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Review

Decision-Making Approach to Urban Energy Retrofit—A Comprehensive Review

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Abstract: This research presents a comprehensive review of the research on smart urban energy retrofit decision-making. Based on the analysis of 91 journal articles over the past decade, the study identifies and discusses five key categories of approaches to retrofit decision-making, including simulation, optimization, assessment, system integration, and empirical study. While substantial advancements have been made in this field, opportunities for further growth remain. Findings suggest directions for future research and underscore the importance of interdisciplinary collaboration, data-driven evaluation methodologies, stakeholder engagement, system integration, and robust and adaptable retrofit solutions in the field of urban energy retrofitting. This review provides valuable insights for researchers, policymakers, and practitioners interested in advancing the state of the art in this critical area of research to facilitate more effective, sustainable, and efficient solutions for urban energy retrofits.

Keywords: urban energy retrofit; decision-making; energy simulation; optimization model

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1. Introduction

The demand for energy increases when cities expand, and the increasing energy consumption in buildings and cities increases greenhouse gas (GHG) emissions and contributes to climate change. Growing concerns have been attached to reducing GHG emissions over the last few decades to avoid climate deterioration. Cities are the largest energy consumers, accounting for 78% of energy consumption and generating 60% of GHG emissions [1]. The transition for cities towards a high-energy-efficiency and low-carbon scenario, such as the green building movement [2], can significantly promote district and national sustainable development. Urban energy retrofit is an important step toward a sustainable transition. Over the last few years, urban energy retrofits have been researched on individual buildings or at a district scale. Interaction effects of building technologies and occupant behaviors on building energy consumption pose challenges for conducting building energy retrofits [3,4]. Appropriate retrofit solutions for large-scale buildings must also consider energy network allocation [5] and building interactions [6]. Policymakers face challenges when deciding how to proceed with urban energy retrofitting. Therefore, this research aims to systematically review the literature on urban energy retrofit decision-making in the last decade. The review categorizes and discusses the following five decision approaches: 1. evaluating different energy retrofit scenarios based on energy simulation; 2. determining optimal retrofit solutions through optimization models; 3. assessing urban building energy performance through data analytics; 4. supporting retrofit decision-making through integrated systems; 5. obtaining retrofit experience from empirical projects.

2. Methods

To comprehensively review the literature of urban energy retrofit decision-making research, clusters of synonyms for keywords were identified and used for screening satisfied research. “Renovate” and “refurbish” were used as alternatives to “retrofit”. “Community”, “neighborhood”, “district”, “urban”, “regional”, and “city” were to constrain the retrofit to a large district scale. “Smart”, “AI”, “intelligent”, and “artificial intelligence” were used as one keyword cluster to target the smart solutions. Peer-reviewed journals ranging from 2012 to 2022 were searched by keywords, titles, and abstracts on the Web of Science and Scopus databases. Then, articles that focus on smart decision-making from an energy policymakers’ perspective were selected. In total, 91 peer-reviewed papers about smart urban energy retrofit decision-making solutions were identified to be thoroughly reviewed. These papers were published in 43 journals, and the journals that covered three or more reviewed articles are listed in Table 1. Table 1 shows that Energy and Buildings contains the most research papers, with a total of 15.

Table 1. List of journals with the largest number of articles by the researched topic.

Journal	Number of Papers
Energy and Buildings	15
Energy	6
Applied Energy	5
Sustainable Cities and Society	5
Energies	4
Journal of Building Engineering	4
Sustainability	4
Energy Conversion and Management	3
Journal of Cleaner Production	3
Renewable and Sustainable Energy Reviews	3
Smart Cities	3

3. Data

Figure 1 shows the number of publications each year. The number of papers published each year gradually increased with slight fluctuations. The surge in the number of papers published in 2017 could be attributed to the adoption of the Paris Climate Agreement in 2015 and the United Nations’ Sustainable Development Goals (SDGs) in 2016. In addition, a few research papers—published in late 2022 and available in 2023—were not included in this research, which resulted in a decrease in the number of journal articles observed in 2022.

