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Review

Data-Driven Decision Support for Smart and Efficient Building Energy Retrofits: A Review

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Abstract: This review explores the novel integration of data-driven approaches, including artificial intelligence (AI) and machine learning (ML), in advancing building energy retrofits. This study uniquely emphasizes the emerging role of explainable AI (XAI) in addressing transparency and interpretability challenges, fostering the broader adoption of data-driven solutions among stakeholders. A critical contribution of this review is its in-depth analysis of innovative applications of AI techniques to handle incomplete data, optimize energy performance, and predict retrofit outcomes with enhanced accuracy. Furthermore, the review identifies previously underexplored areas, such as scaling data-driven methods to diverse building typologies and incorporating future climate scenarios in retrofit planning. Future research directions include improving data availability and quality, developing scalable urban simulation tools, advancing modeling techniques to include life-cycle impacts, and creating practical decision-support systems that integrate economic and environmental metrics, paving the way for efficient and sustainable retrofitting solutions.

Keywords: energy retrofits; building energy performance; energy efficiency; artificial intelligence; machine learning

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1. Introduction

Buildings in the European Union (EU) consume nearly 40% of the total energy [1] (in 2020), significantly contributing to energy demand and associated emissions (European Commission, 2018). Building operations account for 30% of global final energy consumption and 26% of global energy-related emissions (8% being direct emissions in buildings and 18% indirect emissions from the production of electricity and heat used in buildings). Direct emissions from the buildings sector decreased in 2022 compared to the year before, despite extreme temperatures driving up heating-related emissions in certain regions. In 2022, energy use in the building sector increased by around 1% [2]. Given the substantial impact of the sector, there is considerable potential for cost-effective enhancements in energy efficiency and reductions in greenhouse gas emissions. To meet the EU's ambitious energy and environmental targets for 2030 and 2050, there is a strong focus on improving the energy performance of buildings through legislative measures like the Energy Performance of Buildings Directive [3]. This directive seeks to accelerate the renovation of buildings, particularly those with the poorest performance, enhance air quality, promote the digitization of energy systems, and support the development of infrastructure for sustainable mobility. Despite these efforts, global progress in implementing energy efficiency measures in existing buildings remains insufficient, falling short of the actions needed to reach net-zero carbon dioxide emissions by 2050. Regarding existing buildings, making up over 97% of the building stock, 75% are considered energy inefficient, heavily dependent on fossil fuels, and equipped with outdated technologies and appliances [4]. In the EU, over 220 million building units exist, with 85% constructed before 2001, and it is projected that 85–95% of these buildings will still be in use by 2050 [5].

Globally, improving the energy performance of buildings is critical to meeting the United Nations' Sustainable Development Goals (SDGs) for 2030. The building sector, as the largest energy consumer worldwide, accounts for 37% of the final energy consumption (UN, 2022) [6]. In 2022, buildings consumed 132 exajoules (EJ) of energy. This sector's significant contribution to global warming is evident. From 2010 to 2022, energy consumption in buildings increased from 119 EJ to 132 EJ, driven by improved energy access in developing countries and the growing use of energy-intensive devices.

To meet the Paris Agreement's emission reduction targets [7], the building sector must adopt more effective retrofit strategies. The International Energy Agency (IEA) projects that significant declines in global energy demand in buildings can be achieved through energy efficiency improvements, aiming for a 40% reduction by 2040 [8]. This includes the deployment of more efficient heating systems, better insulation, and the increased use of renewable energy sources. The 'Low Energy Demand' scenario by Grubler et al. [9] targets limiting global warming to 1.5 °C by 2050, which requires doubling the current retrofit rate and adopting advanced thermal end-use technologies.

