/logistics and energy sectors accounted for approximately 14% and 5% of the respondents, respectively.

In the fourth phase, we analyzed all 22 responses inductively to generate first-order concepts, second-order themes, and aggregate dimensions, as described below.

3.4 | Data analysis

We followed the iterative coding process suggested by Gioia et al. (2013) to analyze the data, presenting the findings through a data structure diagram comprising first-order concepts, second-order themes, and aggregate dimensions. Our choice of the Gioia et al. (2013) approach was guided by the knowledge that using an established coding method enhances the credibility and rigor of the data analysis process. We were also motivated by the knowledge that qualitative researchers widely adopt the coding method proposed by Gioia et al. (2013) due to its effectiveness in analyzing textual data and generating meaningful insights (Hannigan et al., 2019; Petrescu et al., 2023).

Following this approach to analyzing the data purely inductively, we used respondents' words to populate first-order concepts. Thereafter, we systematically developed the second-order themes, consolidating them into aggregate dimensions. We kept the first-order concepts as close to informants' voices as possible, with the second-order theme being researcher-based.

Adequate precautions were taken to ensure objectivity and minimize confirmation bias in our coding process. We followed a multi-step process, wherein, first, two authors independently coded the data to generate zero-order codes, which were then consolidated into first-order concepts. Discrepancies in coding were discussed to achieve inter-coder reliability. All coding was done manually. In the second step, the remaining members of the author team, who were not a part of the initial coding, checked the codes generated by the coders. They added their comments and observations. In the third step, we compared the results of both groups to determine the second-order themes and aggregate dimensions. Since the responses were solicited from experienced professionals working in firms with relevant, hands-on experience in using AI to achieve CN targets, there was quite a lot of clarity and preciseness in the collected data. As a result, there were very few discrepancies in the coding executed independently by the author team. While we found minor discrepancies in the naming of aggregate dimensions, the consensus was easy to achieve.

3.5 | Validity and reliability

In qualitative research, ensuring validity and reliability is crucial for maintaining the credibility and trustworthiness of the findings.

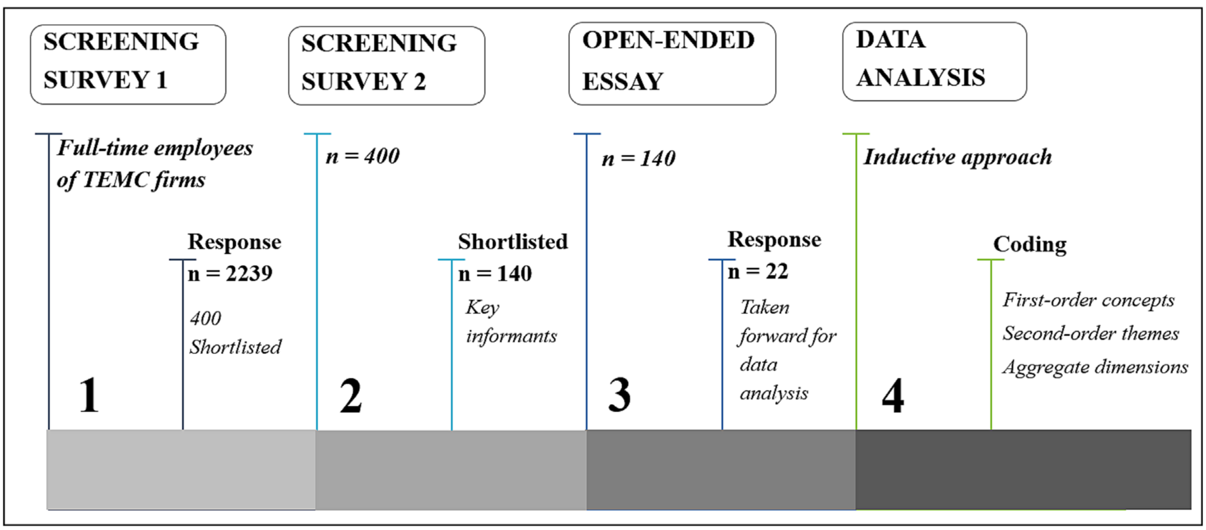

FIGURE 1 Phases of data collection and analysis.

Following the seminal recommendations of constructive and evaluative procedures (e.g., Guba & Lincoln, 1981; Whittemore et al., 2001), as used varyingly in recent studies (e.g., Iyanna et al., 2022), we employed several strategies to enhance the validity and reliability of our study, as tabulated in Table 2.

4 | RESULTS

Through the three-step coding process described above, we developed 18 second-order constructs and consolidated them to obtain seven aggregate dimensions. The data structure diagram is presented in Figures 2(a–c).

For ease of understanding and clarity of explanation, we have further categorized the aggregate dimensions under four illustrative heads: implementation, trade-offs, impediments, and impact. *Implementation* captures how the firms are using AI for CN. We have grouped direct emission control measures and indirect emission control measures under this head. Herein, direct emission control measures comprise three second-order themes: emission management (measurement and reduction), energy consumption, and sustainability-oriented practices, and indirect emission control measures comprise three second-order themes: leanness, operational efficiency, and functional effectiveness.

Next, *trade-offs* represent the give and take the firms had to consider in executing their plans to use AI for CN. In our data structure, trade-offs comprise only one aggregate dimension—strategic trade-offs—with three second-order themes: seeking funding support, addressing data and systems concerns, and acknowledging social priorities.

TABLE 2 Validity and reliability.

Strategy	Operationalization	Process
Sample appropriateness	Identification of key informants for participating in the study	Two-step screening survey
Prolonged engagement	Dedicating sufficient time to understanding the research context, screening the participants, collecting the data, and analyzing it	Comprehensive literature review A two-step screening survey followed by the main study Data analysis through a series of iterative steps
Member checking	Designating two authors to independently code the data, followed by checking the same by two other authors who were not part of the initial analysis	Coding of data

The third category, *impediments*, captures the resistance faced by firms in their endeavor to use AI for CN. Under this category, we have grouped two aggregate dimensions—organizational impediments and people impediments. Of these, organizational impediments comprise two second-order themes: financial concerns and operational concerns, and people impediments comprise two second-order themes: steep learning curve and stakeholder resistance.

Finally, the fourth and last category, *impact*, represents the outcomes and consequences of implementing AI for CN. We grouped two aggregate dimensions—business model efficiencies and achieving CN targets—under impact, with the former comprising three second-order themes: stakeholder impact, process impact, and bottom-line impact, and the latter comprising two second-order themes: measurable emission outcomes and better alignment with CN goals.

4.1 | Implementation of AI

4.1.1 | Direct emission control measures

The direct impact on emissions dimension captures the AI-based initiatives of firms introduced with the express purpose of controlling emissions that increase the carbon and other harmful content in the atmosphere. These activities broadly include actions such as emission management through measurement and reduction, tracking and optimizing energy consumption, and supporting sustainability-oriented practices. Analysis of textual responses indicated that about 70% of firms were deploying AI for activities that can be considered direct emission control measures.

One of the control activities is the measurement of emissions being released. Responses confirmed that firms were explicitly using AI for measuring GHG emissions arising from their business activity. Aligned with their commitment to act as per their environmental accountability, these firms were using AI for the daily measurement of GHG levels. As a respondent stated:

> "*To help measure the amounts of greenhouse gases released into the atmosphere by our primary oil and natural gas drilling, extraction, and refining activities*"
> [P3, M, 51 or above, Energy]

In addition to measuring emissions, AI is also being used to reduce them. In this regard, key approaches used by the firms were tracking energy consumption, analyzing where the consumption was not as justified, and optimizing machine settings and production operations to avoid wasteful consumption and exhaust. As highlighted by one respondent,

> "*Artificial intelligence has helped us in optimizing the consumption of electricity at all our facilities. This has helped us prevent and eliminate any leakages*"
> [P14, M, 41–45, Construction]

