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IMPROVING URBAN ENERGY RESILIENCE WITH AN INTEGRATIVE FRAMEWORK BASED ON MACHINE LEARNING METHODS

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Abstract
Introduction: Climate change and global warming are among the greatest challenges facing the world today. A new concept, known as urban resilience, has been developed in response. There are various approaches to urban resilience. Among them, is the urban energy resilience (UER) approach, which poses a considerable challenge. Machine learning (ML), as an application of artificial intelligence (AI), provides powerful and affordable computing resources, large-scale data mining, advanced algorithms, and real-time monitoring. However, very few studies have investigated how such aspects can be integrated into urban resilience in general, and UER in particular. **Purpose of the study:** The study develops an integrative framework that can improve UER, based on ML methods. **Methodology:** We carried out a bibliometric analysis and a systematic review of UER in accordance with AI concepts, models, and applications. **Results:** The findings of this study were used to create an integrative framework, based on three hierarchical phases, which effectively addressed the main capabilities of UER, identified its priorities, and shed light on how ML can benefit UER as a whole. **Novelty:** The framework developed in this study also offers insights in integrating ML methods into UER as strategically as possible, especially in the context of climate change and urban energy systems. This framework can serve as reference for specialists and decision-makers aiming to expand AI and ML applications to optimize UER.

Keywords
urban energy resilience; artificial intelligence; machine learning; climate change; energy systems; demand response.

Introduction

The 21st century has been referred to as the "century of the city", since more than half of the world's population currently resides in cities and urban areas (Nik et al., 2021; Ragheb et al., 2017). However, such areas are complex dynamic systems that face various social, economic, and environmental threats, all of which challenge their resilience and/or expose their vulnerabilities (Elzeni et al., 2022; Gültekin, 2021). Thus, the urban energy resilience (UER) concept is seeing increasing application in the fields of climate change, sustainability, and natural disaster risk analysis. Meanwhile, climate change and global warming present numerous challenges to energy resources in cities and urban areas (Ismail et al., 2022b; EL-Mokadem et al., 2016b; Noaman et al., 2022; Perera et al., 2021; Sharifi and Yamagata, 2014a). In fact, 60 to 80% of global energy is consumed in urban areas (Hassan et al., 2020a, 2020b; Olazabal et al., 2012; Sharifi, 2019; Sharifi and Yamagata, 2016a), which can lead to negative consequences, for instance an increase in blackouts and grid failures (Erker et al., 2017; Sharifi and Yamagata, 2016a). With regard to meeting future demand and climate targets, Perera et al. (2021) highlighted the importance of promoting energy generation through sustainable approaches, including a significant transformation in the energy infrastructure to utilize renewable energy technologies. In response, researchers and policymakers have made noticeable shifts in mitigation and adaptation strategies, taking the effects of both past and present emissions into consideration (Sharifi and Yamagata, 2014a). In this context, the concepts of resilience in general, and UER in particular, have been applied to effectively prepare for, combat, absorb, adapt to, and recover from adverse disruptions (Eslamlou et al., 2022; Francis and Bekera, 2014; Gültekin, 2021; Masnavi et al., 2018; Hunter, 2021; Kapucu et al., 2021; Olazabal et al., 2012; Tumini et al., 2017). Tien et al. (2022) considered the resilience-focused approach to energy systems to be multifaceted, having found that many studies only focused on energy supply network faults on a spatial scale larger than a single city, while ignoring the complications specific to urban environments. In this context, Erker et al. (2017) demonstrated that an energy-resilient system can successfully manage and rapidly recover from energy-related disruptions, while continuing to deliver affordable energy services. Currently, cities are characterized by a high energy demand and use, with adverse implications for energy availability, accessibility, and affordability (Perera et al., 2021). Under such circumstances, an effective demand response can create a cost-effective energy system that is both flexible and reliable (Antonopoulos et al., 2020). Wide-scale responses to energy challenges have increasingly incorporated machine learning (ML) and artificial intelligence (AI) applications, which have been used for site selection, parameter assessment, operation and maintenance optimization, planning, feasibility analysis, discharge forecasts, energy generation projections, and maintenance (Kumar and Saini, 2021).

Although the application of ML methods to UER has been gaining popularity, the topic has yet to be sufficiently investigated in light of recent climate change developments. This also indicates a growing need for an integrative framework that can bridge the gap in previous research and enhance UER as a whole (Bosisio et al., 2021; Du et al., 2014; Xie et al., 2020). Therefore, the present study creates an integrative framework that can integrate ML into UER in an acceptable and affordable manner.

We have arranged our study as follows. The research methodology is discussed in the next section, followed by a systematic review and bibliometric analysis of related works. Moreover, the relationships between climate change, the United Nations' (UN) Sustainability Development Goals (SDGs), and multiple dimensions of urban resilience are described, and urban energy systems resilience in more detail are discussed. Furthermore, AI technologies and applications with a detailed explanation of the proposed framework are identified. Finally, the conclusion is conducted.

Methodology

In order to create an integrative framework that can use ML methods to improve UER, we subjected the concept of UER to bibliometric analysis and a systematic review in accordance with AI concepts, models, and applications. First, we searched Scopus and Web of Science Core Collection for works with "resilience", "UER concept", "climate change", "urban energy systems", or "AI applications" in the title, abstract, or keywords. This was followed by a systematic review using the PRISMA method (preferred reporting items for systematic reviews and meta-analysis). The data extracted underwent bibliometric analysis in the VOSviewer software.

This keyword search yielded 3260 results. We applied "quick filters" to databases to sort results by broad categories such as document type (our study was limited to books, book chapters, journals, and conference proceedings), language (we focused on studies written in English only), and publication date (between 2012 and 2023). As the first step, duplicate results were excluded from further investigation, and the initial results were reduced to 1138 documents. Then the titles, abstracts, and introduction of every publication were manually screened and assessed for relevance to the research topic. After irrelevant papers were excluded, the final dataset for this study was reduced to a total of 33 publications, as shown in Fig. 1. We carried out a bibliometric analysis to detect co-occurrence and co-authorship of related studies.

Literature Review

Previous studies have revealed various approaches to blending the UER concept and ML applications. As shown in the bibliometric analysis carried out in VOSviewer (Fig. 2), we have identified two major clusters: ML methods and resilience. However, limited studies have focused on the intersection of these clusters. Thus, the literature review below focuses on various concepts, starting with the concept of urban resilience in general, followed by the specific concepts of UER, AI applications, and ML methods (see Table 1).

Regarding the concept of urban resilience in general, several studies have emphasized its multidimensional nature, which encompasses infrastructure, climate, and social resilience, as well as resilience assessment (Carta et al., 2021; Francis and Bekera, 2014; Khalili et al., 2015; Krishnan et al., 2021; Sharifi, 2016). That said, the work of Woolf et al. (2016) stands out here, as it investigates resilience-related projects for localized infrastructure, specifically the pilot tests under the Kenya Slum Upgrading Program in Kibera, Nairobi.

In general, previous studies on the urban resilience concept have been based on theoretical frameworks that illustrate urban dynamics over time and show how the physical structure of cities can facilitate urban resilience (Olazabal et al., 2012; Sharifi, 2019; Sharifi and Yamagata, 2014a, 2018). However, more recent studies by Sharifi and Yamagata (2016b), Ohshita and Johnson (2017), Ragheb et al. (2017), and Nik et al. (2021) indicate how energy systems can be integrated into the infrastructure that fosters urban resilience. Moreover, Hasselqvist et al. (2022) provide a complex perspective of such resilience, by using households as a starting point. Conversely, several works focus on AI applications and their contributions to building urban systems, resilience in general, infrastructure resilience, and a sustainable urban environment (Abdul-Rahman et al., 2021; Bibri, 2021a; Haggag et al., 2021; Huang and Ling, 2019; Huang and Wang, 2020; Konila Sriram et al., 2019; Ladi et al., 2022; Ortiz et al., 2021; Rahimian et al., 2020; Tekouabou et al., 2021; Zhang et al., 2022). Regarding the relationship between AI applications and energy systems, Rahimian et al.