In this context, data-driven decision support systems are emerging as a pivotal component in enhancing building energy retrofits. Leveraging advanced analytics, machine learning algorithms, and big data, these systems provide accurate predictions, optimize energy use, and suggest the most cost-effective and impactful retrofit measures. Current methods for building energy modeling can be categorized into white-box, gray-box, and black-box models. White-box models, based on building physics principles, require detailed inputs and are often cumbersome. Gray-box models combine physics-based approaches with in situ measurements, while black-box models rely entirely on measured data and use statistical and machine learning techniques. Recent years have seen an increased use of black-box models for building energy modeling due to their ability to handle complex system dynamics and update with new data.

This review aims to synthesize current research on data-driven decision support systems for smart and efficient building energy retrofits, with a particular focus on AI and machine learning algorithms. By examining the latest advancements and applications in these technologies, we seek to provide a comprehensive understanding of their role in meeting both global and regional energy and emission reduction targets, ultimately contributing to a more sustainable and efficient building stock for the future. The rest of the paper is organized as follows: Section 2 provides an overview of building energy retrofitting, discussing its importance and the evolution of retrofitting strategies. Section 3 outlines the methodology of this study, detailing the databases used, keywords and search terms, the time frame, inclusion and exclusion criteria, and the process of data extraction and analysis. Section 4 focuses on data-driven approaches to building energy retrofitting, exploring the types of data utilized and their sources. Section 5 delves into the application of AI and machine learning algorithms in energy retrofitting, describing the various types of algorithms employed in this field. Section 6 introduces explainable AI (XAI) and its significance in energy retrofitting, particularly in ensuring transparency and interpretability in AI-driven processes. Section 7 presents a discussion of the key findings and the challenges encountered in implementing these approaches. Finally, Section 8 concludes the paper by summarizing the findings, suggesting directions for future research, and offering final thoughts on the progress and potential of energy retrofitting of buildings.

1.1. Scope of Data-Driven Building Energy Retrofitting

This review covers data-driven retrofitting strategies across residential, commercial, and public buildings, each presenting distinct energy demands and retrofit challenges. In residential buildings, retrofitting typically focuses on cost-effective improvements to energy efficiency and occupant comfort. For example, Seraj et al. [10] demonstrated the use of machine learning models to predict energy performance in UK residential buildings, improving retrofit decision-making by accurately forecasting energy savings. Commercial buildings require more complex energy management systems, where retrofitting efforts must balance energy efficiency with operational needs. Seyedzadeh et al. [11] employed gradient-boosted decision trees to predict non-domestic building energy performance, enabling deep energy retrofits by identifying optimal energy-saving strategies. Public buildings, including schools and hospitals, present additional challenges such as regulatory compliance and sustainability goals. Jradi [12] applied digital twin technology in public buildings, optimizing retrofitting strategies by integrating real-time operational data, which improved both decision-making and energy savings. Across these sectors, the primary goals of retrofitting are to reduce energy consumption, minimize greenhouse gas emissions, and enhance occupant comfort and productivity.

1.2. Review Novelty

This review stands out by critically examining the application of AI and ML in building energy retrofits, focusing on emerging areas such as explainable AI (XAI) and its role in enhancing stakeholder trust and decision-making. Unlike traditional reviews, it delves into underexplored challenges like addressing incomplete datasets, ensuring scalability across diverse building types, and integrating future climate considerations into retrofit planning. By synthesizing findings across a range of sectors—residential, commercial, and public—this review not only identifies research gaps but also provides a roadmap for leveraging data-driven innovations to achieve impactful and sustainable retrofit solutions. This novel perspective bridges the technical and practical aspects of retrofitting, offering a comprehensive guide for researchers, policymakers, and industry stakeholders.

2. Building Energy Retrofitting: An Overview

Building energy retrofitting focuses on improving energy efficiency and reducing energy consumption in existing buildings, addressing the significant energy use and greenhouse gas emissions from the building sector. This is particularly important in regions like the EU, where over 220 million building units exist, 75% of which are energy inefficient, with more than 85% expected to still be in use by 2050 [13]. Despite ongoing renovations, the process is slow, leaving many buildings reliant on outdated technologies and fossil fuels [14]. Retrofitting these structures presents opportunities for significant energy efficiency improvements and emission reductions [15].