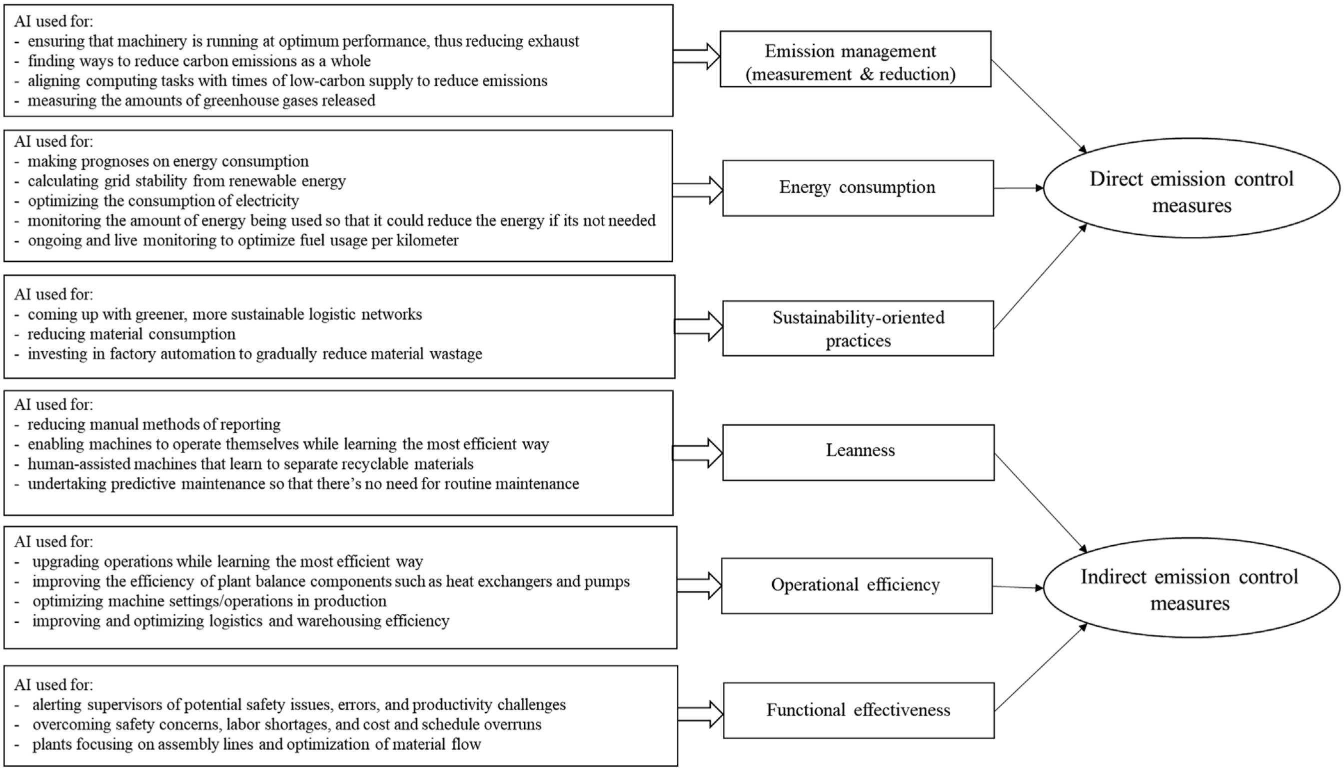

FIGURE 2a Data structure of direct and indirect emission control measures.

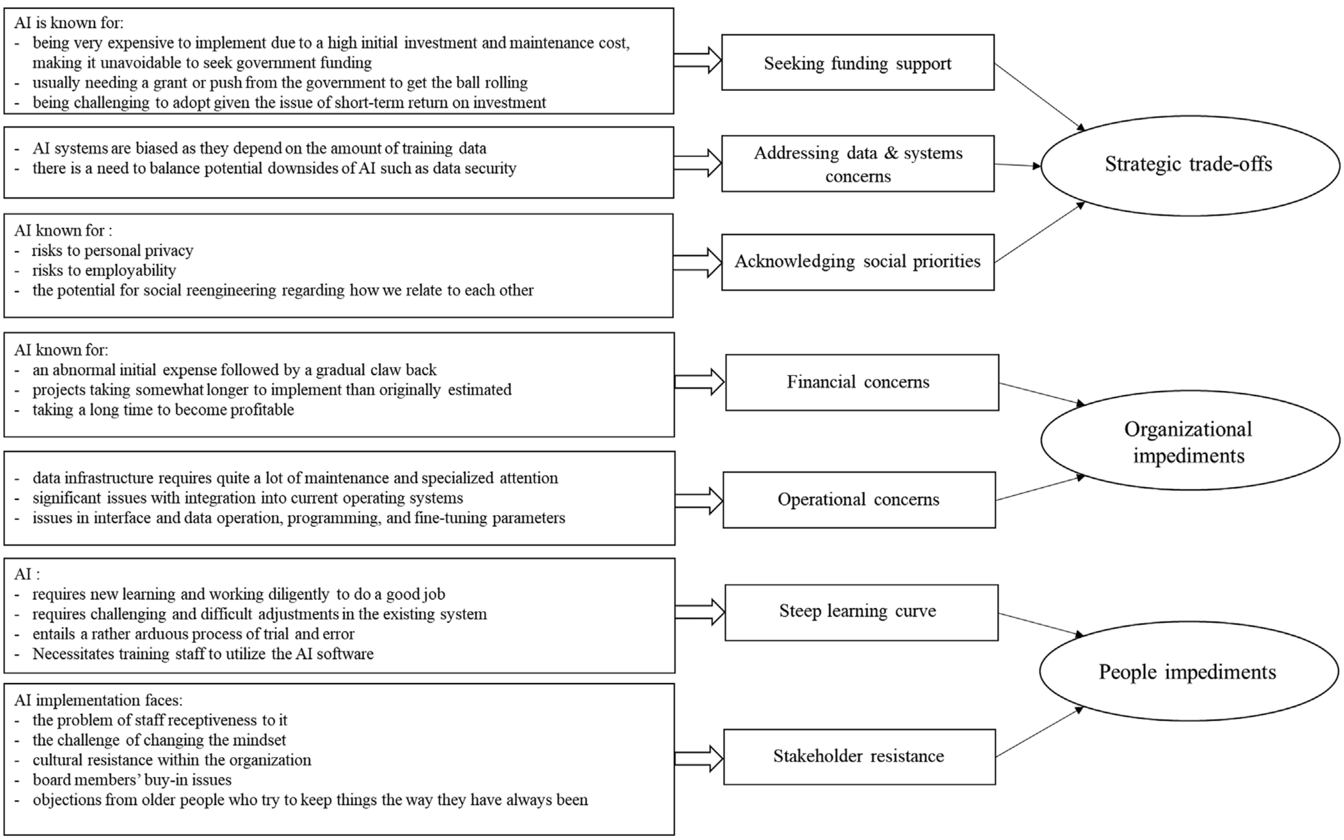

FIGURE 2b Data structure of strategic trade-offs, organizational impediments, and people impediments.

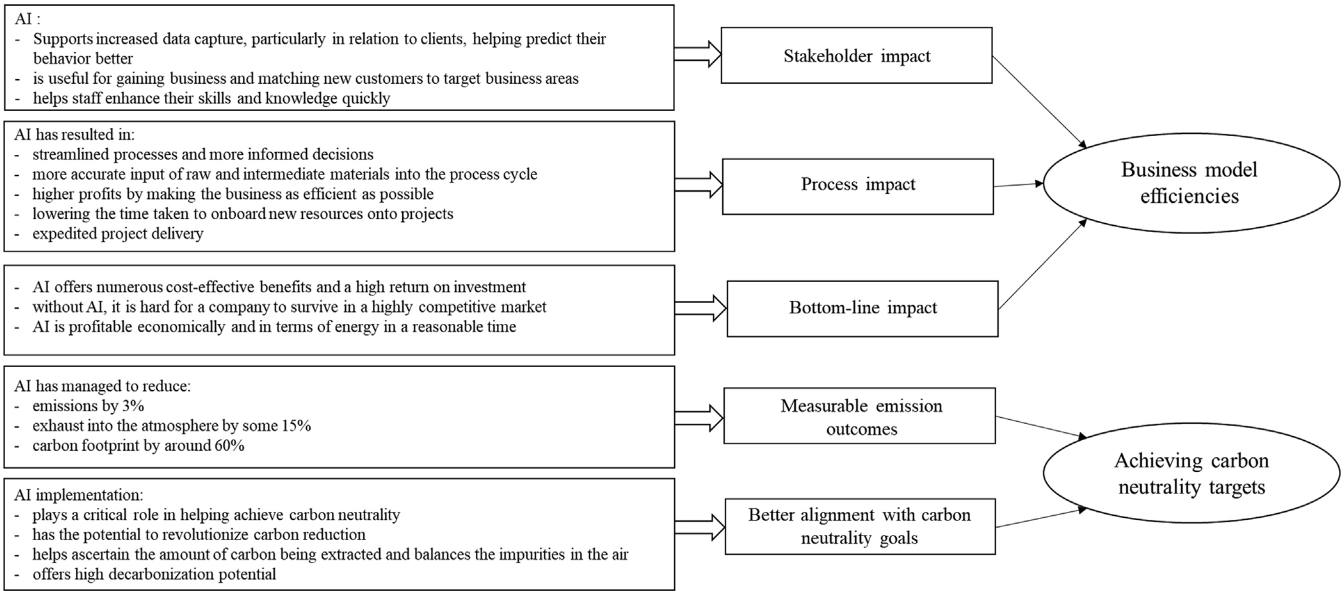

FIGURE 2c Data structure of business model efficiencies and carbon neutrality targets.