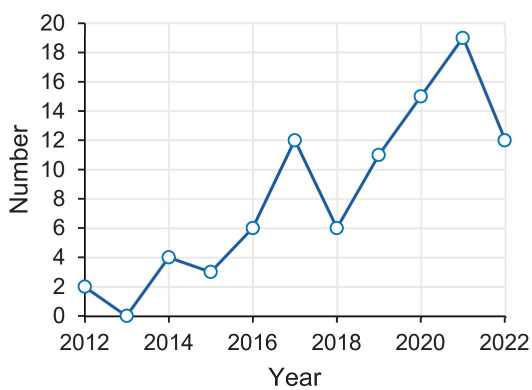

Figure 1. Number of publications by year.

Figure 2 displays the countries of affiliation for the reviewed papers. These studies were conducted in 29 different countries or regions. Italy held the largest portion, accounting for 26% of urban energy retrofit decision-making research. This is not surprising given Italy’s rich cultural heritage, where preserving historic properties and making them more energy efficient are important. China followed with 9% of the research, while the UK and Switzerland equally held 7%. The remaining 6% of the research was conducted separately in the US and Canada. These six countries conducted more than half of the research about smart urban energy retrofit decision-making.

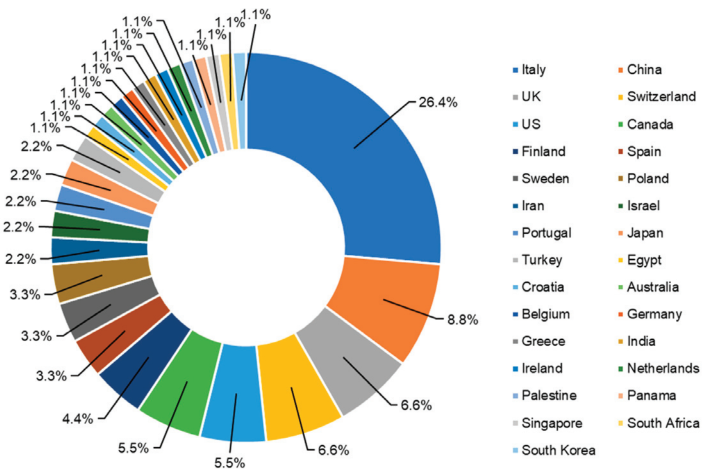

Figure 2. Distribution of research articles by the country of affiliation (Round-off error may occur).

Figure 3 shows the eight major expertise fields of the authors of the reviewed publications, indicating that research on urban building energy retrofit is highly interdisciplinary. The expertise fields in which more than one investigator participated were only counted once in each research paper. Researchers from architecture, construction, and civil engineering accounted for 31% of the total. When combining the researchers from energy and environmental engineering (19%), they summed up to 50% together and indicated a strong role of these disciplines in advancing urban energy retrofit research. The remaining fields and their share of the research in descending order were industry and industrial engineering (14%), urban planning (11%), electrical engineering and computer science (11%), mechanical engineering (8%), business (5%), and sociology (1%). The relatively low share percentages suggested greater opportunities for potential interdisciplinary collaborations in urban energy retrofit research by involving researchers from these areas.

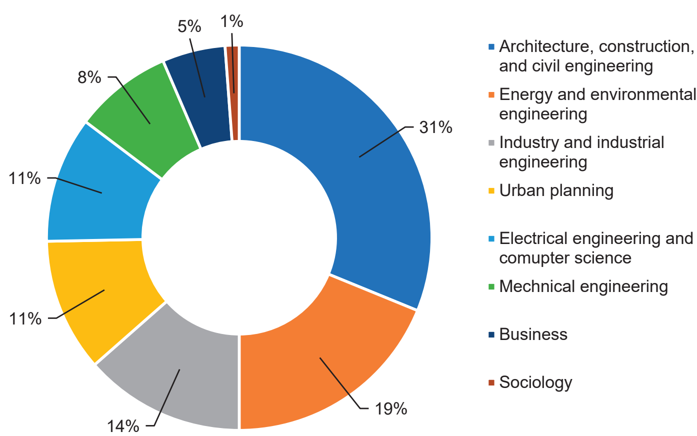

Figure 3. Distribution of research articles by the research field.