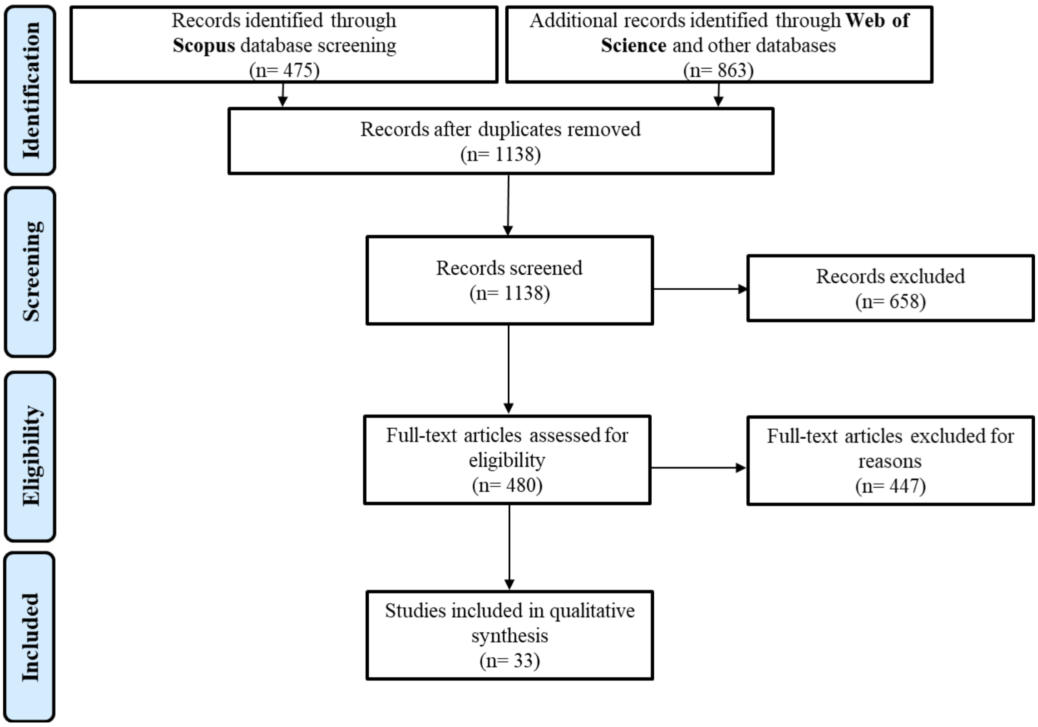

Fig. 1. Paper vetting process based on the PRISMA method

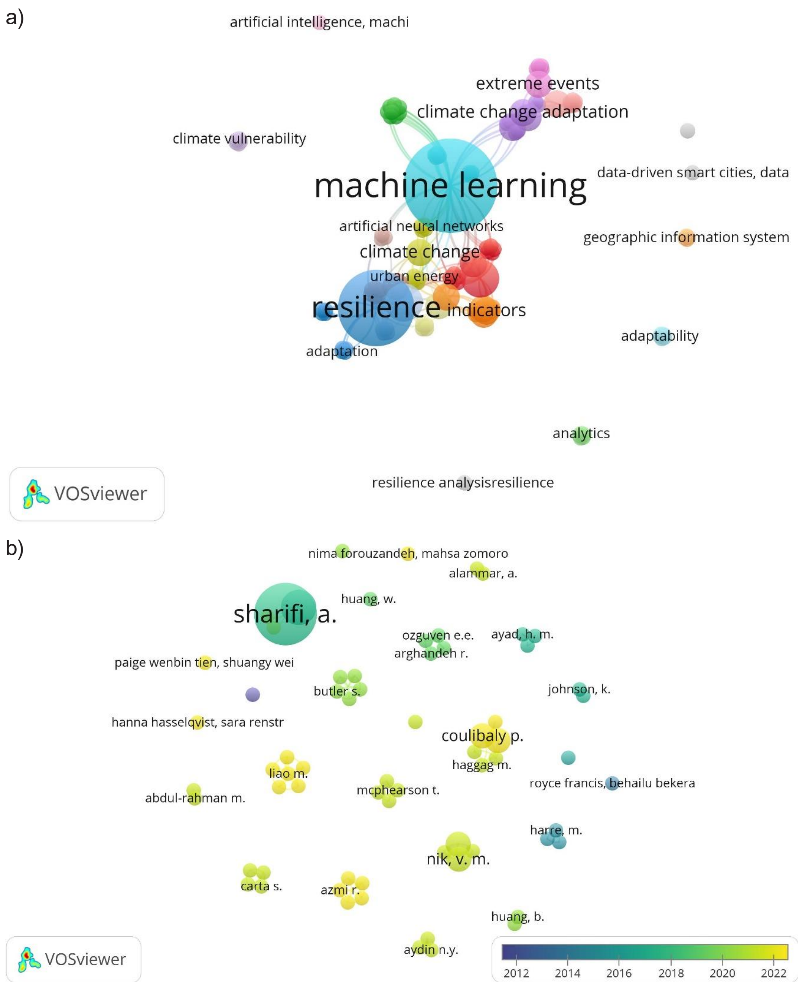

Fig. 2. Bibliometric analysis of: a — co-occurrence
and b — authors of related studies

(2020) and O'Dwyer et al. (2020) discussed the impact of AI applications on energy combustion and management, while Perera et al. (2021) researched co-optimization of energy systems in cities. As for building environments, Alammar et al. (2021), Forouzandeh et al. (2022), and Tien et al. (2022) outlined AI applications' contribution to energy efficiency.

Some limited related research also focused on the integration of AI applications and energy systems for the benefit of UER. Thus, this study bridges this gap by creating an integrative framework that can improve UER with ML methods in an acceptable and affordable manner.

Climate Change, SDGs, and Dimensions of Urban Resilience

The resilience and stability of ecological systems is a concept proposed by Holling (1973), who described it as the "ability of a system to absorb changes of state variables, driving variables, and parameters" (Saikia et al., 2022; Satterthwaite et al., 2020; Woolf et al., 2016). Since sustainability addresses the requirement for a long-term equilibrium among all systems, Ragheb et al. (2017) clarified that resilience as a concept is essential for comprehending the notion of sustainability. Resilience can also be considered a new way of thinking that can help people adjust to vulnerabilities, unprecedented changes, and unforeseen circumstances. Additionally, this concept is closely related to sustainability, an overarching idea that aims to preserve desirable human-environment interactions across time on a social, economic, and environmental level. In this context, resilience has become a central target of the UN's SDGs. For example, a resolution by the UN General Assembly described resilience as "the ability of a system, community or society exposed to hazards to resist, absorb, accommodate, adapt to,

Table 1. **Related studies on UER and ML methods**

Cluster	Concept	Aims	Main insights	Ref.
Resilience	**Resilience and infrastructure systems**	To provide a framework for resilience analysis and a metric for measuring resilience.	Proposal for an analysis framework, including: system identification, resilience objective setting, vulnerability analysis, and stakeholder engagement.	(Francis and Bekera, 2014)
	Climate resilience	To identify the research objectives and gaps that must be filled when planning support systems and addressing climate resilience.	A research agenda that integrates the full range of variables and supports choosing appropriate planning responses across multiple infrastructure systems.	(Krishnan et al., 2021)
	Social resilience	To identify, categorize, and evaluate key social resilience indicators, according to the stages of the disaster cycle.	A novel general framework for studying social resilience within communities in different disaster phases.	(Khalili et al., 2015)
	Community resilience	To analyze the similarities and differences between the various assessment tools.	A six-criteria analytical framework for measuring the effectiveness of resilience assessments.	(Sharifi, 2016)
		To analyze and improve resilient communities by optimizing sustainable design principles and using quantitative methods.	Proximity pattern observations in urban typologies, along with density and preliminary correlations.	(Carta et al., 2021)
	Resilience in slums	To examine the need for applying a universal technique to evaluate resilience-related programs in slums.	A framework tool, which was tested in a pilot project for the Kenya Slum Upgrading Program in Kibera, Nairobi.	(Woolf et al., 2016)
	Urban resilience	To carry out a comprehensive analysis of urban resilience studies.	A case study-backed conclusion that urban resilience is a multidisciplinary framework for examining the transformative capabilities of urban systems.	(Olazabal et al., 2012)
		To present a set of standards for creating an index that measures urban resilience.	A list of several major resilience principles, providing decision-makers with resilience-related information.	(Sharifi and Yamagata, 2014a)
		To present a theoretical framework for evaluating and studying the resilience of the urban form.	A framework proposal with emphasis on urban dynamics over time and space.	(Sharifi and Yamagata, 2018)
		To analyze and synthesize theoretical and empirical data on how a city's physical layout affects its resilience.	A conclusion that the urban form has significant impact on cities' resilience and sustainability, as well as on their social, ecological, and economic functions.	(Sharifi, 2019)

Table 1 (continued)

Cluster	Concept	Aims	Main insights	Ref.
Resilience	**UER**	To review the literature related to energy resilience to develop a conceptual framework for assessing UER.	An integrated framework that provides urban energy systems with the capacity for planning and preparing for, absorbing, recovering from, and adapting to adverse events.	(Sharifi and Yamagata, 2016a)
		To analyze how urban energy systems can remain energy-efficient, low-carbon, and resilient in a changing climate. To consider how climate change impacts both energy supply and energy demand in cities.	An analysis that identifies some common beneficial strategies for urban energy systems: Distributed energy resources Passive and efficient energy systems in buildings Partnerships across governments, businesses, and communities	(Ohshita and Johnson, 2017)
		To bridge the gap in UER by reviewing the concept of urban resilience and related principles.	An UER matrix that addresses energy shortages in cities.	(Ragheb et al., 2017)
		To review the steps taken to adapt urban energy systems to climate change, with a focus on climate resilience.	A methodology for evaluating the effects of climate change, particularly extreme conditions, on the operation of energy systems.	(Nik et al., 2021)
	Energy resilience	To offer a comprehensive outlook on resilience, taking households as a research starting point.	A definition of household energy resilience based on the availability of electricity. A framework for exploring household energy resilience.	(Hasselqvist et al., 2022)
AI applications and ML methods	**ML and urban lifeline system resilience**	To present a methodology for measuring system resilience.	A methodology capable of categorizing system resilience and offering guidelines for allocating resources and preventing economic loss.	(Huang and Ling, 2019)
	ML and infrastructure co-resilience	To present an advanced causal inference approach with ML integration to describe the multi-domain vulnerability of urban infrastructure systems.	A multi-network technique proposal for vulnerability assessments that can better predict disaster consequences and evaluate overall system resilience.	(Konila Sriram et al., 2019)
	Big spatial data and urban sustainability	To analyze four case studies using deep learning (DL) to identify and assess urban quality of life, as well as classify urban land use.	A set of integrated methods that combine advantages of both traditional data and big spatial data.	(Huang and Wang, 2020)
	ML, urban form, and energy consumption in cities	To discuss the multidimensional effects of urban form on the amount of energy consumed while operating community buildings.	The study found that adding the spatial dimension can improve the energy performance of community microgrids.	(Rahimian et al., 2020)
AI applications and ML methods	**Digital twins and energy management tools**	To present an energy management solution that can control, schedule, and make forecasts under user-defined objectives.	A single adaptable tool for integrating and improving energy systems, which includes a combination of predictive, modeling, and control features.	(O'Dwyer et al., 2020)
	Big data and community resilience	To review a selection of 12 global community resilience assessment tools.	The researchers found that none of the assessment tools selected use big data.	(Abdul-Rahman et al., 2021)
	ML and the impact of incident solar radiation on a building's envelope	To outline two ML models that can be used to estimate the impact of solar radiation intensity.	Input data with a substantial impact on model selection and prediction accuracy.	(Alammar et al., 2021)
	DL and climate-induced disasters	To develop a DL model for making spatial-temporal disaster predictions.	A food disaster prediction model with a 96% accuracy rate.	(Haggag et al., 2021)

Table 1 (end)

Cluster	Concept	Aims	Main insights	Ref.
AI applications and ML methods	**ML applications in urban planning**	To present a comprehensive review of ML applications that can be used for mitigating urban planning challenges.	A list of urban form modeling challenges posed by ML methods, as well as future research directions.	(Tekouabou et al., 2021)
	Data-based scenarios and vulnerability in cities	To examine the climate risks of local land use through numerical models.	Co-produced scenarios that can improve the ecosystem services offered to residents.	(Ortiz et al., 2021)
	Climate resilience and co-optimization of energy systems	To present a novel methodology that will optimize urban energy systems as interconnected infrastructures affected by urban morphology.	The study found that an optimized urban morphology can reduce the cost of energy infrastructure by up to 30%.	(Perera et al., 2021)
	Data-based smart eco-cities	To develop an integrated, case study-based model of strategic sustainable urban development.	A model that incorporates the top worldwide paradigms of urbanism, eco-cities, and data-based smart cities.	(Bibri, 2021b)
	Data-based methods of increasing energy efficiency	To examine the feasibility of seven ML algorithms for forecasting annual energy usage and thermal comfort.	A framework for predicting thermal comfort and energy demand compliance at the initial design stage.	(Forouzandeh et al., 2022)
	ML and DL methods in climate change mitigation and adaptation	To examine the most widely used ML and DL techniques in climate change adaptation and mitigation.	The study found that artificial neural networks (ANN) are the most widely used ML technology when it comes to both mitigating and adapting to climate change.	(Ladi et al., 2022)
	ML and DL methods of improving energy efficiency	To review the existing literature on the ML and DL methods used in construction environments over the last 10 years.	The study found that ML and DL have been successfully applied in assessing the energy efficiency of buildings.	(Tien et al., 2022)
	ML and structural resilience	To propose ML methods for evaluating the resilience of buildings in a mountainous area.	Optimization models with random forest generation and support vector features, and a 97.4% accuracy level.	(Zhang et al., 2022)

transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management" (Attia et al., 2022; Satterthwaite, 2013).