Another respondent shared:

> "*We have bespoke, in-house developed AI software which monitors and, in some cases, commences maintenance of machinery. This is a proactive software program and it ensures machinery is running at optimum performance, thus reducing exhaust to the atmosphere*"
>
> [P5, F, 51 or above, Manufacturing]

To elaborate, firms use AI to control machine operations, turning them on only when needed. AI is also used to monitor the amount of energy being used so that it can prevent energy use when it is not needed. The objective is to save as much power and fuel as possible.

Furthermore, AI is being used in these firms to support sustainability-oriented practices such as reduced reliance on manual reporting methods, resulting in decreased paper usage and electronic device consumption, thereby conserving valuable resources. At the same time, AI is being used to support material waste reduction in manufacturing processes and encourage more sustainable practices. To explain further, AI has been implemented to analyze production processes, identify opportunities for minimizing material waste, and optimize resource usage. By implementing AI algorithms, firms are trying to find ways to use fewer materials in their day-to-day operations, contributing to a decreased environmental footprint and promoting sustainable practices. The following statement exemplifies this commitment to resource efficiency and sustainability:

> "*My organization is making use of artificial intelligence and machine learning to achieve carbon neutrality mostly to reduce material consumption in manufacturing and to build different things and also to come up with greener, more sustainable logistic networks*"
>
> [P15, F, 30–35, Manufacturing]

4.1.2 | Indirect emission control measures

The indirect impact on emissions dimension captures the AI-based initiatives of firms introduced to support activities that would ultimately contribute to controlling emissions, even though the link might not be apparent. Such initiatives are broad-based, covering a plethora of activities that make the business efficient, less wasteful, and profitable. Analysis of responses helped us identify three distinct activities undertaken by the surveyed firms that reduced carbon emissions and other harmful content in the atmosphere. These activities broadly include actions taken to enhance leanness, operational efficiency, and the functional effectiveness of the business as a whole.

Analysis of responses confirmed that all surveyed firms had integrated AI into their businesses to make them less wasteful, efficient, and effective. The responses provide insights into how organizations are utilizing AI to reduce manual monitoring, reporting, and recycling methods by empowering machines to operate themselves while learning to do so most efficiently. In addition, the analysis reveals that firms are using AI to optimize resource allocation, enhance productivity, minimize errors, and reduce project durations, resulting in reduced environmental impact associated with their projects and cost savings. As a respondent highlighted,

> "*We have human-assisted machines that learn to separate recyclable materials from non-recyclable ones. These machines learn from the instructions of humans and their mistakes to work autonomously in the future*"
>
> [P6, M, 41–45, Construction]

Firms are also using AI algorithms for upgrading production operations, improving the efficiency of plant balance components, and optimizing logistics and warehousing operations to improve operational and functional effectiveness. To elaborate, AI helps firms optimize the movement of goods, streamline supply chains, and minimize unnecessary material handling and transportation. These advancements indirectly contribute to reducing carbon emissions associated with logistics operations. As one respondent stated:

> "*My organization uses AI to improve and optimize logistics and warehousing efficiency, to find a way to use as little materials as possible in day-to-day operations, and all around find ways to reduce carbon emissions as a whole*"
>
> [P7, M, 21–25, Manufacturing]

4.2 | Trade-offs

4.2.1 | Strategic trade-offs

The strategic trade-offs dimension encapsulates the conscious balancing of factors that may accompany the roll-out of their AI implementation. These trade-offs encompass considerations related to governmental interference, data safety issues, and social concerns. Analysis of the collected responses helped us identify three components of such trade-offs: seeking funding support, addressing data and systems concerns, and acknowledging social priorities.

To elaborate, a significant trade-off identified is the need to accept that AI implementation projects require extensive investment, making it almost unavoidable for firms to seek funding support from the government. Seeking government funding is more than likely to bring with it increased scrutiny and various regulatory checks and balances. However, given the long recovery period of such investments, firms need to accept government funding as more of a facilitating factor. Analysis of responses confirmed that this is how firms perceived seeking government funding for implementing AI for CN. In the words of a respondent:

> "*The main problem is to make it profitable to achieve an adequate performance of artificial intelligence in this field in a reasonable time, and to obtain subsidies and economic aid if necessary from the government to be successful in the shortest possible time*"
>
> [P6, M, 41–45, Construction]

Another trade-off is the common threat associated with digital technologies, data security, and the general perception that AI systems' decisions are biased based on the data used to train them. Accordingly, firms using AI for CN have to accept the calculated risk of potentially biased decisions and data leaks. The final set of strategic trade-offs consists of proceeding despite knowing that using AI for CN might conflict with certain social priorities. The conflict may arise due to personal privacy risks, which any data-driven setup can be exposed to. In addition, the respondents acknowledged that there was a fear of AI replacing humans completely, leading to job loss. Furthermore, a trade-off is required in accepting the impersonal nature of AI changing social interactions and reducing human interfacing. A respondent quoted below expressed the entire quandary rather succinctly:

> "*I think that if we but aside money, than the biggest problems and challenges are people who are a bit older and/or are not so ongoing with all the new technologies and changes and are trying to keep things the same way as they have always been, because it works, and can't see the bigger picture. Some of them are also afraid that artificial intelligence will take away everyones jobs*"
>
> [P15, F, 31- 35, Manufacturing]

4.3 | Impediments

4.3.1 | Organizational impediments

The organizational impediments dimension comprises the barriers or inhibiting factors that temper the enthusiasm and efforts of firms to integrate AI for achieving CN targets. Analysis of responses reveals two key drivers of organizational impediments: financial concerns and operational concerns. The main source of financial concern is that not only is the initial investment high, but there is also a long gestational period before the AI project starts delivering on profitability promises. This slow crawl to break even can become a grave challenge for firms that are constantly facing topline–bottom-line pressures. Our findings indicate that there is a consensus that, despite the substantial upfront investment, firms can realize significant long-term financial benefits from using AI for CN. The following quote from a respondent highlights this view:

> "*The initial expense in developing the in-house software was large; however, in the five years since it has been used, it has certainly paid for itself several times over, not only in helping the company achieve carbon neutrality but also in maintenance costs*"
>
> [P5, F, 51 or above, Construction]

Another impediment arises from managing a smooth transition to a new operating system and handling data infrastructure effectively. Making room for AI entails several adjustments, which are somewhat challenging to manage. As one respondent admitted,

> "*Biggest issue was integration into current operating systems as these are shared with our local authority as we are a sub-contractor organisation*"
>
> [P9, M, 46–50, Transportation]

4.3.2 | People impediments

People impediments encompass the man-made challenges and barriers associated with using AI for CN. The analysis of qualitative responses helped us identify two key manifestations of people's impediment and their causes. One set of such impediments arises from the steep learning curve accompanying the new-fangled AI systems in terms of acquiring new knowledge to use them initially and maintain their consistent performance thereafter. Learning to use the new systems requires several adjustments and the rather uphill task of acquiring the relevant skills. One respondent described this impediment using the following words:

> "*Well, even if we don't have yet this methods implemented on our company, we have already studied them. We will certainly face some issues in the begining because AI must learn and must be working very well to do a good job. Maybe we'll need a full time team working exclusively on AI, to support it*"
>
> [P20, M, 31–35, Transportation]