4. Results

Table 2 shows the summary of all research approaches in the reviewed papers. The table includes techniques used in each approach, remarks for each technique, and examples with references.

Table 2. Summary of all research approaches of reviewed papers.

Approach	Technique	Example	Reference	Remark
Energy simulator-based approach	Energy simulation software	EnergyPlus	[7–9]	The simulation software based on scientific principles is trustworthy. However, it requires detailed input data that may not easily be available.
		EnergyPlus + DesignBuilder	[10–21]	
		EnergyPlus + Rhino + Grasshopper	[22,23]	
		EnergyPlus + MATLAB	[10,11,17–19,24–26]	
		EnergyPlus + Python	[26–29]	
		TRNSYS	[30–33]	
		EnergyPLAN	[34,35]	
		IES-VE	[36,37]	
		IDA ICE	[38]	
		ESP-r	[39]	
		PHPP	[40]	
		HOMER	[41]	
	Self-developed simulation method	Thermal balance-based building energy simulation	[42–44]	The self-developed simulation method is flexible to different customized requirements.
		Geographic information system (GIS)-based solar energy simulation	[45–47]	
Optimization modeling-based approach	Industrial and Systems Engineering (ISE) model	Mixed-Integer Linear Programming (MILP) model	[48,49]	ISE models focus on the sociotechnical balance of different urban energy systems.
		Analytical Hierarchy Process (AHP) model	[50–52]	
		Analytical Network Process (ANP) model	[53]	
		Data Envelopment Analysis (DEA) model	[54]	
		Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH) and the "Playing Cards" method	[55]	
		Weighted Sum Model (WSM)	[56]	
		Recurrent Neural Network (RNN) model	[57]	
		Quality Function Deployment (QFD) framework	[58]	
		Enhanced Water Strider Optimization (EWSO) model	[59]	
		Ant Colony Optimization (ACO) model	[60]	
		Technologies and Urban Resource Networks (TURN) model	[61]	
		Open-source sector coupling model (GRIMSEL-FLEX)	[62]	
		Data-driven life-cycle optimization model	[63]	
		Techno-economic-risk decision-making methodology (TERDMM) model	[64]	
		Information model	[65]	
		Maturity matrix assessment model	[66]	
		Hybrid decision-making workflow	[67,68]	

Table 2. *Cont.*

Approach	Technique	Example	Reference	Remark
	Mechanical Engineering (ME) model	Hierarchical decision-making model for urban energy management	[69]	ME models focus on the technological advancement of specific energy systems.
		Genetic Algorithm (GA) for the optimization of pumping system operation	[70]	
		Decision-making model for street lighting control	[71–73]	
		Decision-making model for indoor lighting control	[74]	
		Intelligent supervisory predictive control model for heating, ventilation, and air conditioning (HVAC) system	[75]	
		Expert system for an adaptable energy retrofit façade system	[76]	
	Social, Behavioral, and Economic sciences (SBE) model	Decision-making model considering socio-economic issues	[77–79]	SBE models focus on the social benefits of the urban retrofit plan.
		Decision-making model considering demographic dynamics	[80,81]	
Assessment-based approach	Data analytics	Retrofit solution assessment	[82–84]	Assessment-based decision-making can be applied to various scales if the data for different scales is available, from individual buildings to entire urban areas.
		Energy saving prediction	[85–87]	
		Life cycle assessment	[88,89]	
System integration-based approach	GIS	GIS-based urban building retrofit platform	[90–92]	Integrated systems can provide user-friendly interfaces for decision-making.
Empirical study-based approach	Case study	Lessons from completed and ongoing energy retrofit project	[93–97]	Empirical study can reveal unexpected challenges that may not be apparent in simulations and offer insights into the engagement and collaboration of stakeholders.