Aligned with the EU Green Deal, the European Commission's Renovation Wave Strategy aims to double renovation rates in the next decade. This initiative targets improving energy performance in 35 million buildings by 2030, potentially creating up to 160,000 jobs [16]. It also addresses energy poverty, with 34 million Europeans unable to afford adequate heating or cooling, while enhancing health, well-being, and energy security.

The energy retrofit process consists of five phases according to Ma et al. [17] (Figure 1):

1. Project Setup and Pre-Retrofit Survey: Define the project scope, engage stakeholders, and collect baseline data on building design, HVAC systems, and energy use.
2. Energy Audit and Performance Assessment: Evaluate energy consumption using tools such as thermal imaging and blower door tests to identify inefficiencies.

3. Identification of Retrofit Options: Analyze measures using simulations and modeling to select cost-effective strategies aligned with project objectives.
4. Site Implementation and Commissioning: Install measures like insulation, energy-efficient systems, and renewable technologies, ensuring proper operation through testing and adjustments.
5. Validation and Verification: Monitor post-retrofit energy performance and compare it to pre-retrofit levels to validate savings and identify further optimization opportunities.

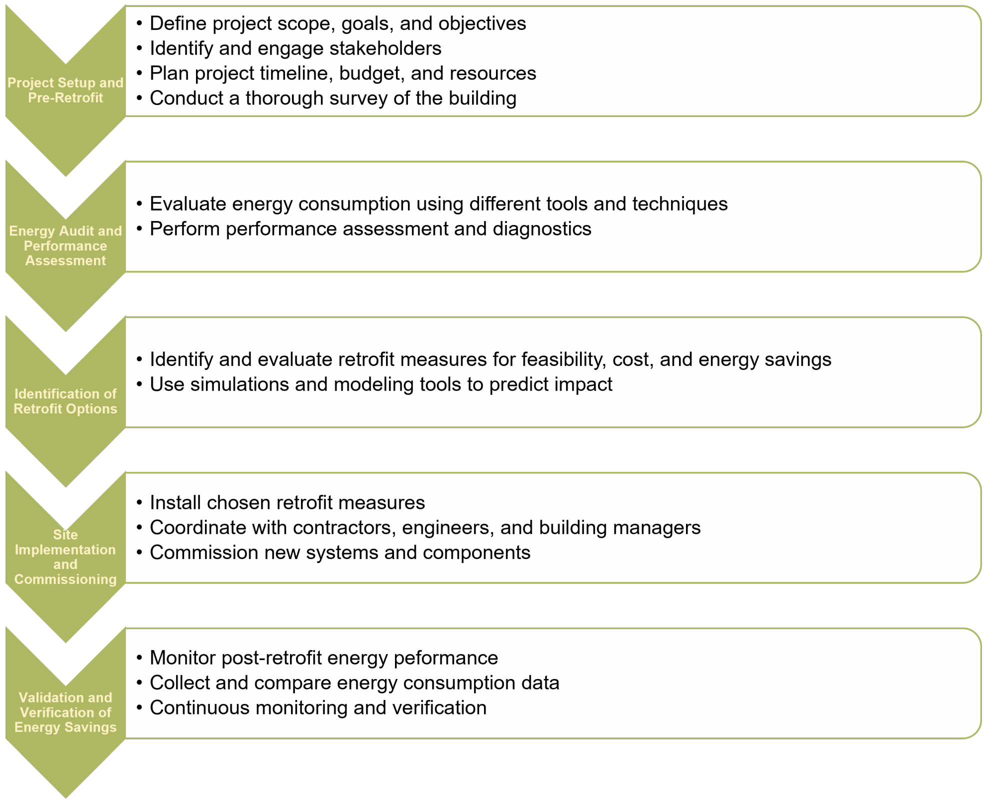

Figure 1. Typical energy retrofitting process adapted from Ma et al. [17].