Another set of people impediments arises from stakeholder resistance. The staff, as well as top management, may resist the use of AI for CN. Most of such resistance is due to strong resistance to change along with a generational divide, with older employees showing more status quo bias. In the words of a respondent:

> "*Our biggest challenge was to get the buy-in from staff as it was challenging to change their minds and to get staff and even clients to think differently towards CO_2 emissions as many felt it's not their responsibility*"
>
> [P14, M, 41–45, Construction]

4.4 | Impact

4.4.1 | Business model efficiencies

The business model efficiencies dimension embodies the positive impact of using AI to achieve CN targets on people, processes, and profits. It emphasizes the potential of AI to enable machines to make decisions and perform tasks without human collaboration. Analysis of the collected qualitative data helped us capture these efficiencies in a fine-grained manner through three themes: stakeholder impact, process impact, and bottom-line impact. These responses provide insights into how AI can enhance business models and drive efficiencies in the TEMC sectors. The theme of stakeholder impact reflects how optimal outcomes accrue for firms when AI is leveraged to engage different stakeholder groups, both internal (e.g., employees) and external (e.g., customers). In the words of a respondent:

> "*In our experience AI technologies and machine learning play a critical role in helping to achive carbon neutrality. Examples would be tracking assets cars lorrys, electric devices and wareables* via *telematics, driving efficencies of energy, cost, time and money. Other examples include workflow management helping employees, customers, and vendors to be targeted when where ans as needed. To sum up, we see AI, ML as the potential to revelutionise cardon reduction but we are not there quite yet*"
>
> [P2, M, 51 or above, Manufacturing]

At the same time, the responses indicate how the use of AI has led to a positive impact in terms of streamlining processes, aiding informed decision-making, supporting the accurate input of materials into the process cycle, reducing the time taken to onboard new resources, enabling faster project delivery, and generating higher profits. Pinpointing the impact of AI-enabled decision-making in firms, a respondent opined:

> "*Modernization technologies are solutions that deal with the sources of emissions from major industrial units that are the heart of the industrial process - for example, replacing an ethylene steam cracker powered by fossil fuels with an electric steam cracker*"
>
> [P18, M, 41–45, Manufacturing]

Analysis of responses showed that the use of AI for achieving CN targets positively impacted the bottom line by offering several cost-effective benefits and a high return on investment (ROI), albeit after some time lag. Respondents also noted how AI was effective in helping their firms survive in a highly competitive market. In the words of a respondent:

> "*Artificial intelligence helps us so that in the future machines alone can make decisions and separate materials without the collaboration of a human, thus saving time and energy. All this will take us a few years to fully implement and allow intelligence to work autonomously*"
>
> [P6, M, 41–45, Construction]

4.4.2 | Achieving carbon neutrality targets

The achieving CN targets dimension captures how effective the implementation of AI technologies has been in achieving firms' emissions-related goals. We identified two themes within this dimension: measurable emission outcomes and better alignment with CN goals to lucidly illustrate how using AI for CN delivers the anticipated positive outcomes. About 65% of the respondents indicated that the implementation of AI in their firms' day-to-day operations had garnered significant reductions in their carbon footprint and a substantial decrease in emissions so far. These respondents ventured to quote specific percentages of reduction, as is evident from the response quoted verbatim:

> "*They have been quite effective. Numbers have been shown by our statistics team that since the start of AI implementation in the organization's day-to-day operations, we have reduced our carbon footprint by around 60%. The most impactful circumstance is the reduction in*

trips taken by our transportation vehicles. Routes have been immensely optimized so we take as few trips as possible"

[P7, M, 21–25, Manufacturing]

Our findings indicate that the gains in emission reductions are likely to continue since the adoption of AI has made firms better aligned with CN objectives. This ensures that all the activities of firms are geared up to reduce emissions or make business efficient in optimizing decision-making and resource use. The response reproduced below communicates this idea quite unequivocally:

"*By using automation, not only does it reduce human error and in some cases human involvement altogether, it ensures accurate input of raw and intermediate materials into the process cycle and minimises waste at the end process too. Monitoring of the systems allows less energy to be used at the same time which also contributes to our carbon neutrality goal*"

[P4, M, 51 or above, Manufacturing]

5 | DISCUSSION

We sought to answer how firms were leveraging AI in their businesses to pursue and achieve their CN targets, and the offsets its adoption has entailed for them. The findings of our study indicate that the use of AI for achieving CN by firms can be understood clearly through four aspects: implementation (i.e., what it is being used for), trade-offs (i.e., the balancing offsets firms have to accept and deal with), impediments (i.e., the barriers that inhibit its effective adoption or use), and impact (i.e., the outcomes and consequences of implementing AI).

With regard to implementation, our coding of the qualitative responses revealed that AI was being employed by firms for initiating and supporting several direct and indirect emission control measures covering activities such as reducing the release of GHGs, measuring those released, and making efforts to increase the efficiency and effectiveness of businesses. Our findings resonate with past studies that have emphasized the use of AI for emission management. However, our study offers a comprehensive discussion on direct and indirect emission control measures, in comparison to past literature, which has focused primarily on emissions forecasting models such as the new information-based gray model (Ding & Zhang, 2023), predictive models capable of estimating global warming (Babatunde et al., 2020), and ensemble prediction system offering both point and interval estimates of future emissions (Z. Liu et al., 2022).

Our findings further indicate that organizations actively utilize AI to streamline operations and promote resource conservation, consistent with existing literature (e.g., Allal-Chérif et al., 2021; Damoah et al., 2021; Su & Fan, 2019). However, our study covers a broader set of avenues compared to the more specific focus of past studies on a singular aspect of their choice. For instance, Allal-Chérif et al. (2021) noted AI's contribution to enhancing firms' purchasing function by strengthening its cross-functional and interactive role, and Su and Fan (2019) showed that major obstacles, such as end distribution in logistics operations, can be overcome, and the entire logistics system can be made more resource-efficient, cost-effective, and low-carbon intensive by rationally deploying AI in tandem with big data.

Next, our findings show that firms adopting AI for CN need to settle for many strategic trade-offs. The essence of trade-offs here is that the firms have to proceed with the implementation and continued usage of AI, knowing there may be some undesirable consequences or at least some serious concerns. Such trade-offs include dependence on government support, balancing performance and financial viability, addressing social and data-related concerns, and ensuring long-term sustainability. These trade-offs arise since upfront costs need to be weighed against long-term benefits such as efficiency, emissions reductions, and safety improvements. This finding is consistent with past studies that have underscored the need to understand the trade-offs, such as loss of accuracy, unknown future costs, and higher emissions associated with AI applications (e.g., Ma et al., 2023). On the whole, the past literature has remained bereft of a wide-ranging discussion on the complex trade-offs that need to be accepted by firms desirous of rolling out AI implementation for pursuing CN. Our study addresses this narrowness by presenting an elaborate set of trade-offs related to governmental interference on account of providing funding support, data safety issues inherent in such technologies, and social concerns due to unknown elements that AI encapsulates.

Coming to impediments, our study brought forth several organizational and people impediments related to organizational culture, generational divides, resistance to change, top management buy-in, the need for extensive workforce training, integrating AI systems with existing systems, etc. Although past studies have not delved as deeply into barriers and impediments toward the use of AI for CN, our findings are in concordance with the available evidence in the extended literature (e.g., Ahmed et al., 2022; Cichosz et al., 2020; Garzoni et al., 2020). Our study contributes substantially in this regard because not only are the available insights limited but they also lack the depth and consensus required to guide future research and practice. To elaborate, while past studies have focused more on climate-related challenges of using AI (Fan et al., 2022; Gupta et al., 2021), we bring forth a broad gamut of impediments, not only economic but also those related to culture, behavior, and psychology.

Finally, with regard to impact, the coding of textual responses helped us confirm that firms were indeed garnering several anticipated positive outcomes associated with business model efficiencies and the achievement of CN targets. These findings are consistent with and build upon the available insights in the area (e.g., Allal-Chérif et al., 2021; Hai et al., 2022; Su & Fan, 2019). However, where past studies have noticeably discussed the impact of AI on CN through the lens of energy systems and management of renewable energy (e.g., Diao et al., 2021; Li & Maréchal, 2023; Natgunanathan et al., 2023), our study presents a more comprehensive perspective spanning business models, in addition to direct discussion on CN.