4.1. Energy Simulator-Based Approach

Energy simulators are used to evaluate building energy retrofit measures and help policymakers select reasonable retrofit solutions regarding energy savings, CO_2 emissions, and the cost of retrofit solutions. The baseline building energy performance can be obtained by accessing the urban energy database or building the baseline urban building model. Then, tested retrofit measures, such as improving building envelope insulation, replacing windows, changing heating, ventilation, and air conditioning (HVAC) systems, and integrating renewable energy systems, are implemented on the baseline model. By simulating the energy consumption of the urban building model with various retrofit solutions, the effectiveness of different retrofits and their combinations can be assessed. The following various software tools can be used to perform these simulations.

EnergyPlus is a widely used energy simulation engine that has supported various urban energy retrofit studies [7–29]. DesignBuilder is a user-friendly graphical interface for EnergyPlus that simplifies the modeling process. Numerous researchers utilized DesignBuilder to create visual building models and input data for building components and systems, and then executed energy simulations using the EnergyPlus engine [10–21]. Some researchers modeled buildings in Rhino and Grasshopper and then ran energy simulations in EnergyPlus [22,23]. Rhino and Grasshopper together form a powerful combination of 3D modeling and parametric design tools. They can help create and optimize urban building design solutions. Some researchers integrated MATLAB with EnergyPlus, which can help streamline the simulation process, postprocess results, and optimize energy retrofit performance [10,11,17–19,24–26]. EnergyPlus package also provides a Python API that allows researchers to set up optimization algorithms to explore various combinations of retrofit solutions [26–29].

In addition to EnergyPlus, which is widely used, there are alternative energy simulation tools that specialize in various aspects. Transient System Simulation Tool (TRNSYS) is widely used for simulating the behavior of energy systems, such as HVAC systems [30], solar thermal or photovoltaic (PV) systems [31,32], and other renewable energy technologies [33]. EnergyPLAN is an advanced energy system analysis software that can model grid flexibility and perform economic analysis. It was utilized for achieving large-scale energy system retrofits within a viable investment [34,35]. Integrated Environmental Solutions Virtual Environment (IES-VE) is a comprehensive building performance analysis software suite that incorporates a range of simulation and analysis tools. It was employed to investigate optimal decision-making for building energy retrofits [36,37]. IDA Indoor Climate and Energy (IDA ICE) is a building simulation software that was utilized to evaluate the potential of four large-scale building energy retrofit scenarios on the Finnish building stock [38]. ESP-r is an open-source building energy simulation software that was employed to develop strategies approaching large-scale nearly-zero energy targets [39]. Passive House Planning Package (PHPP) is a comprehensive energy modeling tool specifically for the design and certification of Passive House buildings. It was used to estimate the energy savings of measures [40]. Hybrid Optimization of Multiple Energy Resources (HOMER) allows for designing and analyzing hybrid power systems, and it was employed to explore the strategy for a net-zero energy building transition [41]. Moreover, the following self-developed energy simulation tools were applied in urban energy retrofit decision-making research: thermal balance-based building energy simulators were used to simulate urban building energy consumption [42–44]; geographic information system (GIS)-based solar energy calculation algorithms were developed to simulate the energy production of PV panels [45–47].

Overall, decision-making for urban retrofit solutions using energy simulators has a few benefits. This method is trustworthy because it is a physics-based simulation grounded in scientific principles and considers various factors, such as weather, human behavior, building materials, and energy system efficiency. In addition, weather data and occupant behavior parameters can be changed in the energy model to analyze their impacts on the same energy retrofit solutions. Considering the impact of weather on retrofit solutions helps make informed decisions for larger-scale energy retrofit projects that occupy multiple climate zones. Occupant behavior parameters can be easily changed to study human-relative retrofit solutions. For example, the window opening schedule can be changed to study its impact on the energy consumption of ventilation, heating, and cooling system. Then the window opening schedule corresponding to the minimum energy consumption can be suggested as a human-relative retrofit measure.