Energy retrofitting can be categorized into three main types:

- Envelope Retrofits: Improve insulation, windows, doors, and roofing to reduce heat loss and gain. Studies show substantial energy savings, particularly in poorly insulated buildings as shown by Nutkiewicz and Jain [18].
- System Upgrades: Replace HVAC systems, lighting, and hot water systems with energy-efficient technologies, including renewable energy sources like solar panels. These upgrades reduce energy consumption while enhancing occupant comfort as shown by Ali et al. [19].
- Operational Improvements: Implement smart controls and optimize system operations to improve efficiency without major physical changes. Examples include intelligent energy management systems and occupant behavior modifications as shown by Jradi et al. [20].

Energy retrofits offer numerous benefits, including lower energy consumption [21], reduced greenhouse gas emissions, enhanced indoor comfort, increased property values, and job creation. For instance, Jradi [12] analyzed the impact of retrofitting on three schools, highlighting significant energy savings and operational improvements as shown in Table 1.

Table 1. School information and retrofit measures implemented. Adapted from Jradi [12].

	School A	School B	School C
Indoor Floor Area	11,900 m^2	8700 m^2	8900 m^2
Construction Date	1954	1955	1961
Number of Blocks	16	12	11
Number of Students (2018)	677	536	507
Number of Teachers (2018)	31	27	28
Operation Hours	6:30–19:00	6:30–19:00	6:30–19:00
Retrofit Measures Implemented	• Energy-efficient T5 and T8 LED lighting throughout. • 250 mm mineral wool insulation in 7400 m^2 attic space. • 95 m^2 of exterior walls insulated with 190 mm mineral wool. • Double-glazed windows and glass doors with U-value of 1.3 W/m^2-K in 7 blocks. • Skylights upgraded to U-value of around 1.4 W/m^2-K in 8 blocks. • Replacement of four hot water circulation pumps. • Improved heating setpoint management across all blocks. • Insulation of pipes, valves, and pumps in technical rooms.	• Energy-efficient T5 LED lighting in 10 out of 12 blocks. • 200 mm mineral wool insulation in 150 m^2 attic space. • 120 m^2 of exterior walls insulated with 150–200 mm mineral wool. • Thermal double-glazed windows and glass doors with U-value around 1.4 W/m^2-K in 4 blocks. • Replacement of three hot water circulation pumps. • Proposed heating setpoint management framework. • Motion sensors installed in some classrooms. • Insulation of pipes, valves, and pumps in technical rooms.	• Energy-efficient T5 and T8 LED lighting throughout. • 150–300 mm bat insulation in 1800 m^2 flat roof area. • 850 m^2 of exterior walls insulated with 100 mm mineral wool. • Double-glazed windows, glass doors, and some skylights with U-value of 1.3 W/m^2-K in 6 blocks. • Replacement of two hot water circulation pumps. • Proposed heating system setpoint management in some blocks. • Insulation of pipes, valves, and pumps in technical rooms.

The retrofitting measures in the three schools, as discussed by Jradi [12], showed varied energy savings. Schools A and B achieved significant heating reductions of 15.7% and 15.4%, respectively, while School C saw lower savings of 9.3%, likely due to differences in the initial conditions or measures implemented. For electricity consumption, School B had the highest reduction at 15.0%, followed by School C at 13.2%, and School A with 2.2%, indicating a greater focus on heating improvements in School A. These results emphasize tailoring retrofitting strategies to each building's specific needs to maximize energy efficiency.

Challenges to retrofitting adoption include high upfront costs, regulatory complexities, and limited scalable tools [22]. Awareness of retrofit benefits remains low, highlighting the need for education and outreach [23]. Overcoming these barriers requires collaboration among policymakers, industry stakeholders, and building owners.