5.1 | Conceptual framework

Climate risk has become an abiding discussion during the past decade (e.g., Kumar et al., 2021), mandating strong action on emissions. Highlighting technology as a potential means of effective action on emissions, our study confirms that leveraging AI for achieving CN targets requires a keen understanding and balancing a host of business and climate-related challenges and outcomes. Our findings underscore the idea that bringing together AI, which is a complex technology, and CN, which has multiple drivers, is not a simple undertaking. It entails a deep understanding of various aspects. The existing scholarship has also acknowledged this, with researchers arguing that it is difficult to apply any available adoption model to conceptualize and examine the use of AI for CN (Allal-Chérif et al., 2021). As a result, we bring together our findings and consolidate them systematically to develop a conceptual framework, which we call the convergence–divergence model (Figure 3).

The intuition behind this model is that the landscape of using AI for CN is a dynamic mix of factors, some of which act to propel the firms on the path of neutrality and others that detract from the anticipated gains. We conceptualize the first set of factors as *converging factors*. These factors serve as incentives for firms in terms of profitability, environmental performance, and productivity, motivating them to commit to using AI for achieving CN.

The second set of factors represents the *diverging factors*, which we conceptualize as the counterbalancing part of our model since they take away from or temper the positives arising from implementing AI for achieving CN. These factors unleash several organizational and people-related challenges that impede the smooth integration of AI in existing systems and potentially delay the gains arising from the adoption of AI.

We break down the converging factors into three distinct parts: the use of AI leading to decision optimization, process efficiencies, and commensurate climate action. We contend that *decision optimization* by implementing AI for the express purpose of achieving CN results in topline and bottom-line gains, unlocking value by mitigating climate risks and strengthening the firm's resilience to climate change shocks.

Process efficiencies arising from the implementation of AI for CN become apparent through gains in the maintenance schedule, where preventive monitoring and predictive maintenance ensure fewer instances of breakdowns. Similarly, AI aids in optimizing machine settings to automate many processes and material selection to reduce wastage.

Climate action, representing the third converging factor in our model, captures the apparent and unavoidable outcomes that need to be derived from the application of AI for CN. These pertain to emissions reductions, prioritizing the use of renewable energy, monitoring vehicle movement and logistics to make it more environmentally efficient, and managing energy consumption in different activities.

In our model, the diverging factors are also divided into three parts. We conceptualize these challenges as resource constraints, managerial constraints, and resistance. *Resource constraints* capture the uncertainties in value generation that arise from the large amount of investment required for AI projects and the long and slow process to break even that becomes even more excruciating due to the requirement of specific technical expertise.

The next diverging factor in our model, *managerial constraints*, embodies the counterbalancing issues arising due to top management skepticism, which has a dampening effect on the enthusiasm of the entire organization. Managerial issues can also arise due to regulatory pressures from the government to implement the AI project in a certain way, normative pressures from the community to advance social interests, and mimetic pressures driven by a need to ape competitors' actions. Operationally, managerial constraints arise from the extensive change management required for transitioning from the existing systems to the AI systems and ensuring seamless integration, which is fraught with challenges.

The final diverging factor in our model comes in the form of *resistance* of employees and customers to the adopted AI system, which

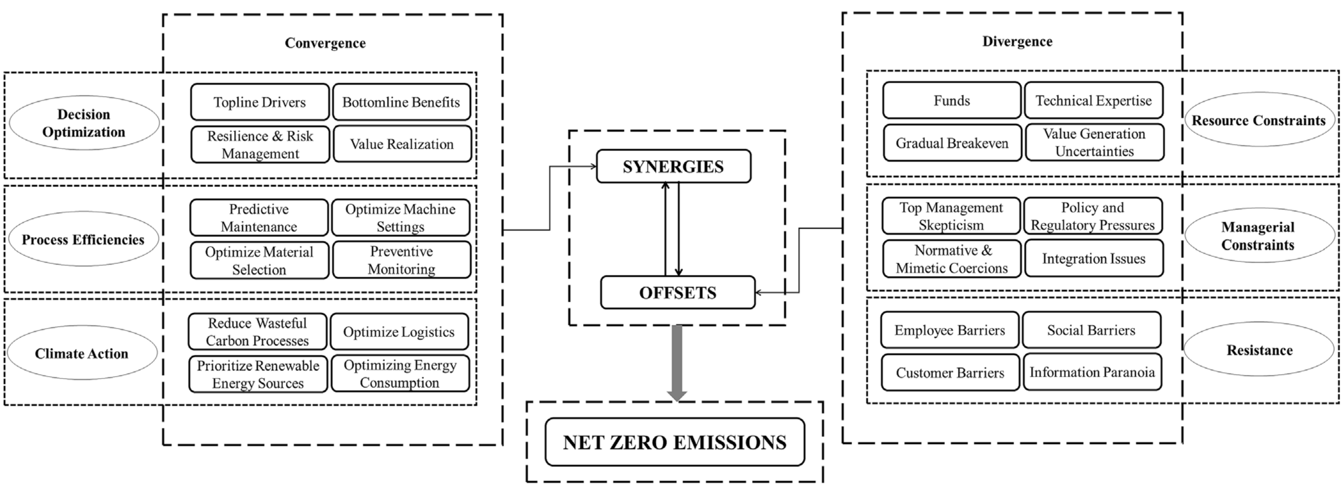

FIGURE 3 Convergence–divergence model.

might impede the expected efficacious outcomes. Resistance also captures the inhibiting factors that arise from social concerns about AI in terms of biases, human redundancy in certain roles, and the decline in human interaction. We further include in our model data safety issues and the large amount of data associated with AI systems that create barriers arising from information paranoia and technostress.

The third part of our model captures the path to net zero, which entails reducing GHG emissions drastically to near zero and absorbing emissions, if any remain, from the atmosphere. Through this part, we consolidate our findings to contend that the synergies unlocked by converging forces can lead firms toward the state of net zero emissions when they consciously and continuously work towards offsetting the detracting effect of diverging factors.

6 | CONCLUSION

6.1 | Theoretical implications

Our study offers three valuable theoretical implications: First, we conducted an exploratory qualitative study through a novel yet provenly efficacious method of open-ended essays to understand and map the on-the-ground experiences of firms that have implemented AI with the express purpose of achieving CN. Our analysis uncovered four dimensions of the AI–CN debate—implementation, strategic trade-offs, impediments, and impact. By bringing these four dimensions into the same space, we consolidate and systematize the conversations that have remained anecdotal, dispersed, and fragmented so far. Most of the existing investigations of AI adoption and its impact on CN have used a narrow lens, focusing either on benefits or on potential negative outcomes (e.g., Agrawal et al., 2022; Ahmed et al., 2022), which has left many aspects less understood, or even unacknowledged. Scholars have noted this, raising a call for further research in the area (e.g., Shashi, 2022; Walsh et al., 2020). Our study answers this call by providing a multi-dimensional perspective on using AI for CN. As a result, we have created a suitable knowledge base for future research to explore more granular aspects of the implementation of AI for pursuing and achieving CN targets.

Second, we contribute to advancing research in the area by formulating a comprehensive conceptual framework that brings together various convergent and divergent factors impacting AI-related outcomes for firms. Conceptual models presenting a comprehensive overview of the area under focus are acknowledged for their agenda-setting contribution to theoretical advancement (e.g., Dhir et al., 2020). In addition, we add a strategic perspective to the debate on the application of AI for CN by revealing that despite several positive, well-documented outcomes and synergies of AI, the decision to implement AI for achieving CN entails several trade-offs, which need to be weighed by firms and elucidated by researchers. Furthermore, not only does our framework advance the theoretical understanding of the area, but it also contributes to promoting industry-oriented research by motivating academic researchers to examine critical variables related to value, risk, and the top and bottom lines. Future studies can work on empirically testing the entire framework or some parts. For instance, only convergences can be subjected to a more in-depth examination.

Finally, we provide a concrete direction for future research by offering an efficacious methodological choice in the form of open-ended essays, which are becoming an increasingly popular mode of data collection, preferred by scholars working on a wide variety of research topics (e.g., Dhir et al., 2017; Talwar et al., 2021b). Given the complex nature of the area and the evolving state of research, clarity on the research method suitable for the context can add the desired momentum to the research, yielding robust results. At the same time, the open-ended essay protocol of our study provides useful inputs for future empirical studies in the area.