Despite its benefits, urban building energy modeling has limitations. It requires detailed input data that may not easily be available, such as the thickness and thermal resistance of different layers of the envelope insulation. Furthermore, inputting such details is time-consuming and requires expertise. More details lead to higher accuracy in simulation but can be computationally intensive, especially when dealing with large-scale urban environments. Most researchers only simulated representative individual buildings' energy performance and projected the simulation results to an urban scale.

4.2. Optimization Modeling-Based Approach

Recent studies have explored various urban energy retrofit optimization models in different fields, including industrial and systems engineering (ISE), mechanical engineering (ME), and social, behavioral, and economic sciences (SBE).

In the ISE field, typical decision-making methods include the multi-criteria decision-making (MCDM) and multi-objective optimization (MOO) models, which were employed to address challenges associated with urban energy retrofit strategies. The mixed-integer linear programming (MILP) model was used to maximize the energy efficiency of district energy systems [48,49]. The analytical hierarchy process (AHP) model was widely applied to urban energy retrofits to tackle multiple conflicting criteria and decision alternatives [50–52]. The analytical network process (ANP) model, an extension of AHP to accommodate complex interdependencies among criteria and alternatives, was employed to prioritize urban retrofit solutions [53]. The data envelopment analysis (DEA) model—commonly used to empirically measure the productive efficiency of decision-making units—was utilized to evaluate the efficiency of building retrofit projects [54]. The measuring attractiveness by a categorical based evaluation technique (MACBETH) and the "Playing Cards" methods were used to define and analyze different urban scenarios [55]. The weighted sum model (WSM), a simple and widely used MCDM method, was used to decide the optimal energy retrofit plan for a whole stock of buildings [56]. The recurrent neural network (RNN) model has been trained to derive the cost-optimal retrofit solution [57]. The quality function deployment (QFD) framework was used to determine the best retrofit technologies with regard to stakeholders' opinions [58]. Furthermore, a few optimization algorithms, such as the enhanced water strider optimization (EWSO) algorithm and the ant colony optimization (ACO) algorithm, were used on urban building energy operation and lifecycle optimization [59,60].

Some new decision-making models have been developed to target urban energy retrofit and planning. Keirstead and Calderon presented a technologies and urban resource networks (TURN) model to create an urban strategic energy plan with regard to spatial and temporal variations in energy demand [61]. Rinaldi et al. proposed an open-source sector coupling model (GRIMSEL-FLEX) to minimize the total urban energy cost for electricity and heating supply [62]. Luo and Oyedele proposed a novel data-driven life-cycle optimization model for urban building retrofitting [63]. Zheng et al. proposed a techno-economic-risk decision-making methodology (TERDMM) model that integrated life cycle cost analysis and Monte Carlo (MC) simulation [64]. Syal et al. developed an information model that can serve as the basis for an intelligent decision support system [65]. González et al. presented a maturity matrix assessment model of energy efficiency measures to determine future appropriate implementation [66]. Wang et al. developed a novel hybrid modeling approach to quantify the sustainability of retrofit solutions considering embodied energy and GHG emissions [67]. Stanica et al. proposed an integrative method to evaluate a large variety of energy conservation and renewable energy generation measures at different scales [68].

In the ME field, decision-making control models are essential for optimizing system performance. Various studies were performed to explore the energy-saving potential of intelligent control for a wide range of energy systems. For urban scale retrofit, a hierarchical decision-making strategy model was designed to manage the urban energy system that can help deal with the energy retrofit of urban subsystems as a whole in an integrated way [69]. A genetic algorithm (GA) was used to optimize the operation of pumping stations to achieve the minimum energy cost for water supply [70]. Several research explored the energy-saving feasibility of street lighting retrofits within the available budget and proposed methods aiming at maximizing energy reduction while achieving optimal allocation and light quality [71–73]. A decision-making control system was studied to realize the energy-saving goal of indoor lighting systems [74]. For building retrofits, an intelligent supervisory predictive control model of HVAC systems was proposed to minimize energy consumption without compromising occupants' thermal comfort [75]. An expert system applied in an adaptable energy retrofit façade system of residential buildings was proposed to suggest suitable retrofit alternatives [76].