In light of global trends, such as climate change, urbanization, and globalization, energy demand is increasing, which, in turn, drives the continued use of fossil fuels, with their destructive environmental effects (Forootan et al., 2022). Additionally, the reliability and resilience of energy systems, along with different aspects of the energy flow, from generation to demand, are influenced by the climate. Urban resilience is associated with these three global mega-trends, given that an ability to quickly recover from extreme and unexpected disruptions is what helps cities survive (Holling, 1973; Sharifi and Yamagata, 2014b; Zekry et al., 2020). Hence, urban resilience is one of the most essential topics within SDG discourse, because it addresses such issues as risk reduction and disaster prevention (Huang and Ling, 2019). For instance, SDG 3 focuses on health and well-being; SDG 9, on industry, innovation, and infrastructure; SDG 11, on sustainable cities and communities; and SDG 13, on climate action. In this context, a resilient system is defined as one capable of retaining its usual functions, structure, identity, and feedback after undergoing change, absorbing disturbance, and reorganizing behavior (Li, 2020; Sharifi and Yamagata, 2018).

Resilience has also been described as a "multidimensional" phenomenon (Erker et al., 2017), which needs to be clarified in order to provide decision-makers with a comprehensive framework for understanding this concept better. To facilitate this, the London School of Economics and Political Science listed four key factors that measure urban resilience: physical, environmental, social, and economic. Moreover, UN-Habitat presented a framework for evaluating urban resilience across five dimensions: spatial, organizational, physical, functional, and temporal (Zekry et al., 2020). Sharifi

(2016, 2019) and Sharifi and Yamagata (2014a) also proposed five criteria that can be used to develop an urban resilience assessment index, including materials and environmental resources, society and well-being, economy, the built environment and infrastructure, and governance and institutions. In this context, the present study starts by defining urban resilience across multiple dimensions: the environmental dimension, the social and well-being dimension, the economic dimension, the organizational dimension, the physical dimension, and the functional dimension (see Fig. 3). We then show ties between these dimensions and specific SDGs that relate to such features of urban resilience as robustness, stability, and creativity (Bibri et al., 2020; Gharai et al., 2018; Satterthwaite and Dodman, 2013; Sharifi, 2016, 2019; Sharifi and Yamagata, 2014a, 2015).

Urban Energy System Resilience

Urban energy systems are responsible for meeting the energy demand in cities and urban areas by employing promising energy strategies. The Fifth Assessment Report (AR5) of the UN Intergovernmental Panel on Climate Change has defined an energy system as “all components related to the production, conversion, delivery, and use of energy” (Tien et al., 2022), while the International Energy Agency has defined energy system resilience as “the capacity of the energy system and its components to cope with a hazardous event or trend, to respond in ways that maintain its essential functions, identity and structure as well as its capacity for adaptation, learning, and transformation” (Jasiūnas et al., 2021; Molyneaux et al., 2016; To et al., 2021). Additionally, a resilient energy system can rapidly recover from vulnerabilities or disruptions, while continuing to provide affordable energy services (Erker et al., 2017; Jasiūnas et al., 2021; Sharifi, 2016). The aforementioned disruptions include: weather-related incidents, technical failures, and cyberattacks (Farhoumandi et al., 2021; Jasiūnas et al., 2021; Ohshita and Johnson, 2017).

In this context, Tien et al. (2022) indicated that energy systems are becoming the backbone of

Fig. 3. Multiple dimensions of urban resilience and their ties to the UN’s SDGs. Source: The authors’ insights, based on reviewing (Bibri et al., 2020; Gharai et al., 2018; Ragheb et al., 2017; Satterthwaite and Dodman, 2013; Sharifi, 2016, 2019; Sharifi and Yamagata, 2014a, 2015, 2016b, 2018)

urban infrastructures (despite the many challenges) and their resilience includes four dimensions that address vulnerabilities: climate, resources, infrastructure, and community. Regarding the climate dimension, climate change brings about various physical phenomena. Meanwhile, energy, food, and water are the main resources of cities, and the urban populations are highly vulnerable when they lack such resources. Moreover, infrastructure is a vital need for cities to meet in order to function as centers of habitation, production, and consumption.

Ohshita and Johnson (2017) discussed three initiatives for improving UER. The first initiative includes energy efficiency and renewable energy, while the second initiative focuses on reducing greenhouse gas (GHG) emissions (e.g., low-carbon development and climate change mitigation). The third initiative includes climate resilience or adaptation plans. In other words, the first initiative can directly promote the second and third initiatives. Consequently, this initiative can impact the acceptability, affordability, availability, and accessibility of sustainability-related dimensions via various pathways and subpathways (see Fig. 4). In addition, it mainly covers energy security, including the energy demand, supply, storage, monitoring, and management system subpathways (see Table 2).

AI Technology and Applications

The Third Industrial Revolution significantly impacted the digital age, as production was mechanized, and information, and subsequently technology, became more widely used. Subsequently, 21st-century advancements brought along the Fourth Industrial Revolution, and the focus has shifted to big data and AI applications (Abo El-Einen et al., 2015; Arfanuzzaman, 2021; Megahed, 2017; Megahed et al., 2022). As a multidisciplinary phenomenon, AI can be used for forecasting power demand and generation, optimizing the maintenance and use of energy assets, gaining a better understanding of energy usage patterns, and making systems more stable and efficient (Elzeni et al., 2021; Hassan et al., 2022; Williams, 1983). AI can also lighten the load on humans by partially automating decision-making, scheduling, and controlling multiple devices (Ahmad et al., 2022; Antonopoulos et al., 2020; Chan et al., 2020; Chan and Zhang, 2019; Megahed, 2015).

Overall, AI applications facilitate real-time monitoring and control, peer-to-peer energy transmission, smart contracts, and cyber protection of energy assets. These aspects can result in expedient supply, better demand management, and energy storage services that are reliable, resilient, flexible, and sustainable. AI applications can also perform highly complex tasks using knowledge- and data-based models (see Fig. 5). Knowledge-based methods include causal models (fault trees) that use human knowledge to support decision-making and pattern classification. This requires predictive modeling of production, consumption, and demand (Dey et al., 2020; Mosavi et al., 2019). Data-based methods, in turn, include principal component analysis of related data and general knowledge of certain systems (Alzghoul et al., 2014; Dey et al., 2020; Mosavi et al., 2019). Data-based methods can be expanded further in several ways, e.g., to ML and deep learning (DL), which offer practical modeling algorithms and techniques (Forootan et al., 2022).

Machine Learning (ML)

ML is based on three technology trends: the rapid advancement of sensors and IoT, which provide a large amount of data (Cantelmi et al., 2022; Huang et al., 2022); ML-oriented chips, such as graphic processing units and tensor processing

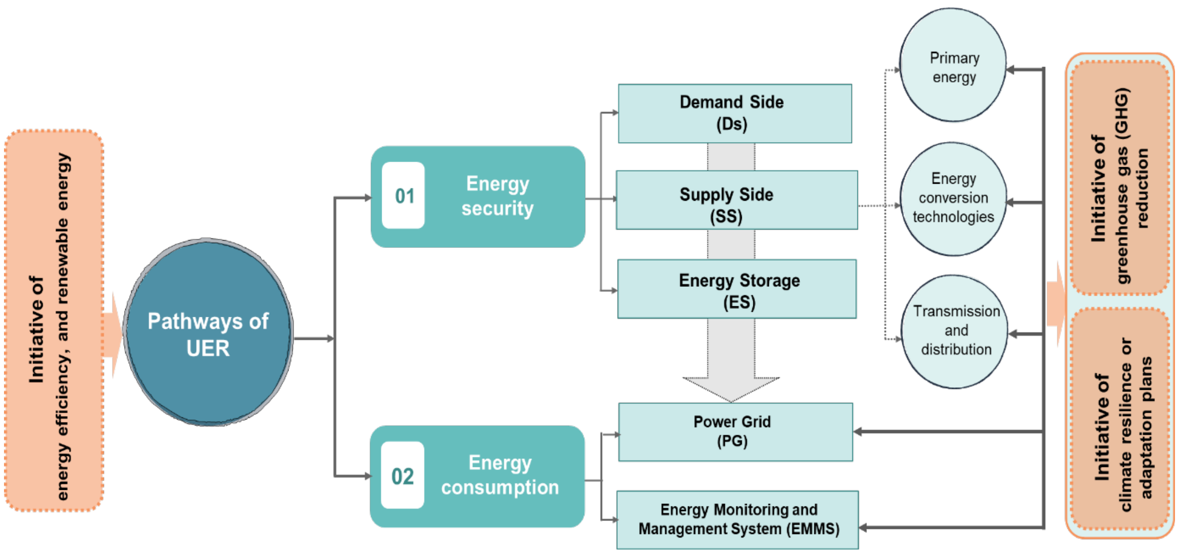

Fig. 4. Urban energy system initiatives and their ties to UER pathways and subpathways. Source: The authors' insights, based on reviewing (Hasselqvist et al., 2022; Sharifi, 2016, 2019; Sharifi and Yamagata, 2014a, 2016b, 2018)

Table 2. **UER pathways, subpathways, and descriptions. Source: The authors' insights, based on reviewing (Allegrini et al., 2015; Badawy et al., 2022; Bibri and Krogstie, 2020b; Chelleri and Olazabal, 2012; Cai et al., 2021; Elgheznawy et al., 2022; Elmokadem et al., 2016a; Hassan et al., 2022; Ismail et al., 2022a; Jasiūnas et al., 2021; Liu et al., 2021; Megahed and Ghoneim, 2021; Noaman et al., 2022; Paraschos et al., 2022; Sugahara and Bermont, 2016)**