6.2 | Practical implications

Our study offers three key practical implications for different stakeholders: First, our findings reveal that although firms can benefit immensely from the adoption of AI for achieving their CN targets, the high initial investment and the long gestational period of these projects act as dissuading factors preventing firms from taking any initiative. In addition, some unknown costs can arise in the future while implementing AI (Ma et al., 2023), which can add to the uncertainty. Against this backdrop, our findings highlight the criticality of government funding for promoting the use of AI for CN. Given the severity of climate change and the impact of climate risk at a much broader level, we recommend that governments institute formal funding packages at reasonable terms, with no restrictive covenants to motivate firms to adopt AI.

Second, our findings show that the resistance of internal and external stakeholders is one of the major impediments that might prevent firms from adopting AI for CN in the future if they have not done it so far. Even for firms that have adopted AI, the resistive attitude of different stakeholders can inhibit the successful integration of the new systems with the old ones. The source of resistance is the newness of the idea of using AI for CN since, currently, in many sectors, AI tools are largely being used for incremental improvements in technologies rather than nurturing new low-carbon technologies (John et al., 2022). Based on this evidence, we recommend that any AI implementation project for CN should not only be approached by firms as a long-term investment decision but also as an organizational process mandating due change management. Furthermore, we suggest that the resistance of staff can be overcome by altering their mindset and perception that emissions are not their responsibility. This would require addressing gaps in awareness and cultivating a sense of shared responsibility toward sustainable practices. By fostering such collective understanding and commitment, firms can overcome people's impediments and promote a culture of sustainability.

Finally, the majority of respondents indicated that the most challenging issue their firms faced while implementing AI for achieving CN targets was finding experts to implement this technology and make it profitable adequately. It is apparent from our findings that AI implementation has been constrained by the limited availability of skilled personnel capable of understanding and handling AI from the CN perspective. Thus, specialized training is required to develop climate technology know-how. Offering a potential solution, we recommend a multi-pronged approach, spearheaded by deep university–industry collaboration for training personnel equipped with the required skills, competence, and ability to understand how best AI can be leveraged to lead firms toward the state of net zero emissions. Since most firms lack the readiness and relevant experience to adopt AI in their business processes (Allal-Chérif et al., 2021), competence-building can go a long way toward making firms more receptive to adopting and effectively leveraging AI technologies.

6.3 | Limitations and future research insights

Our study offers several tangible contributions, but as with any research undertaking, it is also not devoid of shortcomings. Since noting and articulating key limitations of any study also paves the way for future research, we have given them careful attention. The first limitation is that while at the time of data collection, we invited participation from individuals employed in the TEMC sectors only, and we have not coded the data or reported the result to present sector-wise findings. Reporting the results sector-wise could have made the insights more granular. Future studies can remedy our limitation by investigating each sector individually to test our findings and highlight the deviations. In addition, specific sub-sectors that are known to be highly polluting can be examined, such as the leather industry (Moktadir et al., 2020). Second, we have remained confined to an inductive approach, offering only key themes and a theoretical framework. Going beyond this to put forth testable hypotheses, and even testing them, could have enhanced the contribution of our study multifold. However, this would have increased the scope of our study. This limitation opens an opportunity for future researchers to extend our study by incorporating propositions and testing them with cross-sectional data. Finally, we consider a holistic convergence–divergence model for mapping all potential factors associated with AI implementation in business operations. However, our conceptualization is not grounded in any existing theory, being more closely grounded in the findings of the qualitative study. This creates scope for researchers to identify theories likely to fit our conceptualization. Accordingly, we recommend that future research consider landmark theories that have been used effectively in pro-environmental settings.

In addition, we suggest that future researchers can build up on our exploratory study to offer more granular insights on using AI for achieving CN by considering firm-level differences such as small versus large, location in developed versus developing countries, listed versus privately held firms, and ownership status.

AUTHOR CONTRIBUTION

Adeel Luqman and Qingyu Zhang participated in the conceptualization and writing—original draft preparation. Shalini Talwar and Amandeep Dhir participated in methodology, formal analysis, validation, writing—original draft preparation, and writing—review and editing. Meena Bhatia participated in validation and review.

CONFLICT OF INTEREST STATEMENT

The authors do not have any competing interests to declare.

ORCID

Shalini Talwar https://orcid.org/0000-0002-2819-5685
Meena Bhatia https://orcid.org/0000-0003-4579-0109
Amandeep Dhir https://orcid.org/0000-0002-6006-6058

REFERENCES

Agrawal, R., Wankhede, V. A., Kumar, A., Luthra, S., & Huisingh, D. (2022). Progress and trends in integrating Industry 4.0 within circular economy: A comprehensive literature review and future research propositions. *Business Strategy and the Environment*, *31*(1), 559–579. https://doi.org/10.1002/bse.2910

Ahmed, I., Zhang, Y., Jeon, G., Lin, W., Khosravi, M. R., & Qi, L. (2022). A blockchain-and artificial intelligence-enabled smart IoT framework for sustainable city. *International Journal of Intelligent Systems*, *37*(9), 6493–6507. https://doi.org/10.1002/int.22852

Algarvio, H. (2021). The role of local citizen energy communities in the road to carbon-neutral power systems: Outcomes from a case study in Portugal. *Smart Cities*, *4*(2), 840–863. https://doi.org/10.3390/smartcities4020043

Allal-Chérif, O., Simón-Moya, V., & Ballester, A. C. C. (2021). Intelligent purchasing: How artificial intelligence can redefine the purchasing function. *Journal of Business Research*, *124*, 69–76. https://doi.org/10.1016/j.jbusres.2020.11.050

Babatunde, D. E., Anozie, A. N., Omoleye, J. A., Oyebode, O., Babatunde, O. M., & Agboola, O. (2020). Prediction of global warming potential and carbon tax of a natural gas-fired plant. *Energy Reports*, *6*, 1061–1070. https://doi.org/10.1016/j.egyr.2020.11.076

Bhowmik, S., Paul, A., Panua, R., Ghosh, S. K., & Debroy, D. (2018). Performance-exhaust emission prediction of diesosenol fueled diesel engine: An ANN coupled MORSM based optimization. *Energy*, *153*, 212–222. https://doi.org/10.1016/j.energy.2018.04.053

Cao, Z., Zhou, X., Hu, H., Wang, Z., & Wen, Y. (2022). Towards a systematic survey for carbon neutral data centers. *IEEE Communication Surveys and Tutorials*, *24*, 895–936. https://doi.org/10.1109/COMST.2022.3161275

Chasan, A. (2023). Some experts see AI as a tool against climate change. Others say its own carbon footprint could be a problem. Available at: https://www.cbsnews.com/news/artificial-intelligence-carbon-footprint-climate-change/#:~:text=But%20experts%20largely%20see%20AI,the%20effects%20of%20climate%20change

Cheng, Y., Sinha, A., Ghosh, V., Sengupta, T., & Luo, H. (2021). Carbon tax and energy innovation at crossroads of carbon neutrality: Designing a sustainable decarbonization policy. *Journal of Environmental Management*, *294*, 112957. https://doi.org/10.1016/j.jenvman.2021.112957

Cichosz, M., Wallenburg, C. M., & Knemeyer, A. M. (2020). Digital transformation at logistics service providers: Barriers, success factors and leading practices. *The International Journal of Logistics Management*, *31*(2), 209–238. https://doi.org/10.1108/IJLM-08-2019-0229

Damoah, I. S., Ayakwah, A., & Tingbani, I. (2021). Artificial intelligence (AI)-enhanced medical drones in the healthcare supply chain (HSC) for sustainability development: A case study. *Journal of Cleaner Production*, *328*, 129598. https://doi.org/10.1016/j.jclepro.2021.129598

Dhir, A., Chen, G. M., & Chen, S. (2017). Why do we tag photographs on Facebook? Proposing a new gratifications scale. *New Media & Society*, *19*(4), 502–521. https://doi.org/10.1177/1461444815611062

Dhir, A., Talwar, S., Kaur, P., & Malibari, A. (2020). Food waste in hospitality and food services: A systematic literature review and framework development approach. *Journal of Cleaner Production*, *270*, 122861. https://doi.org/10.1016/j.jclepro.2020.122861