Energy retrofitting offers immense potential to reduce energy use and emissions. Addressing financial, regulatory, and technical challenges, alongside leveraging AI and data-driven approaches, can unlock significant environmental and economic benefits.

3. Methodology

To ensure a comprehensive review of the current research on data-driven decision support systems for building energy retrofits, we conducted a systematic literature search using Google Scholar and Scopus. The search strategy was designed to capture a broad range of studies related to the application of data analytics, machine learning, and AI in energy retrofitting of buildings. To ensure a comprehensive literature review, citation chasing was employed as a methodological strategy. This involved systematically examining the references cited in selected papers to identify additional relevant studies and sources.

3.1. Databases Used

- Google Scholar: The primary database for this review, chosen for its extensive and interdisciplinary coverage of academic research.
- Scopus: Selected for its comprehensive database of peer-reviewed literature across various disciplines.

3.2. Keywords and Search Terms

The following keywords and search terms were used to identify relevant studies:

- "Data-driven energy retrofit";
- "AI in building energy retrofit";
- "Machine learning for building energy retrofit";
- "Data-driven building retrofit".

3.3. Time Frame

The literature search focused on studies published in the last 10 years (2014–2024) to ensure that the review reflects the most recent advancements and current state of the field.

3.4. Inclusion and Exclusion Criteria

- Inclusion Criteria:
  - Studies that specifically focus on data-driven approaches to building energy retrofits;
  - Research involving AI and machine learning in building energy efficiency;
  - Papers discussing smart building technologies and their applications in energy retrofits;
  - Studies providing empirical results, case studies, or comprehensive reviews;
  - Additional studies deemed relevant after an initial analysis of the retrieved literature.
- Exclusion Criteria:
  - Studies not focused on building energy retrofits;
  - Studies with outdated technologies or methodologies;
  - Research not providing sufficient methodological details;
  - Review papers.

3.5. Data Extraction and Analysis

To systematically analyze the selected studies, the following data extraction and analysis steps were undertaken:

- Data Extraction:
  - Title, authors, and publication year;
  - Abstract summery;
  - Methodological approach (e.g., type of data-driven model and AI technique used);
  - Research objectives and questions;
  - Research gap;
  - Dataset used;
  - AI and machine learning methods used;

- Key findings and results.

- Data Analysis:
  Several analytical approaches were employed to examine the data types, data sources, and machine learning techniques used for building energy retrofits. Thematic analysis was used to categorize studies based on different data types (e.g., sensor data, utility bills, and energy audit reports) and data sources (e.g., real-time monitoring systems, historical records, and building management systems). To enhance the depth of the analysis, Elicit [24], an AI-powered research assistant, was utilized to streamline the identification and extraction of key insights from relevant studies. Additionally, machine learning techniques were assessed, including supervised learning, unsupervised learning, and explainable artificial intelligence, to understand their applications in areas such as energy consumption prediction, optimization, and fault detection. Comparative analysis was conducted to evaluate how various data types and sources are utilized with these machine learning techniques, highlighting their effectiveness, limitations, and applicability across different retrofit scenarios. The integration of Elicit facilitated a more efficient and comprehensive examination of the diverse methodologies and technologies in the field.

By employing this structured methodology, we obtained 52 papers, and we aim to provide a comprehensive and detailed review of the current state of research on data-driven energy retrofits, highlighting the role of AI and machine learning in advancing building energy efficiency.

4. Data-Driven Approaches to Building Energy Retrofitting

Data-driven building energy retrofit refers to the utilization of data analytics, machine learning, and advanced computational methods to guide, optimize, and implement energy efficiency measures in existing buildings. These approaches leverage extensive datasets and sophisticated algorithms to pinpoint effective retrofit strategies, forecast energy savings, and continuously monitor and enhance building performance. The scope of data-driven retrofitting includes residential, commercial, and public buildings, aiming to cut energy consumption, reduce greenhouse gas emissions, and improve occupant comfort and productivity.