<table>
<tr><th>UER Path-ways</th><th>UER Subpathways</th><th colspan="2">Description</th></tr>
<tr><td rowspan="5">Energy security</td><td>Demand side</td><td colspan="2">Includes the aspects of efficiency, flexibility, and resilience at a relatively low cost for the overall energy system, which requires dealing with increased complexity and less well-established structures.</td></tr>
<tr><td rowspan="3">Supply side</td><td>Primary energy</td><td>Fossil fuels and renewable energy sources face the issues of security and import dependency.</td></tr>
<tr><td>Energy conversion technologies</td><td>Secure against extreme weather and technical failures.</td></tr>
<tr><td>Transmission and distribution</td><td>Renewable sources have been powering other energy sectors, especially in recent years.</td></tr>
<tr><td>Energy storage</td><td colspan="2">Inherent balance versus supply and demand disruptions. Energy resilience is ensured by inbuilt storage capacity at various points.</td></tr>
<tr><td rowspan="2">Energy consumption</td><td>Power grid</td><td colspan="2">Requires smart meters and communication technologies within electricity networks, supported by hardware, software, and network tools that allow generators to route power to consumers more efficiently.</td></tr>
<tr><td>Energy monitoring and management systems</td><td colspan="2">Such systems let the owners use smart technology for remotely regulating, controlling, and monitoring a building's mechanical and electrical subsystems, such as heating, ventilation, air conditioning, lighting, power, and security.</td></tr>
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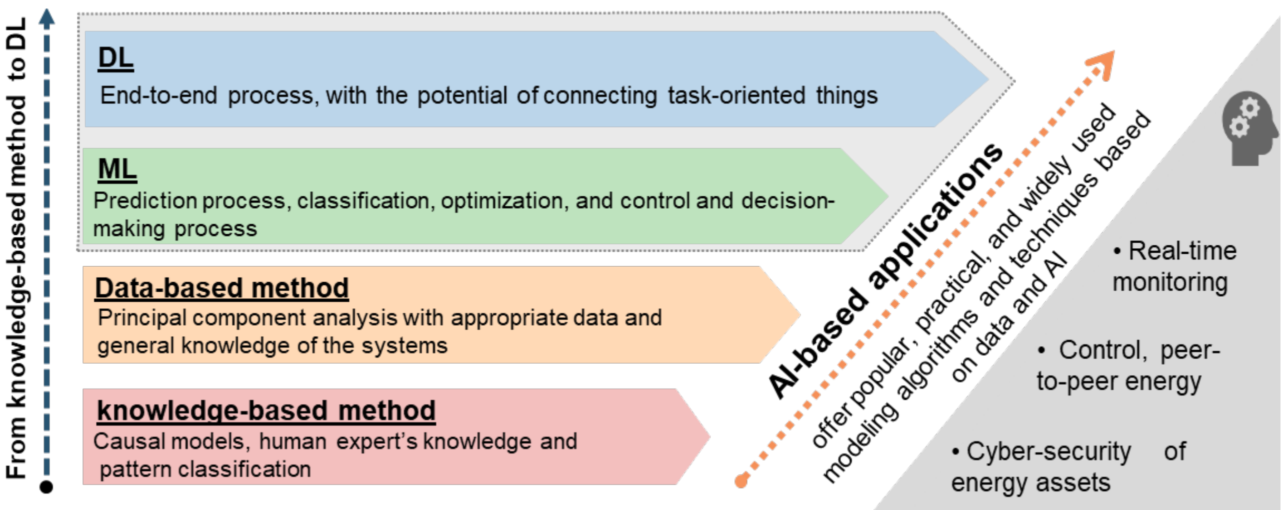

Fig. 5. Evolution of AI and energy system models. Source: The authors' insights, based on reviewing (Alzghoul et al., 2014; Bibri, 2021a; Bibri and Krogstie, 2019; Dey et al., 2020; Forootan et al., 2022; Mosavi et al., 2019; Seneviratne et al., 2022; Thomas et al., 2021; Wang et al., 2022)

units, which offer better access to powerful and affordable computational resources; and advanced ML algorithms (S. Bibri, 2021b; O'Dwyer et al., 2020; Nashaat, Elmokadem and Waseef, 2022). ML also allows for image-data-based (RGB) numeric labeling, collecting and clustering useful information, and semantic segmentation from large, complex datasets (Alammar et al., 2021). Additionally, accumulating large volumes of data can support comparisons via data deductions and distance calculations (Bibri, 2019; Seneviratne et al., 2022).

Typical ML and UER Workflow

The typical ML workflow includes a process that starts by generating data and then trains and deploys the model (El-Mowafy et al., 2022). Specifically, the first phase includes acquiring input data with parameters that impact or correlate with the output data. ML models can be classified into three main types: supervised, unsupervised, and reinforcement learning. In the context of energy systems, ML can help identify nonlinear correlations within energy systems, such as the relationship between cooling demand and related variables (e.g., outdoor temperature and occupancy activities), by using mapping functions from a dataset (Tien et al., 2022).

The first learning type, supervised learning, allows for developing algorithms that use fully labeled datasets to classify and regress problems. Regression algorithms can be deployed for determining continuous values or quantities. Classification algorithms, in turn, help predict discrete or distinct values, e.g., when the result needs to be a category. Regression models can also be used in energy demand forecasting to comprehend the variables that influence energy usage, such as building morphology, material, and orientation (Liang, 2020).

In unsupervised learning, the algorithm, once developed, interprets unlabeled data by independently extracting patterns and characteristics, without specific guidance on what to do with its findings. Unsupervised learning techniques are frequently used for various tasks, including dimensionality reduction, association, and clustering. The most common task carried out with unsupervised learning techniques is clustering, which can reveal the structure in an unlabeled dataset (Gull et al., 2021; Wang and Biljecki, 2022).

Finally, reinforcement learning allows algorithms to react to an environment independently. Such methods, via their agents, can maximize the numerical reward signal through trial and error, which makes it possible to learn how to map situations to actions. As the last phase of deploying the model, reinforcement learning methods can also provide optimal strategies for decreasing building energy demand based on real-time data (Tien et al., 2022).

In the context of ML and UER, existing historical input data (collected via energy meters, wireless networks, and sensors, as well as by using the Internet of Things-based techniques that allow energy monitoring solutions to generate vast amounts of data) are highly accurate and relatively easy to deploy. The output parameters, in turn, predict energy demand, energy planning, management, and conservation. They can be used in strategies for reducing energy consumption and CO2 emissions.

Based on the above, this study uses the Sankey diagram to visualize the relationship flows between pathways that represent UER and their associated ML categories, including: regression, classification, clustering, and models with examples of proposed processes (see Fig. 6). The regression process is based on evaluating the relationship between a dependent variable and independent variables. Regression analysis is one of the most fundamental methods for prediction in the field of ML. In our case, regression includes hourly global solar radiation, system power output, irradiance levels (based on photovoltaic electrical characteristics), reduction in wind power, photovoltaic power generation, and reduction in wind power. The classification process can categorize a given set of data, either structured or unstructured. The process starts with predicting and labeling the classes of the given data points. Classification can include building energy consumption, renewable energy loads in microgrids, and electricity loads (Alammar et al., 2021; Hosseini and Parvania, 2021). Clustering refers to an algorithm's capacity to generate probable values for each unknown variable in each new data record, allowing the model builder to identify the probable value. For instance, in one case study, a geothermal pump helped provide a district with heat, while simultaneously improving fuel economy and optimizing a railway electric power system (Chan and Zhang, 2019; Wu et al., 2022). Such ML models include multilayer perception (MLP), extreme learning machines, advanced artificial neural networks (ANNs), support vector machines (SVMs), decision trees, and hybrid models such as wavelet neural networks (WNNs) and adaptive neuro-fuzzy inference systems.

ML-Based Integrative Framework for UER

Certain factors, for instance, weather conditions and power generation that uses solar photovoltaic energy or wind turbines, make achieving UER more challenging. Since peak energy demand does not coincide with peak energy production, compensating for this mismatch necessitates the use of auxiliary technologies, such as energy storage. In order to bridge the gap between the different aspects of the UER concept, it is important to create an integrative framework based on UER's four capabilities: preparation, observation, adaptation, and recovery (Francis and Bekera, 2014; Sharifi and Yamagata, 2016a).

This process starts with measuring resilience before, during, and after a disruption, which is associated with UER capabilities and objectives, as well as ML. The framework proposed in this study consists of the following three phases (see Fig. 7):

1. Addressing resilience capabilities: This phase deals with the main components of UER before, during, and after a disruption. This entails predicting and preparing for a disruption by adopting a wide range of design and planning strategies to minimize the potential adverse impacts on energy acceptability, affordability, accessibility, and availability. Here, resilience refers to a system's ability to absorb the impact of a disruption in advance and afterwards. In turn, adaptation is the ability to flexibly adjust during and after a disruption. Finally, recovery refers to processes that occur during and after a disruption and help restore the energy system's capacity and reliability to a normal operational level.