Diao, C., Liu, T., Yang, Z., & Duan, Y. (2021). Comparison between deep learning and fully connected neural network in performance prediction of power cycles: Taking supercritical CO_2 Brayton cycle as an example. *International Journal of Intelligent Systems*, *36*(12), 7682–7708. https://doi.org/10.1002/int.22603

Ding, S., & Zhang, H. (2023). Forecasting Chinese provincial CO_2 emissions: A universal and robust new-information-based grey model. *Energy Economics*, *121*, 106685. https://doi.org/10.1016/j.eneco.2023.106685

Dolge, K., & Blumberga, D. (2021). Key factors influencing the achievement of climate neutrality targets in the manufacturing industry: LMDI decomposition analysis. *Energies*, *14*(23), 8006. https://doi.org/10.3390/en14238006

Fan, M., Khalique, A., Qalati, S. A., Gillal, F. G., & Gillal, R. G. (2022). Antecedents of sustainable e-waste disposal behavior: The moderating role of gender. *Environmental Science and Pollution Research*, *29*(14), 20878–20891. https://doi.org/10.1007/s11356-021-17275-y

Fan, Z., & Friedmann, S. J. (2021). Low-carbon production of iron and steel: Technology options, economic assessment, and policy. *Joule*, *5*(4), 829–862. https://doi.org/10.1016/j.joule.2021.02.018

Garzoni, A., De Turi, I., Secundo, G., & Del Vecchio, P. (2020). Fostering digital transformation of SMEs: A four levels approach. *Management Decision*, *58*(8), 1543–1562. https://doi.org/10.1108/MD-07-2019-0939

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods*, *16*(1), 15–31. https://doi.org/10.1177/1094428112452151

Glasser, B. G., & Strauss, A. L. (1967). *The development of grounded theory*. Alden.

Guba, E. G., & Lincoln, Y. S. (1981). *Effective evaluation: Improving the usefulness of evaluation results through responsive and naturalistic approaches*. Jossey-Bass.

Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2021). Artificial intelligence for decision support systems in the field of operations research: Review and future scope of research. *Annals of Operations Research*, *308*(1–2), 215–274. https://doi.org/10.1007/s10479-020-03856-6

Hai, T., Alsharif, S., Dhahad, H. A., Attia, E.-A., Shamseldin, M. A., & Ahmed, A. N. (2022). The evolutionary artificial intelligence-based algorithm to find the minimum GHG emission via the integrated energy system using the MSW as fuel in a waste heat recovery plant. *Sustainable Energy Technologies and Assessments*, *53*, 102531. https://doi.org/10.1016/j.seta.2022.102531

Hannigan, T. R., Haans, R. F., Vakili, K., Tchalian, H., Glaser, V. L., Wang, M. S., Kaplan, S., & Jennings, P. D. (2019). Topic modeling in management research: Rendering new theory from textual data. *Academy of Management Annals*, *13*(2), 586–632. https://doi.org/10.5465/annals.2017.0099

Heo, S., Ko, J., Kim, S., Jeong, C., Hwangbo, S., & Yoo, C. (2022). Explainable AI-driven net-zero carbon roadmap for petrochemical industry considering stochastic scenarios of remotely sensed offshore wind energy. *Journal of Cleaner Production*, *379*, 134793. https://doi.org/10.1016/j.jclepro.2022.134793

Huang, X., Hong, S. H., Yu, M., Ding, Y., & Jiang, J. (2019). Demand response management for industrial facilities: A deep reinforcement learning approach. *IEEE Access*, *7*, 82194–82205. https://doi.org/10.1109/ACCESS.2019.2924030

Huseien, G. F., Faridmehr, I., Nehdi, M. L., Abadel, A. A., Aiken, T. A., & Ghoshal, S. (2022). Structure, morphology and compressive strength of alkali-activated mortars containing waste bottle glass nanoparticles. *Construction and Building Materials*, *342*, 128005. https://doi.org/10.1016/j.conbuildmat.2022.128005

IPCC. (2022). Intergovernmental panel on climate change. https://www.ipcc.ch/

Iyanna, S., Kaur, P., Ractham, P., Talwar, S., & Islam, A. N. (2022). Digital transformation of healthcare sector. What is impeding adoption and continued usage of technology-driven innovations by end-users. *Journal of Business Research*, *153*, 150–161. https://doi.org/10.1016/j.jbusres.2022.08.007

John, N., Wesseling, J. H., Worrell, E., & Hekkert, M. (2022). How key-enabling technologies' regimes influence sociotechnical transitions: The impact of artificial intelligence on decarbonization in the steel industry. *Journal of Cleaner Production*, *370*, 133624. https://doi.org/10.1016/j.jclepro.2022.133624

Kempitiya, T., Sierla, S., De Silva, D., Yli-Ojanperä, M., Alahakoon, D., & Vyatkin, V. (2020). An artificial intelligence framework for bidding optimization with uncertainty in multiple frequency reserve markets. *Applied Energy*, *280*, 115918. https://doi.org/10.1016/j.apenergy.2020.115918

Krzywanski, J., Czakiert, T., Nowak, W., Shimizu, T., Zylka, A., Idziak, K., Sosnowski, M., & Grabowska, K. (2022). Gaseous emissions from advanced CLC and oxyfuel fluidized bed combustion of coal and biomass in a complex geometry facility: A comprehensive model. *Energy*, *251*, 123896. https://doi.org/10.1016/j.energy.2022.123896

Kumar, A., Sharma, S., & Verma, A. (2019). Optimal sizing and multi-energy management strategy for PV-biofuel-based off-grid systems. *IET Smart Grid*, *3*(1), 83–97.

Kumar, A., Srikanth, P., Nayyar, A., Sharma, G., Krishnamurthi, R., & Alazab, M. (2020). A novel simulated-annealing based electric bus system design, simulation, and analysis for Dehradun smart city. *IEEE Access*, *8*, 89395–89424. https://doi.org/10.1109/ACCESS.2020.2990190

Kumar, S., Sureka, R., Lim, W. M., Kumar Mangla, S., & Goyal, N. (2021). What do we know about business strategy and environmental research? Insights from business strategy and the environment. *Business Strategy and the Environment*, *30*(8), 3454–3469. Portico. https://doi.org/10.1002/bse.2813

Li, X., & Maréchal, F. (2023). Deep excavation of the impact from endogenous and exogenous uncertainties on long-term energy planning. *Energy and AI*, *11*, 100219. https://doi.org/10.1016/j.egyai.2022.100219

Li, Y., Li, S., Sun, X., & Hao, D. (2022). Prediction of carbon dioxide production from green waste composting and identification of critical factors using machine learning algorithms. *Bioresource Technology*, *360*, 127587. https://doi.org/10.1016/j.biortech.2022.127587

Lippiatt, N., Ling, T.-C., & Pan, S.-Y. (2020). Towards carbon-neutral construction materials: Carbonation of cement-based materials and the future perspective. *Journal of Building Engineering*, *28*, 101062. https://doi.org/10.1016/j.jobe.2019.101062

Liu, Y., Esan, O. C., Pan, Z., & An, L. (2021). Machine learning for advanced energy materials. *Energy and AI*, *3*, 100049. https://doi.org/10.1016/j.egyai.2021.100049

Liu, Z., Jiang, P., Wang, J., & Zhang, L. (2022). Ensemble system for short term carbon dioxide emissions forecasting based on multi-objective tangent search algorithm. *Journal of Environmental Management*, *302*, 113951. https://doi.org/10.1016/j.jenvman.2021.113951

Ma, H., Zhou, Z., Zhang, X., & Chen, X. (2023). Towards carbon-neutral edge computing: Greening edge ai by harnessing spot and future carbon markets. *IEEE Internet of Things Journal*, *10*, 16637–16649. https://doi.org/10.1109/JIOT.2023.3268339

Maxwell, S. E. (2000). Sample size and multiple regression analysis. *Psychological Methods*, *5*(4), 434–458. https://doi.org/10.1037/1082-989X.5.4.434

Minevich, M. (2021). 11 examples of AI climate change solutions for zero carbon. Available at: https://www.forbes.com/sites/markminevich/2021/10/08/11-examples-of-ai-climate-change-solutions-for-zero-carbon/?sh=7806f2462251