4.1. Data Types

In the realm of building energy retrofits, data-driven approaches are pivotal for developing effective strategies and optimizing energy performance. Various types of data play crucial roles in informing these approaches, including energy consumption data, building characteristics, weather data, and operational data.

Energy Consumption Data: Energy consumption data collected from various sensors and meters provide critical insights into consumption patterns and inefficiencies. Sensors placed throughout a building can capture granular data on parameters such as temperature, humidity, and occupancy, which further informs energy usage patterns. For example, in Wiethe et al. [25], the authors used the real-world dataset of 25,000 single and two-family buildings from Germany, with 74 variables related to building characteristics, heating systems, and annual metered thermal energy consumption to employ an agent-based building stock model for the German residential sector to explore the relationship between prediction accuracy and retrofit rates.

Building Characteristics: These include the construction materials, insulation levels, HVAC systems, window types, and occupancy patterns, which are crucial for accurate energy modeling and simulation. Detailed building characteristics can help tailor retrofit measures to specific building types; for example, Nutkiewicz et al. [26] used hourly electricity consumption data for 29 buildings in downtown Sacramento, California, for the years 2016–2018, along with publicly available data on the building geometry, building characteristics, and weather data for the same area and time period, to develop a greedy optimization algorithm that can identify the minimum number of buildings that need to be retrofitted to achieve maximum energy savings across an urban area. Moreover, Nutkiewicz and Jain [18] utilized a dataset that includes building geometries created from GIS data, and non-geometric building properties based on the U.S. Department of Energy (DOE)'s Commercial Reference Buildings to introduce an integrated simulation and data-driven method (Data-driven Urban Energy Simulation or DUE-S) to model large-scale retrofit policies.

Weather Data: Local climate data include temperature, humidity, solar radiation, and wind speed, which impact building energy performance and are necessary for precise simulations and predictions. Weather data are also integral to understanding how external conditions affect energy use and can enhance the accuracy of energy models. In the work of Moraliyage et al. [27], the authors used the UNICON dataset, which is drawn from the La Trobe Energy AI/Analytics Platform (LEAP) and contains energy consumption and weather data for more than 100 buildings across multiple campuses of La Trobe University from 2018 to 2020 to develop and evaluate a robust and explainable AI-based framework for the measurement and verification (M&V) of energy conservation measures (ECMs) in buildings.

Operational Data: Building operations information, such as lighting schedules, equipment usage, and maintenance activities, helps to understand and optimize energy use. Operational data provide context for energy consumption patterns, highlighting potential areas for improvement. Looking at the work of Jradi et al. [20], the authors developed a digital twin solution, presented in Figure 2 that utilizes building operational data and sensor data; this solution will provide decision-making support for energy retrofits through testing and simulation.

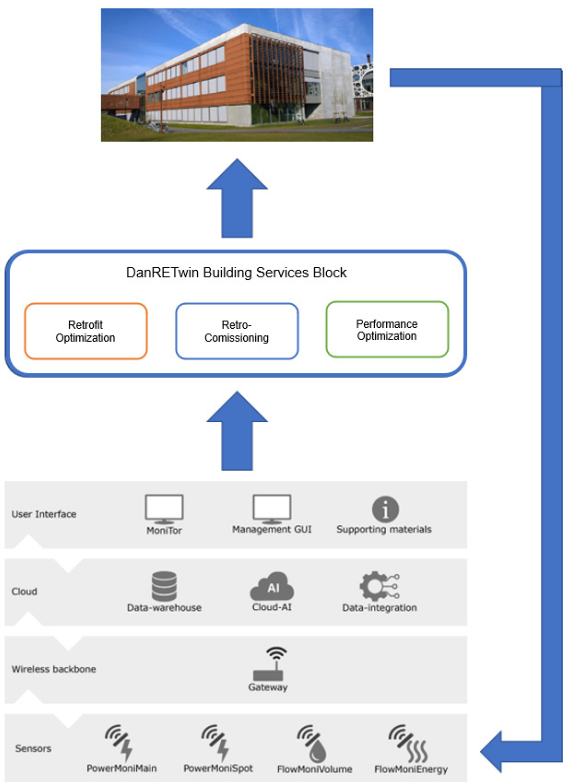

Figure 2. DanRETwin solution illustration with the main technology components and connections. Reprinted from Ref. [20].