There is not much research about urban energy retrofits in the SBE field. Some models for assessing alternative retrofit solutions from socio-economic aspects were developed [77–79]. Some models for urban building energy retrofit plans were proposed considering workmanship capacity and population dynamics [80,81].

Overall, optimization modeling-based decision-making for urban energy retrofits were most widely used in the ISE field. ISE models focus on the performance of different urban energy systems and address techno-economic issues (sociotechnical balance). They aim to find the best solutions for reducing carbon emissions while considering the economic feasibility. ME Models aim to optimize the energy performance of a specific energy system. The focus of these models is on technical aspects (technological advancement). SBE models consider various social factors (social benefits), such as population growth, demographic changes, and labor constraints. These models aim to understand how social factors impact energy consumption patterns. They can help policymakers develop targeted strategies for energy reduction in a specific socio-demographic context.

Each of these fields has its own focus and approach to urban energy retrofit decision-making and optimization. It is essential to consider an integrated approach that combines the strengths of all three domains to develop comprehensive municipal energy retrofit strategies. This approach would address technical, economic, social, and environmental aspects of urban energy systems, leading to more holistic and sustainable solutions.

4.3. Assessment-Based Approach

Various approaches based on data analytics evaluate possible retrofit measure alternatives or predict potential energy savings. An integrated method for predicting the possibility of reducing urban energy consumption by using phase change material (PCM) in municipal heating networks was proposed [82]. A bottom-up evaluation approach was applied to study the techno-economic feasibility of the air-to-water heat pump retrofit in the housing stock [83]. A study was performed to estimate the best-case scenario for the benefits achievable depending on the urban green roof proportion [84]. Some models that could quantify the contribution of building characteristics and systems to energy consumption were investigated to infer the excepted energy savings [85–87]. Some researchers proposed comprehensive life cycle assessment approaches with the consideration of data uncertainties [88,89].

Overall, assessment-based decision-making relies on actual data from existing buildings, which can provide more realistic insights into building performance and energy consumption patterns. It can be applied to various scales, from individual buildings to entire urban areas, if the data for different scales are available. However, the performance of assessments based on data analytics can be constrained by data quality. Availability and expertise in data science may not be readily available for all researchers.

4.4. System Integration-Based Approach

Some systems were developed to support the urban energy retrofit decision-making process. Moghadam and Lombardi developed a multi-criteria spatial decision support systems (MC-SDSS) tool to identify and evaluate alternative urban energy scenarios from a long-term perspective [90]. Buffat et al. proposed a web-based decision support system (DSS) using a GIS-based building stock model [91]. Leandro et al. showed a platform that can help building owners and planners make informed decisions to improve building energy [92].

Overall, the introduced systems provide user-friendly interfaces for decision-making that enable householders and policymakers to easily access the different building retrofit solutions. However, few systems are available for users. More investment in urban energy system integration is necessary.

4.5. Empirical Study-Based Approach

Lessons from ongoing retrofit projects or completed projects can support policymakers' decision-making. The decision-making process of private homeowners was investigated to improve the impact of policies leading to higher adoption of energy retrofit measures by homeowners [93]. A few frameworks assessing ongoing or completed urban energy renovation were proposed, through which lessons from projects could be concluded [94–96]. Jankovic introduced an innovative way to evaluate completed building retrofits through the simulation of dynamic heating tests with a calibrated model [97].

Overall, empirical studies can benefit the decision-making process with the consideration of practical problems. It can reveal unexpected challenges that may not be apparent in simulations and offer insights into the engagement and collaboration of stakeholders. However, lessons from urban retrofit projects may be limited due to the small number of completed projects, and the lessons may not be generalized to other situations.