Moktadir, A., Kumar, A., Ali, S. M., Paul, S. K., Sultana, R., & Rezaei, J. (2020). Critical success factors for a circular economy: Implications for business strategy and the environment. *Business Strategy and the Environment*, Portico, *29*(8), 3611–3635. https://doi.org/10.1002/bse.2600

Natgunanathan, I., Mak-Hau, V., Rajasegarar, S., & Anwar, A. (2023). Deakin microgrid digital twin and analysis of AI models for power generation prediction. *Energy Conversion and Management: X*, *18*, 100370. https://doi.org/10.1016/j.ecmx.2023.100370

Okuyama, A., Yoo, S., Kumagai, J., Keeley, A. R., & Managi, S. (2022). Questioning the sun: Unexpected emissions implications from residential solar photovoltaic systems. *Resources, Conservation and Recycling*, *176*, 105924. https://doi.org/10.1016/j.resconrec.2021.105924

Petrescu, M., Ajjan, H., & Harrison, D. L. (2023). Man vs machine–detecting deception in online reviews. *Journal of Business Research*, *154*, 113346. https://doi.org/10.1016/j.jbusres.2022.113346

Pulselli, R. M., Marchi, M., Neri, E., Marchettini, N., & Bastianoni, S. (2019). Carbon accounting framework for decarbonisation of European city neighbourhoods. *Journal of Cleaner Production*, *208*, 850–868. https://doi.org/10.1016/j.jclepro.2018.10.102

Rocha, H. R., Honorato, I. H., Fiorotti, R., Celeste, W. C., Silvestre, L. J., & Silva, J. A. (2021). An artificial intelligence based scheduling algorithm for demand-side energy management in smart homes. *Applied Energy*, *282*, 116145. https://doi.org/10.1016/j.apenergy.2020.116145

Sadoudi, S., Boudour, M., & Kouba, N. E. Y. (2021). Multi-microgrid intelligent load shedding for optimal power management and coordinated control with energy storage systems. *International Journal of Energy Research*, *45*(11), 15857–15878. https://doi.org/10.1002/er.6819

Scherz, M., Hoxha, E., Kreiner, H., Passer, A., & Vafadarnikjoo, A. (2022). A hierarchical reference-based know-why model for design support of sustainable building envelopes. *Automation in Construction*, *139*, 104276. https://doi.org/10.1016/j.autcon.2022.104276

Shashi, M. (2022). Sustainable digitalization by leveraging digitainability matrix in supply chain. *International Journal of Innovative Technology and Exploring Engineering*, *11*, 16–20. https://doi.org/10.35940/ijitee.K9297.10111122

Shi, T., Si, S., Chan, J., & Zhou, L. (2021). The carbon emission reduction effect of technological innovation on the transportation industry and its spatial heterogeneity: Evidence from China. *Atmosphere*, *12*(9), 1169. https://doi.org/10.3390/atmos12091169

Shukhobodskiy, A. A., Zaitcev, A., Pogarskaia, T., & Colantuono, G. (2021). RED WoLF hybrid storage system: Comparison of CO_2 and price targets. *Journal of Cleaner Production*, *321*, 128926. https://doi.org/10.1016/j.jclepro.2021.128926

Su, Y., & Fan, Q.-M. (2019). The green vehicle routing problem from a smart logistics perspective. *IEEE Access*, *8*, 839–846. https://doi.org/10.1109/ACCESS.2019.2961701

Talwar, S., Kaur, P., Okumus, B., Ahmed, U., & Dhir, A. (2021a). Food waste reduction and taking away leftovers: Interplay of food-ordering routine, planning routine, and motives. *International Journal of Hospitality Management*, *98*, 103033. https://doi.org/10.1016/j.ijhm.2021.103033

Talwar, S., Kaur, P., Yadav, R., Sharma, R., & Dhir, A. (2021b). Food waste and out-of-home-dining: Antecedents and consequents of the decision to take away leftovers after dining at restaurants. *Journal of Sustainable Tourism*, *31*, 1–26. https://doi.org/10.1080/09669582.2021.1953512

Tien, P. W., Wei, S., Calautit, J. K., Darkwa, J., & Wood, C. (2020). A vision-based deep learning approach for the detection and prediction of occupancy heat emissions for demand-driven control solutions. *Energy and Buildings*, *226*, 110386. https://doi.org/10.1016/j.enbuild.2020.110386

Walsh, T., Evatt, A., & de Witt, C. S. (2020). Artificial intelligence & climate change: Supplementary impact report. *Oxford*, *1*, 1–15.

Wang, S., Li, J., Liu, X., Zhao, E., & Eghbalian, N. (2022). Multi-level charging stations for electric vehicles by considering ancillary generating and storage units. *Energy*, *247*, 123401. https://doi.org/10.1016/j.energy.2022.123401

WEF. (2022). The world economic forum. https://www.weforum.org/

Whittemore, R., Chase, S. K., & Mandle, C. L. (2001). Validity in qualitative research. *Qualitative Health Research*, *11*, 117–132. https://doi.org/10.1177/104973201129119299

Wu, J., Wang, J., & Kong, X. (2022). Strategic bidding in a competitive electricity market: An intelligent method using multi-agent transfer learning based on reinforcement learning. *Energy*, *256*, 124657. https://doi.org/10.1016/j.energy.2022.124657

Xi, H., Wu, X., Chen, X., & Sha, P. (2021). Artificial intelligent based energy scheduling of steel mill gas utilization system towards carbon neutrality. *Applied Energy*, *295*, 117069. https://doi.org/10.1016/j.apenergy.2021.117069

Zhang, A., Alvi, M. F., Gong, Y., & Wang, J. X. (2022). Overcoming barriers to supply chain decarbonization: Case studies of first movers. *Resources, Conservation and Recycling*, *186*, 106536. https://doi.org/10.1016/j.resconrec.2022.106536

Zhang, J., Huang, Y., Aslani, F., Ma, G., & Nener, B. (2020). A hybrid intelligent system for designing optimal proportions of recycled aggregate concrete. *Journal of Cleaner Production*, *273*, 122922. https://doi.org/10.1016/j.jclepro.2020.122922

Zhao, J., Xi, X., Na, Q., Wang, S., Kadry, S. N., & Kumar, P. M. (2021a). The technological innovation of hybrid and plug-in electric vehicles for environment carbon pollution control. *Environmental Impact Assessment Review*, *86*, 106506. https://doi.org/10.1016/j.eiar.2020.106506

Zhao, L.-T., Miao, J., Qu, S., & Chen, X.-H. (2021b). A multi-factor integrated model for carbon price forecasting: Market interaction promoting carbon emission reduction. *Science of the Total Environment*, *796*, 149110. https://doi.org/10.1016/j.scitotenv.2021.149110

Zhao, X., Ma, X., Chen, B., Shang, Y., & Song, M. (2022). Challenges toward carbon neutrality in China: Strategies and countermeasures. *Resources, Conservation and Recycling*, *176*, 105959. https://doi.org/10.1016/j.resconrec.2021.105959

Zhou, D., Hu, F., Zhu, Q., & Wang, Q. (2022a). Regional allocation of renewable energy quota in China under the policy of renewable portfolio standards. *Resources, Conservation and Recycling*, *176*, 105904. https://doi.org/10.1016/j.resconrec.2021.105904

Zhou, Q., Li, Y., Zhao, D., Li, J., Williams, H., Xu, H., & Yan, F. (2022b). Transferable representation modelling for real-time energy management of the plug-in hybrid vehicle based on k-fold fuzzy learning and Gaussian process regression. *Applied Energy*, *305*, 117853. https://doi.org/10.1016/j.apenergy.2021.117853

Zhou, Y. (2022a). Artificial intelligence in renewable systems for transformation towards intelligent buildings. *Energy and AI*, *10*, 100182. https://doi.org/10.1016/j.egyai.2022.100182

Zhou, Y. (2022b). Ocean energy applications for coastal communities with artificial intelligence—A state-of-the-art review. *Energy and AI*, *10*, 100189. https://doi.org/10.1016/j.egyai.2022.100189

How to cite this article: Luqman, A., Zhang, Q., Talwar, S., Bhatia, M., & Dhir, A. (2024). Artificial intelligence and corporate carbon neutrality: A qualitative exploration. *Business Strategy and the Environment*, 1–18. https://doi.org/10.1002/bse.3689