2. Identifying UER priorities: At this phase, UER priorities are identified during and after a disruption.

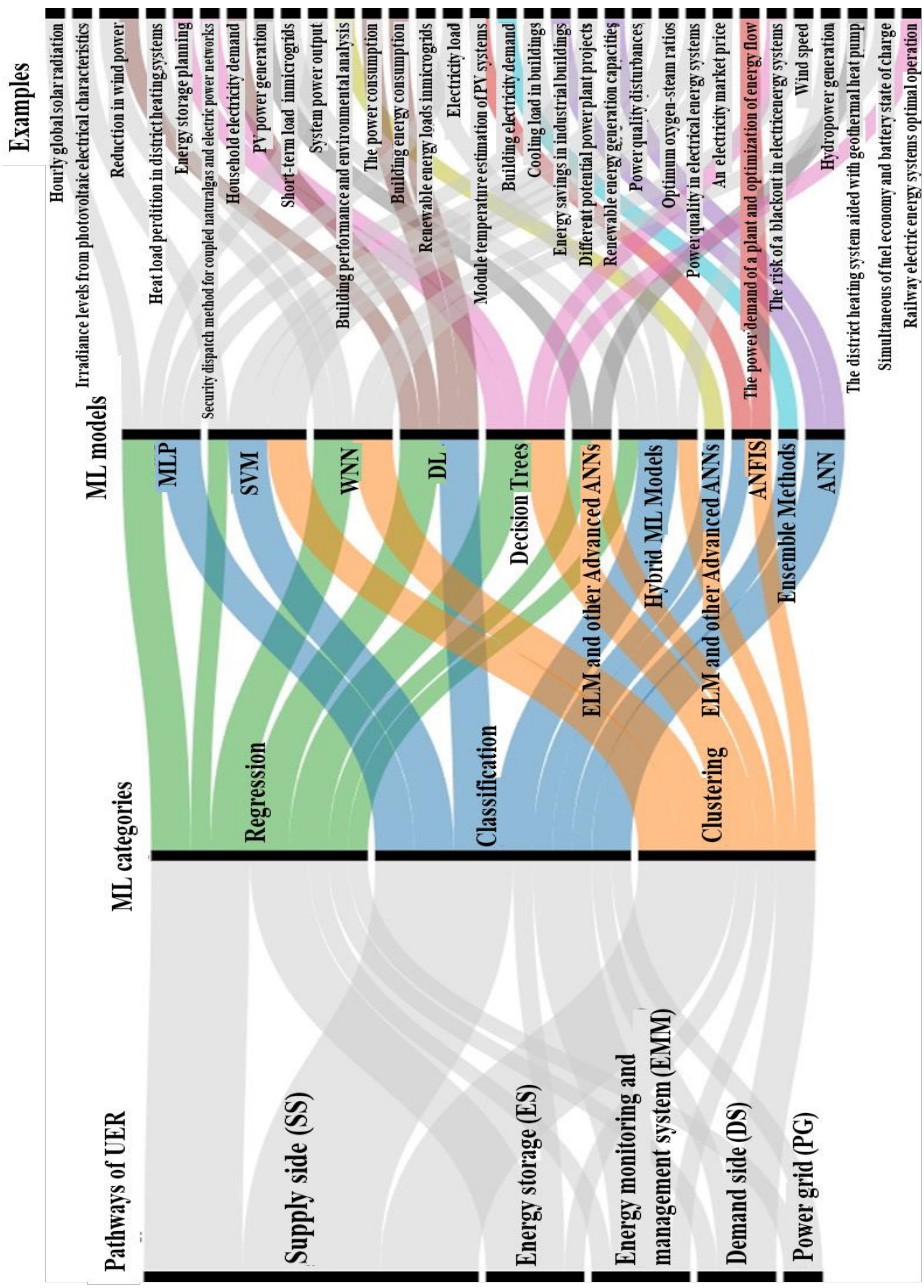

Fig. 6. A Sankey diagram of pathways, representing UER, their associated ML categories, and models with examples. Source: The authors' insights, based on reviewing (Alammar et al., 2021; Bibri and Krogstie, 2020a; Chan and Zhang, 2019; Guvenir et al., 1997; Hasselqvist et al., 2022; Setiadi et al., 2022; Wu et al., 2022)

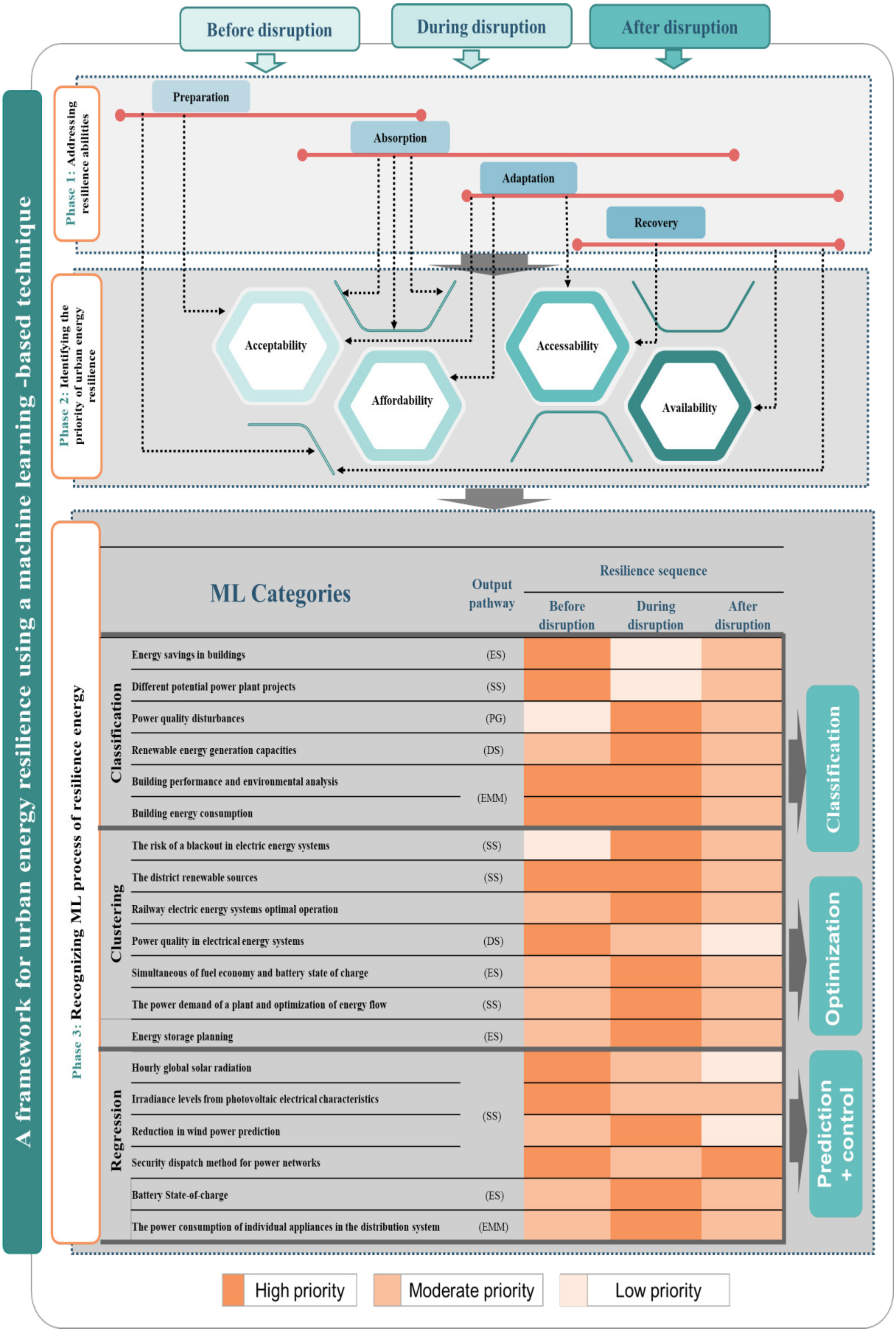

Fig. 7. The ML-based integrative framework for UER

The key capabilities here are preparation, or the process of achieving energy accessibility and affordability, and absorption, which is associated with acceptability, in addition to both accessibility and affordability.

3. Recognizing the ML aspect of energy resilience: At this phase, one identifies how ML can improve UER through three key categories, i.e., regression, classification, and clustering. This involves four main processes: classification, prediction, control, and optimization. This phase is also when one constructs a relationship matrix of the ML categories, the resilience sequences, and their relationships to energy security, including supply- and demand-side management, energy storage, and energy consumption. For instance, ML algorithms, such as SVMs, ANNs, and MLP, can classify potential power plant projects or power quality disturbances that improve energy storage, supply-side management, and power grids, using sensors in a wireless network. These networks first collect data from various sources within a system and then analyze their findings to facilitate real-time preparation, absorption, recovery decision-making, and information transmission, which are high priorities before and during a disruption, and moderate priorities after a disruption. In addition, optimization processes that use ML algorithms, such as MLP, ANNs, and WNNs, predict hourly global solar radiation and irradiance levels based on photovoltaic electrical characteristics, forecast reduction in wind power, assess the risk of blackouts in electric power systems via regression, and operate in clustering categories.

Therefore, the framework proposed in this study can serve as a reference for integrating ML and AI applications in order to improve UER in the three aforementioned phases. Both UER pathways and subpathways can also assist with supply- and demand-side management, power grids, energy storage, and energy monitoring. This framework can ensure that climate risks are considered as part of utility rate cases for investments in new/upgraded infrastructure. It can also provide backup power during emergencies at all critical facilities identified. Moreover, through UER, it is possible to overcome the challenges of global climate change by reducing the demand for fossil fuels, while responding to the increasing need for an expanded sustainable energy supply. Since all of the above aligns with several of the UN's SDGs, future researchers can build on the framework proposed in this study and expand AI and ML applications to optimize UER in general and further support the UN's objectives in particular.

Conclusion

In this study, we created an integrative framework to bridge the gap in previous research on the potential use of AI and ML applications for sustaining UER systems, even during service disruptions. For this purpose, we carried out a bibliometric analysis and a systematic UER overview in accordance with AI concepts, models, and applications. Since the UER concept has been highlighted among the approaches to addressing the impact of climate change, we examined its significance in this field, as well as its alignment with the UN's SDGs.

In this context, our framework proposal included three phases. The first phase addresses key elements of UER through a series of actions before, during, and after a disruption. The second phase determines the varying importance of UER in achieving accessibility and affordability. The third phase explores how ML can improve UER through three key categories, regression, classification, and clustering, in order to support four main processes: classification, prediction, control, and optimization. This step further includes a relationship matrix between the ML processes, the resilience sequences, and their connections to energy, which are identified via priority variations.

The results of our study show that this integrative framework effectively addresses UER's main capabilities, identifies its priorities, and recognizes how ML can benefit UER as a whole. The framework developed in this study also offers insights in integrating ML methods into UER as strategically as possible, especially in the context of climate change and urban energy systems. Moreover, we found that UER efforts follow the pathways of energy management, encompassing energy security and consumption. Such pathways can ensure an energy system's preparation, absorption, adaptation, and recovery under disruption conditions.

Finally, we hope that the proposed framework can serve as an initial step for researchers and decision-makers focusing on UER in the context of climate change. However, more research is necessary to verify the effectiveness of this framework when aiming to expand AI and ML applications in order to optimize UER.

Data and Material Availability

The data that support the findings of this study can be provided by the corresponding author upon request.

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Conflict of Interest

The authors declare that there is no conflict of interest.

References

Abdul-Rahman, M., Chan, E. H. W., Wong, M. S., and Xu, P. (2021). Big Data for community resilience assessment: A critical review of selected global tools. In: Ye, G., Yuan, H., and Zuo, J. (eds.). *Proceedings of the 24th International Symposium on Advancement of Construction Management and Real Estate. CRIOCM 2019*. Singapore: Springer, pp. 1345–1361. DOI: 10.1007/978-981-15-8892-1_94.