5. Discussion and Future Directions

In this study, we present five distinct approaches, each with its own advantages, limitations, and optimal scenarios for implementation. The optimal choice among these approaches depends heavily on the specific conditions of each urban energy retrofit project. The nature of the project, the available data, and the socio-economic context can significantly influence which approach might be most suitable. Furthermore, in many cases, the best outcomes may be achieved through a combination of multiple approaches, leveraging the strengths of each.

We suggest the following six aspects that should be prioritized in the future research on smart urban energy retrofit decision-making.

1. Combine multidisciplinary expertise, such as in ISE, ME, and SBE domains, into the development of comprehensive, integrated decision-making models.

The siloed nature of research and limited interdisciplinary collaboration can hinder the development of comprehensive solutions. In the future, we should encourage interdisciplinary research, knowledge sharing, and collaboration between experts in different domains to create well-rounded decision-making models for urban energy retrofit projects.

2. Enhance data-driven evaluation methodologies by improving data quality and accessibility.

It is suggested to establish data collection standards, promote data sharing, and develop advanced data analytics techniques to improve the accuracy of urban energy retrofit evaluations. This will allow for more exact analyses of urban energy demand and the potential efficient retrofit solutions.

3. Carry out research on the generalization and applicability of the lessons learned from completed urban retrofit projects.

Generalization and applicability of the lessons from projects are challenging because of the limited number of completed retrofit projects and the lack of systematic approaches to knowledge transfer. In the future, we should prioritize the documentation of successful retrofit projects, develop frameworks for knowledge transfer, and invest in research that explores the applicability of best practices in different urban contexts.

4. Investigate methods for collaborating and engaging stakeholders, including residents, building owners, intermediaries, and policymakers.

The understanding of stakeholders' needs is still limited. In the future, we should develop stakeholder-centric frameworks, establish effective communication channels, and design incentive structures that encourage cooperation and active participation in urban energy retrofit projects. This will help ensure that urban energy retrofit projects achieve their desired outcomes.

5. Consider how population migration and climate change may affect urban energy retrofitting strategies.

The lack of long-term strategic planning and understanding of the interplay between population dynamics and urban energy demand may have led to the gap in this research direction. In the future, we should invest in research that explores the complex relationships between climate change, population migration, and urban energy demand, and then develop robust and adaptable urban energy retrofit strategies that can withstand changing climatic and demographic conditions.

6. Develop user-friendly urban energy retrofit systems that can empower householders and policymakers by providing them with easily accessible building retrofit solution plans.

There are only a few such systems available for use so far. This may be caused by the expensive investment in research and development. It is essential to invest more in urban energy system integration in the future, emphasizing the improvement of user-friendly interfaces for urban retrofit solutions. This will facilitate informed decision-making.

6. Limitations

Our review has two limitations. First, the keyword-based search strategy, which focused on "renovate", "retrofit", and "refurbish", might exclude some relevant articles that did not utilize these specific terms. Second, our study concentrated on the decision-making process in urban energy retrofit rather than the specific retrofit solutions employed as a result of these decisions. The research regarding specific solutions for smart urban energy retrofits was outside the scope of this review.

7. Conclusions

This research presents a comprehensive review of the research on smart urban energy retrofit decision-making. A total of 91 journal papers over the last decade were reviewed. Results identified and discussed the following five categories of approaches to retrofit decision-making: simulation, optimization, assessment, system integration, and empirical study. The research on urban energy retrofit decision-making has made significant progress over the past ten years. However, there still exist opportunities for further development. Findings also inform a roadmap for future research to enable the development of more effective, sustainable, and efficient urban energy retrofit solutions, such as integrating decision-making methods, enhancing data availability, transferring knowledge from successful retrofit projects to other contexts, involving stakeholders in the decision-making process, studying the effects of population migration and climate change on urban energy retrofit strategies, and developing user-friendly decision-making systems.

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