Abo El-Einen, O. M., Ahmed, M. M., Megahed, N. A., and Hassan, A. M. (2015). Interactive-based approach for designing facades in digital era. *Port-Said Engineering Research Journal*, Vol. 19, Issue 1, pp. 72–81.

Ahmad, T., Madonski, R., Zhang, D., Huang, C., and Mujeeb, A. (2022). Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm. *Renewable and Sustainable Energy Reviews*, Vol. 160, 112128. DOI: 10.1016/j.rser.2022.112128.

Alammar, A., Jabi, W., and Lannon, S. (2021). Predicting Incident solar radiation on building's envelope using machine learning. In: *SimAUD 2021,* April 15–17, 2021, virtually hosted.

Allegrini, J., Orehounig, K., Mavromatidis, G., Ruesch, F., Dorer, V., and Evins, R. (2015). A review of modelling approaches and tools for the simulation of district-scale energy systems. *Renewable and Sustainable Energy Reviews*, Vol. 52, pp. 1391–1404. DOI: 10.1016/j.rser.2015.07.123.

Alzghoul, A., Backe, B., Löfstrand, M., Byström, A., and Liljedahl, B. (2014). Comparing a knowledge-based and a data-driven method in querying data streams for system fault detection: A hydraulic drive system application. *Computers in Industry*, Vol. 65, Issue 8, pp. 1126–1135. DOI: 10.1016/j.compind.2014.06.003.

Antonopoulos, I., Robu, V., Couraud, B., Kirli, D., Norbu, S., Kiprakis, A., Flynn, D., Elizondo-Gonzalez, S., and Wattam, S. (2020). Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. *Renewable and Sustainable Energy Reviews*, Vol. 130, 109899. DOI: 10.1016/j.rser.2020.109899.

Arfanuzzaman, M. (2021). Harnessing artificial intelligence and big data for SDGs and prosperous urban future in South Asia. *Environmental and Sustainability Indicators*, Vol. 11, 100127. DOI: 10.1016/j.indic.2021.100127.

Attia, S., Holzer, P., Homaei, S., Kazanci, O. B., Zhang, C., and Heiselberg, P. (2022). Resilient cooling in buildings – A review of definitions and evaluation methodologies. In: *CLIMA 2022 Conference*, May 22–25, Rotterdam, the Netherlands. DOI: 10.34641/clima.2022.195.

Badawy, N. M., El Samaty, H. S., and Waseef, A. A. E. (2022). Relevance of monocrystalline and thin-film technologies in implementing efficient grid- connected photovoltaic systems in historic buildings in Port Fouad city, Egypt. *Alexandria Engineering Journal*, Vol. 61, Issue 12, pp. 12229–12246. DOI: 10.1016/j.aej.2022.06.007.

Bibri, S. (2019) 'Generating a Vision for Smart Sustainable City of the Future: A Scholarly Backcasting Approach', European Journal of Futures Research. doi: 10.1186/s40309-019-0157-0.

Bibri, S. E. (2021a). A novel model for data-driven smart sustainable cities of the future: the institutional transformations required for balancing and advancing the three goals of sustainability. *Energy Informatics*, Vol. 4, No. 1, pp. 1–37. DOI: 10.1186/s42162-021-00138-8.

Bibri, S. E. (2021b). Data-driven smart eco-cities of the future: an empirically informed integrated model for strategic sustainable urban development. *World Futures*, pp. 1–44. DOI: 10.1080/02604027.2021.1969877.

Bibri, S. E. and Krogstie, J. (2019). Generating a vision for smart sustainable city of the future: a scholarly backcasting approach. *European Journal of Futures Research*, Vol. 7, Issue 1, pp. 1–20. DOI: 10.1186/s40309-019-0157-0.

Bibri, S. E. and Krogstie, J. (2020a). Smart eco-city strategies and solutions for sustainability: the cases of Royal Seaport, Stockholm, and Western Harbor, Malmö, Sweden. *Urban Science*, Vol. 4, Issue 1, 11. DOI: 10.3390/urbansci4010011.

Bibri, S. E. and Krogstie, J. (2020b). The emerging data–driven Smart City and its innovative applied solutions for sustainability: the cases of London and Barcelona. *Energy Informatics*, Vol. 3, 5. doi: 10.1186/s42162-020-00108-6.

Bibri, S. E., Krogstie, J., and Kärrholm, M. (2020). Compact city planning and development: Emerging practices and strategies for achieving the goals of sustainability. *Developments in the Built Environment*, Vol. 4, 100021. DOI: 10.1016/j.dibe.2020.100021.

Bosisio, A., Moncecchi, M., Morotti, A., and Merlo, M. (2021). Machine learning and GIS approach for electrical load assessment to increase distribution networks resilience. *Energies*, Vol. 14, Issue 14, 4133. DOI: 10.3390/en14144133.

Cai, C., Guo, Z., Zhang, B., Wang, X., Li, B., and Tang, P. (2021). Urban morphological feature extraction and multi-dimensional similarity analysis based on deep learning approaches. *Sustainability*, Vol. 13, Issue 12, 6859. DOI: 10.3390/su13126859.

Cantelmi, R., Steen, R., Di Gravio, G., and Patriarca, R. (2022). Resilience in emergency management: Learning from COVID-19 in oil and gas platforms. *International Journal of Disaster Risk Reduction*, Vol. 76, 103026. DOI: 10.1016/j.ijdrr.2022.103026.

Carta, S., Pintacuda, L., Owen, I. W., and Turchi, T. (2021). Resilient communities: a novel workflow. *Frontiers in Built Environment*, Vol. 7, 767779. DOI: 10.3389/fbuil.2021.767779.

Chan, M. F., Witztum, A., and Valdes, G. (2020). Integration of AI and machine learning in radiotherapy QA. *Frontiers in Artificial Intelligence*, Vol. 3, 577620. DOI: 10.3389/frai.2020.577620.

Chan, J. and Zhang, Y. (2019) *Urban resilience in the smart city*. In: *The 12th Conference of the International Forum on Urbanism: Beyond Resilience,* June 24–26, 2019, Jakarta, Indonesia*.*

Chelleri, L. and Olazabal, M. (eds.) (2012). *Multidisciplinary perspectives on urban resilience*. Bilbao: Basque Centre for Climate Change, *78 p.*

Dey, M., Rana, S.P., and Dudley, S. (2020). A case study based approach for remote fault detection using multi-level machine learning in a smart building. *Smart Cities*, Vol. 3, Issue 2, pp. 401–419. DOI: 10.3390/smartcities3020021.

Du, Z., Palem, K., Lingamneni, A., Temam, O., Chen, Y., and Wu, C. (2014). Leveraging the error resilience of machine-learning applications for designing highly energy efficient accelerators. In: *2014 19th Asia and South Pacific Design Automation Conference (ASP-DAC),* January 20–23, 2014, Singapore. DOI: 10.1109/ASPDAC.2014.6742890.

Elgheznawy, D., El Enein, O. A., Shalaby, G., Seif, A. (2022). An experimental study of indoor air quality enhancement using breathing walls. *Civil Engineering and Architecture*, Vol. 10, No. 1, pp. 194–209. DOI: 10.13189/cea.2022.100117.

Elmokadem, A. A., Megahed, N. A., and Noaman, D. S. (2016a). Systematic framework for the efficient integration of wind technologies into buildings. *Frontiers of Architectural Research*, Vol. 5, Issue 1, pp. 1–14. DOI: 10.1016/j.foar.2015.12.004.

EL-Mokadem, A. A., Megahed, N. A., and Noaman, D. S. (2016b). Towards a Computer Program for building-integrated wind technologies. *Energy and Buildings*, Vol. 117, pp. 230–244. DOI: 10.1016/j.enbuild.2016.02.022.

El-Mowafy, B. N., Elmokadem, A. A., and Waseef, A. A. (2022). Evaluating adaptive facade performance in early building design stage: an integrated daylighting simulation and machine learning. In: Hassanien, A. E., Rizk, R. Y., Snášel, V., and Abdel-Kader, R. F. (eds.). *The 8th International Conference on Advanced Machine Learning and Technologies and Applications (AMLTA2022). AMLTA 2022. Lecture Notes on Data Engineering and Communications Technologies*, Vol. 113. Cham: Springer, pp. 211–223. DOI: 10.1007/978-3-031-03918-8_20.

Elzeni, M. M., Elmokadem, A. A., and Badawy, N. M. (2021). Genetic algorithms application in urban morphology generation. *Port-Said Engineering Research Journal*, Vol. 26, No. 1, pp. 21–34. DOI: 10.21608/pserj.2021.87367.1129.

Elzeni, M. M., ElMokadem, A. A., and Badawy, N. M. (2022). Impact of urban morphology on pedestrians: A review of urban approaches. *Cities*, Vol. 129, 103840. DOI: 10.1016/j.cities.2022.103840.

Erker, S., Stangl, R., and Stoeglehner, G. (2017). Resilience in the light of energy crises – Part I: A framework to conceptualise regional energy resilience. *Journal of Cleaner Production*, Vol. 164, pp. 420–433. DOI: 10.1016/j.jclepro.2017.06.163.

Eslamlou, M. S., Tabibian, M., and Mirmoghtadaee, M. (2022). Developing a conceptual framework of urban resilience for its application in urban literature, through thematic analysis of texts. *Quarterly Journal of Iranian Islamic City Studies*, Vol. 12, Issue 45, pp. 71–84.

Farhoumandi, M., Zhou, Q., and Shahidehpour, M. (2021). A review of machine learning applications in IoT-integrated modern power systems. *The Electricity Journal*, Vol. 34, Issue 1, 106879. DOI: 10.1016/j.tej.2020.106879.

Forootan, M. M., Larki, I., Zahedi, R., and Ahmadi, A. (2022). Machine learning and deep learning in energy systems: a review. *Sustainability*, Vol. 14, Issue 8, 4832. DOI: 10.3390/su14084832.

Forouzandeh, N., Zomorodian, Z. S., Shaghaghian, Z., and Tahsildoost, M. (2022). Room energy demand and thermal comfort predictions in early stages of design based on the Machine Learning methods. *Intelligent Buildings International*. DOI: 10.1080/17508975.2022.2049190.

Francis, R. and Bekera, B. (2014). A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliability Engineering & System Safety*, Vol. 121, pp. 90–103. DOI: 10.1016/j.ress.2013.07.004.

Gharai, F., Masnavi, M., and Hajibandeh, M. (2018). Urban local-spatial resilience: developing the key indicators and measures, a brief review of literature. *The Monthly Scientific Journal of Bagh-e Nazar*, Vol. 14, Issue 57, pp. 19–32.

Gull, C. Q., Aguilar, J., and R-Moreno, M. D. (2021). A semi-supervised learning approach to study the energy consumption in smart buildings. In: *2021 IEEE Symposium Series on Computational Intelligence (SSCI),* December 5–7, 2021, Orlando, FL, USA. DOI: 10.1109/SSCI50451.2021.9659911.

Gültekin, Y. (2021). Strategies to improve urban energy efficiency for urban resilience. *IOP Conference Series: Materials Science and Engineering*, Vol. 1203, 022020. DOI: 10.1088/1757-899X/1203/2/022020.

Guvenir, H. A., Acar, B., Demiroz, G., and Cekin, A. (1997). A supervised machine learning algorithm for arrhythmia analysis. In: *Computers in Cardiology 1997*. Lund: IEEE, pp. 433–436. DOI: 10.1109/CIC.1997.647926.

Haggag, M., Siam, A. S., El-Dakhakhni, W., Coulibaly, P., and Hassini, E. (2021). A deep learning model for predicting climate-induced disasters. *Natural Hazards*, Vol. 107, Issue 1, pp. 1009–1034. DOI: 10.1007/s11069-021-04620-0.

Hassan, A. M., El Mokadem, A. A. F., Megahed, N. A., and Abo Eleinen, O. M. (2020a). Improving outdoor air quality based on building morphology: Numerical investigation. *Frontiers of Architectural Research*, Vol. 9, Issue 2, pp. 319–334. DOI: 10.1016/j.foar.2020.01.001.

Hassan, A. M., ElMokadem, A. A., Megahed, N. A., and Abo Eleinen, O. M. (2020b). Urban morphology as a passive strategy in promoting outdoor air quality. *Journal of Building Engineering*, Vol. 29, 101204. DOI: 10.1016/j.jobe.2020.101204.

Hassan, S. R., Megahed, N. A., Abo Eleinen, O. M., and Hassan, A. M. (2022). Toward a national life cycle assessment tool: Generative design for early decision support. *Energy and Buildings*, Vol. 267, 112144. DOI: 10.1016/j.enbuild.2022.112144.

Hasselqvist, H., Renström, S., Strömberg, H., and Håkansson, M. (2022). Household energy resilience: Shifting perspectives to reveal opportunities for renewable energy futures in affluent contexts. *Energy Research & Social Science*, Vol. 88, 102498. DOI: 10.1016/j.erss.2022.102498.

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, Vol. 4, pp. 1–23. DOI: 10.1146/annurev.es.04.110173.000245.

Hosseini, M. M. and Parvania, M. (2021). Artificial intelligence for resilience enhancement of power distribution systems. *The Electricity Journal*, Vol. 34, Issue 1, 106880. DOI: 10.1016/j.tej.2020.106880.

Huang, Y., Huang, L., and Zhu, Q. (2022). Reinforcement Learning for feedback-enabled cyber resilience. *Annual Reviews in Control*, Vol. 53, pp. 273–295. DOI: 10.1016/j.arcontrol.2022.01.001.

Huang, W. and Ling, M. (2019). Machine learning-based method for urban lifeline system resilience assessment in GIS*. In: Rocha, J. and Abrantes, P. (eds.). *Geographic Information Systems and Science. Chapter 3*. London: IntechOpen. DOI: 10.5772/intechopen.82748.

Huang, B. and Wang, J. (2020). Big spatial data for urban and environmental sustainability. *Geo-spatial Information Science*, Vol. 23, Issue 2, pp. 125–140. DOI: 10.1080/10095020.2020.1754138.

Hunter, M. (2021). Resilience, fragility, and robustness: cities and COVID-19. *Urban Governance*, Vol. 1, Issue 2, pp. 115–125. DOI: 10.1016/j.ugj.2021.11.004.

Ismail, R. M., Megahed, N. A., and Eltarabily, S. (2022a). Numerical investigation of the indoor thermal behaviour based on PCMs in a hot climate. *Architectural Science Review*, Vol. 65, Issue 3, pp. 196–216. DOI: 10.1080/00038628.2022.2058459.

Ismail, R. M., Megahed, N. A., and Eltarabily, S. (2022b). The strategy of using PCMs in building sector applications. *Port-Said Engineering Research Journal*, Vol. 26, No. 3, pp. 1–12. DOI: 10.21608/pserj.2022.135558.1185.

Jasiūnas, J., Lund, P. D., and Mikkola, J. (2021). Energy system resilience – a review. *Renewable and Sustainable Energy Reviews*, Vol. 150, 111476. DOI: 10.1016/j.rser.2021.111476.

Kapucu, N., Ge, Y., Martín, Y., and Williamson, Z. (2021). Urban resilience for building a sustainable and safe environment. *Urban Governance*, Vol. 1, Issue 1, pp. 10–16. DOI: 10.1016/j.ugj.2021.09.001.

Khalili, S., Harre, M., and Morley, P. (2015). A temporal framework of social resilience indicators of communities to flood, case studies: Wagga wagga and Kempsey, NSW, Australia. *International Journal of Disaster Risk Reduction*, Vol. 13, pp. 248–254. DOI: 10.1016/j.ijdrr.2015.06.009.

Konila Sriram, L. M., Ulak, M. B., Ozguven, E. E., and Arghandeh, R. (2019). Multi-network vulnerability causal model for infrastructure co-resilience. *IEEE Access*, Vol. 7, pp. 35344–35358. DOI: 10.1109/ACCESS.2019.2904457.

Krishnan, S., Aydin, N. Y., and Comes, T. (2021). Planning support systems for long-term climate resilience: a critical review. In: Geertman, S. C. M., Pettit, C., Goodspeed, R., and Staffans, A. (eds.). *Urban Informatics and Future Cities. The Urban Book Series*. Cham: Springer, pp. 465–498. DOI: 10.1007/978-3-030-76059-5_24.

Kumar, K. and Saini, R. P. (2021). Application of artificial intelligence for the optimization of hydropower energy generation. *EAI Endorsed Transactions on Industrial Networks and Intelligent Systems*, Vol. 8, Issue 28, e1. doi: 10.4108/eai.6-8-2021.170560.

Ladi, T., Jabalameli, S., and Sharifi, A. (2022). Applications of machine learning and deep learning methods for climate change mitigation and adaptation. *Environment and Planning B: Urban Analytics and City Science*, Vol. 49, Issue 4, pp. 1314–1330. DOI: 10.1177/23998083221085281.

Li, Q. (2020). Resilience thinking as a system approach to promote China's sustainability transitions. *Sustainability*, Vol. 12, Issue 12, 5008. DOI: 10.3390/su12125008.

Liang, X. (2020). Supervised and unsupervised learning models. In: Liang, X. (ed.). *Social Computing with Artificial*

Intelligence. Singapore: Springer, pp. 27–82. DOI: 10.1007/978-981-15-7760-4_4.

Liu, J., Jian, L., Wang, W., Qiu, Z., Zhang, J., and Dastbaz, P. (2021). The role of energy storage systems in resilience enhancement of health care centers with critical loads. *Journal of Energy Storage*, Vol. 33, 102086. DOI: 10.1016/j.est.2020.102086.

Masnavi, M. R., Gharai, F., and Hajibandeh, M. (2018). Exploring urban resilience thinking for its application in urban planning: a review of literature. *International Journal of Environmental Science and Technology*, Vol. 16, Issue 1, pp. 567–582. DOI: 10.1007/s13762-018-1860-2.

Megahed, N. A. (2015). Towards a theoretical framework for HBIM approach in historic preservation and management. *Archnet-IJAR: International Journal of Architectural Research*, Vol. 9, Issue 3, pp. 130–147. DOI: 10.26687/archnet-ijar.v9i3.737.

Megahed, N. A. (2017). An exploration of the control strategies for responsive umbrella-like structures. *Indoor and Built Environment*, Vol. 27, Issue 1, pp. 7–18. DOI: 10.1177/1420326X16669750.

Megahed, N. A., Abdel-Kader, R. F., and Soliman, H. Y. (2022). Post-pandemic education strategy: framework for artificial intelligence-empowered education in engineering (AIEd-Eng) for lifelong learning. In: Hassanien, A. E., Rizk, R. Y., Snášel, V., and Abdel-Kader, R. F. (eds.). *The 8th International Conference on Advanced Machine Learning and Technologies and Applications (AMLTA2022). AMLTA 2022. Lecture Notes on Data Engineering and Communications Technologies*, Vol. 113. Cham: Springer, pp. 544–556. DOI: 10.1007/978-3-031-03918-8_45.

Megahed, N. A. and Ghoneim, E. M. (2021). Indoor air quality: rethinking rules of building design strategies in post-pandemic architecture. *Environmental Research*, Vol. 193, 110471. DOI: 10.1016/j.envres.2020.110471.

Molyneaux, L., Brown, C., Wagner, L., and Foster, J. (2016). Measuring resilience in energy systems: Insights from a range of disciplines. *Renewable and Sustainable Energy Reviews*, Vol. 59, pp. 1068–1079. DOI: 10.1016/j.rser.2016.01.063.

Mosavi, A., Salimi, M., Faizollahzadeh Ardabili, S., Rabczuk, T., Shamshirband, S., and Varkonyi-Koczy, A. R. (2019). State of the art of machine learning models in energy systems, a systematic review. *Energies* , Vol. 12, Issue 7, 1301. DOI: 10.3390/en12071301.

Nashaat, B., Elmokadem, A. and Waseef, A. (2022) 'Evaluating Adaptive Facade Performance in Early Building Design Stage: An Integrated Daylighting Simulation and Machine Learning', in, pp. 211–223. doi: 10.1007/978-3-031-03918-8_20.

Nik, V. M., Perera, A. T. D. and Chen, D. (2021). Towards climate resilient urban energy systems: A review. *National Science Review*, Vol. 8, Issue 3, nwaa134. DOI: 10.1093/nsr/nwaa134.

Noaman, D. S., Moneer, S. A., Megahed, N. A., and El-Ghafour, S. A. (2022). Integration of active solar cooling technology into passively designed facade in hot climates. *Journal of Building Engineering*, Vol. 56, 104658. DOI: 10.1016/j.jobe.2022.104658.

O'Dwyer, E., Pan, I., Charlesworth, C., Butler, S., and Shah, N. (2020). Integration of an energy management tool and digital twin for coordination and control of multi-vector smart energy systems. *Sustainable Cities and Society*, Vol. 62, 102412. DOI: 10.1016/j.scs.2020.102412.

Ohshita, S. and Johnson, K. (2017). Resilient urban energy: making city systems energy efficient, low carbon, and resilient in a changing climate. *ECEEE Summer Study Proceedings*, pp. 719–728. [online] Available at: https://www.eceee.org/library/conference_proceedings/eceee_Summer_Studies/2017/3-local-action/resilient-urban-energy-making-city-systems-energy-efficient-low-carbon-and-resilient-in-a-changing-climate.

Olazabal, M., Chelleri, L., Waters, J. J., and Kunath, A. (2012). Urban resilience: towards an integrated approach. In: *1st International Conference on Urban Sustainability & Resilience,* November 5–6, 2012, London, UK.

Ortiz, L., Mustafa, A., Rosenzweig, B., Carrero, R., and McPhearson, T. (2021). Correction to: Modeling urban futures: Data-driven scenarios of climate change and vulnerability in cities. In: Hamstead, Z. A., Iwaniec, D. M., McPhearson, T., Berbés-Blázquez, M., Cook, E. M., and Muñoz-Erickson, T. A. (eds.). *Resilient Urban Futures. The Urban Book Series*. Cham: Springer, p. C1. DOI: 10.1007/978-3-030-63131-4_13.

Paraschos, P. D., Xanthopoulos, A. S., Koulinas, G. K., and Koulouriotis, D. E. (2022). Machine learning integrated design and operation management for resilient circular manufacturing systems. Computers & Industrial Engineering, Vol. 167, 107971. DOI: 10.1016/j.cie.2022.107971.

Perera, A. T. D., Javanroodi, K., and Nik, V. M. (2021). Climate resilient interconnected infrastructure: Co-optimization of energy systems and urban morphology. *Applied Energy*, Vol. 285, 116430. DOI: 10.1016/j.apenergy.2020.116430.

Ragheb, S. A., Ayad, H. M., and Galil, R. A. (2017). An energy-resilient city, an appraisal matrix for the built environment. *WIT Transactions on Ecology and the Environment*, Vol. 226, pp. 667–678. DOI: 10.2495/SDP170581.

Rahimian, M., Cervone, G., Duarte, J. P., and Iulo, L. D. (2020). A machine learning approach for mining the multidimensional impact of urban form on community scale energy consumption in cities. In: Gero, J. S. (eds.). *Design Computing and Cognition'20.* Cham: Springer, pp. 607–624. DOI: 10.1007/978-3-030-90625-2_36.

Saikia, P., Beane, G., Garriga, R. G., Avello, P., Ellis, L., Fisher, S., Leten, J., Ruiz-Apilánez, I., Shouler, M., Ward, M., and Jiménez, A. (2022). City Water Resilience Framework: A governance based planning tool to enhance urban water resilience. *Sustainable Cities and Society*, Vol. 77, 103497. DOI: 10.1016/j.scs.2021.103497.

Satterthwaite, D. (2013). The political underpinnings of cities' accumulated resilience to climate change. *Environment and Urbanization*, Vol. 25, Issue 2, pp. 381–391. DOI: 10.1177/0956247813500902.

Satterthwaite, D., Archer, D., Colenbrander, S., Dodman, D., Hardoy, J., Mitlin, D., and Patel, S. (2020). Building resilience to climate change in informal settlements. *One Earth*, Vol. 2, Issue 2, pp. 143–156. DOI: 10.1016/j.oneear.2020.02.002.

Satterthwaite, D. and Dodman, D. (2013). Towards resilience and transformation for cities within a finite planet. *Environment and Urbanization*, Vol. 25, Issue 2, pp. 291–298. DOI: 10.1177/0956247813501421.

Seneviratne, S., Nice, K. A., Wijnands, J. S., Stevenson, M., and Thompson, J. (2022). *Self-supervision, remote sensing and abstraction: representation learning across 3 million locations*. [online] Available at: https://arxiv.org/pdf/2203.04445v1.pdf. DOI: 10.48550/arXiv.2203.04445.

Setiadi, H., Mithulananthan, N., Shah, R., Md. Islam, R., Fekih, A., Krismanto, A. U., and Abdillah, M. (2022). Multi-mode damping control approach for the optimal resilience of renewable-rich power systems. *Energies*, Vol. 15, Issue 9, 2972. DOI: 10.3390/en15092972.

Sharifi, A. (2016). A critical review of selected tools for assessing community resilience. *Ecological Indicators*, Vol. 69, pp. 629–647. DOI: 10.1016/j.ecolind.2016.05.023.

Sharifi, A. (2019). Resilient urban forms: A macro-scale analysis. *Cities*, Vol. 85, pp. 1–14. DOI: 10.1016/j.cities.2018.11.023.

Sharifi, A. and Yamagata, Y. (2014a). Major principles and criteria for development of an urban resilience assessment index. In: *2014 International Conference and Utility Exhibition on Green Energy for Sustainable Development (ICUE),* March 19–21, 2014, Pattaya, Thailand.

Sharifi, A. and Yamagata, Y. (2014b). Resilient urban planning: major principles and criteria. *Energy Procedia*, Vol. 61, pp. 1491–1495. DOI: 10.1016/j.egypro.2014.12.154.

Sharifi, A. and Yamagata, Y. (2015). A conceptual framework for assessment of urban energy resilience. *Energy Procedia*. Vol. 75, pp. 2904–2909. DOI: 10.1016/j.egypro.2015.07.586.

Sharifi, A. and Yamagata, Y. (2016a). Principles and criteria for assessing urban energy resilience: A literature review. *Renewable and Sustainable Energy Reviews*, Vol. 60, pp. 1654–1677. DOI: 10.1016/j.rser.2016.03.028.

Sharifi, A. and Yamagata, Y. (2016b). Urban resilience assessment: multiple dimensions, criteria, and indicators. In: Yamagata, Y. and Maruyama, H. (eds). *Urban Resilience. Advanced Sciences and Technologies for Security Applications*. Cham: Springer, pp. 259–276. DOI: 10.1007/978-3-319-39812-9_13.

Sharifi, A. and Yamagata, Y. (2018). Resilient urban form: a conceptual framework. In: Yamagata, Y. and Sharifi, A. (eds.). *Resilience-Oriented Urban Planning. Lecture Notes in Energy*, Vol. 65. Cham: Springer, pp. 167–179. DOI: 10.1007/978-3-319-75798-8_9.

Sugahara, M. and Bermont, L. (2016) *Energy and resilient cities. OECD Regional Development Working Papers 2016/5*. Paris: OECD Publishing, 94 p. DOI: 10.1787/5jlwj0rl3745-en.

Tekouabou, S. C. K., Diop, E. B., Azmi, R., Jaligot, R., and Chenal, J. (2021). Reviewing the application of machine learning methods to model urban form indicators in planning decision support systems: Potential, issues and challenges. *Journal of King Saud University - Computer and Information Sciences*, Vol. 34, Issue 8, Part B, pp. 5943–5967. DOI: 10.1016/j.jksuci.2021.08.007.

Thomas, E., Wilson, D., Kathuni, S., Libey, A., Chintalapati, A., and Coyle, J. (2021). A contribution to drought resilience in East Africa through groundwater pump monitoring informed by in-situ instrumentation, remote sensing and ensemble machine learning. *Science of The Total Environment*, Vol. 780, 146486. DOI: 10.1016/j.scitotenv.2021.146486.

Tien, P. W., Wei, S., Darkwa, J., Wood, C., and Calautit, J. K. (2022). Machine learning and deep learning methods for enhancing building energy efficiency and indoor environmental quality – a review. *Energy and AI*, Vol. 10, 100198. DOI: 10.1016/j.egyai.2022.100198.

To, L. S., Bruce, A., Munro, P., Santagata, E., MacGill, I., Rawali, M., and Raturi, A. (2021). A research and innovation agenda for energy resilience in Pacific Island Countries and Territories. *Nature Energy*, Vol. 6, pp. 1098–1103. DOI: 10.1038/s41560-021-00935-1.

Tumini, I., Arriagada Sickinger, C., and Baeriswyl Rada, S. (2017). Model to integrate resilience and sustainability into urban planning. In: Mercader-Moyano, P. (ed.). *Sustainable Development and Renovation in Architecture, Urbanism* *and Engineering*. Cham: Springer, pp. 39–49. DOI: 10.1007/978-3-319-51442-0_4.

Wang, J. and Biljecki, F. (2022). Unsupervised machine learning in urban studies: A systematic review of applications. *Cities*, Vol. 129, 103925. DOI: 10.1016/j.cities.2022.103925.

Wang, Y., Qiu, D., and Strbac, G. (2022). Multi-agent deep reinforcement learning for resilience-driven routing and scheduling of mobile energy storage systems. *Applied Energy*, Vol. 310, 118575. DOI: 10.1016/j.apenergy.2022.118575.

Williams, C. (1983). A brief introduction to artificial intelligence. In: *Proceedings OCEANS ’83*, August 29, 1983 – September 1, 1983, San Francisco, CA, USA. DOI: 10.1109/OCEANS.1983.1152096.

Woolf, S., Twigg, J., Parikh, P., Karaoglou, A., and Cheaib, T. (2016). Towards measurable resilience: A novel framework tool for the assessment of resilience levels in slums. *International Journal of Disaster Risk Reduction*, Vol. 19, pp. 280–302. DOI: 10.1016/j.ijdrr.2016.08.003.

Wu, J., Lu, Y., Gao, H., and Wang, M. (2022). Cultivating historical heritage area vitality using urban morphology approach based on big data and machine learning. *Computers, Environment and Urban Systems*, Vol. 91, 101716. DOI: 10.1016/j.compenvurbsys.2021.101716.

Xie, J., Alvarez-Fernandez, I., and Sun, W. (2020). A review of machine learning applications in power system resilience. In: *2020 IEEE Power & Energy Society General Meeting (PESGM)*, August 2–6, 2020, Montreal, QC, Canada. DOI: 10.1109/PESGM41954.2020.9282137.

Zekry, M., Al-Hagla, K., and Saadallah, D. (2020) Urban governance as a tool for enhancing resilient urban form: case study Alexandria, Egypt. In: Schrenk, M., Popovich, V. V., Zeile, P., Elisei, P., Beyer, C., Ryser, J., Reicher, C., and Çelik, C. (eds.). *REAL CORP 2020. Shaping Urban Change – Livable City Regions for the 21st Century,* September 15–18, 2020, Aachen, Germany, pp. 939–948.

Zhang, C., Wei, H., Liao, M., Lin, Y., Wu, Y., and Zhang, H. (2022). Study on machine learning models for building resilience evaluation in mountainous area: a case study of Banan District, Chongqing, China. *Sensors*, Vol. 22, Issue 3, 1163. DOI: 10.3390/s22031163.