Combining these diverse data types allows for a comprehensive analysis and optimization of energy use in buildings. By integrating energy consumption data, building characteristics, weather conditions, and operational insights, stakeholders can develop more effective retrofit strategies, leading to significant improvements in building energy efficiency and performance. Future research should continue to explore innovative ways to integrate and leverage these data sources to further enhance the retrofit outcomes and sustainability.

4.2. Data Sources

Effective data collection is crucial for assessing the performance of energy retrofit interventions in buildings; several methods are employed to gather the necessary data for energy retrofits.

Building Management Systems (BMSs): BMS integrates various building systems and sensors, collecting and managing data related to energy use, indoor environmental quality, and system performance. BMSs are central hubs for data collection, integrating various sensors and systems within a building. The author in Hong et al. [28] used a dataset consisting of real-time monitored data from the Energy Management System (EMS) and Building Automation System (BAS) of the CalSTRS building to gather comprehensive performance data. This dataset includes energy use recorded at hourly intervals and HVAC operating conditions as well as environmental data captured at 15 min or 1 min intervals. The study demonstrated that such high-resolution data are crucial for identifying inefficiencies in energy use and optimizing building performance. For instance, detailed monitoring of the HVAC system revealed opportunities for operational improvements, such as better control strategies and adjustments to equipment settings, which directly informed retrofit decisions. Moreover, the use of real-time data helped overcome common data collection challenges, such as reliance on periodic or aggregated data that may obscure short-term inefficiencies. By leveraging detailed and continuous data, the study provided more accurate insights into building performance, allowing for targeted retrofitting measures. In the work of Piira et al. [29], the authors used the automatic collection of real-time building energy consumption data gathered from the building management systems to develop an advanced retrofitting decision support tool that support step-by-step thinking for retrofitting design and hopefully enable a larger utilization rate for deep building retrofits.

In the industry, solutions like Schneider Electric's EcoStruxure™ Building Operation further illustrate how BMS platforms integrate various building systems, providing critical data that support energy efficiency initiatives and informed decision-making for retrofits.

Sensors and IoT Devices: Sensors are widely used in energy retrofits in buildings because of their ability to provide granular data on specific parameters crucial for optimizing energy use. Temperature sensors measure ambient temperatures across different zones, which is essential for evaluating the performance of heating and cooling systems and ensuring that temperature control is effectively managed after retrofits. Occupancy sensors detect the presence of individuals in a space and adjust lighting and HVAC systems accordingly, thereby enhancing energy efficiency by reducing energy consumption in unoccupied areas. In addition, power meters measure electrical consumption at various points within the building, providing detailed information on the energy usage of specific systems or equipment. This information is invaluable for identifying inefficiencies and opportunities for improvement, enabling more targeted and effective retrofit strategies, according to Nutkiewicz and Jain. [26], Seyedzadeh et al. [11].

In the industry, companies like ReMoni offer advanced sensor solutions that provide the real-time monitoring of energy usage and equipment performance, further demonstrating the critical role of sensors in optimizing building energy efficiency during and after retrofits.

Energy Audits: Energy audits are systematic evaluations of a building's energy use. They involve a combination of visual inspections, data collection, and analysis to identify areas for improvement. Audits typically assess the performance of the building envelope, system efficiencies, and operational practices. The comprehensive nature of energy audits makes them a valuable tool for establishing baseline energy performance and developing targeted retrofit strategies. They are often used in conjunction with other data collection methods to provide a detailed understanding of energy use and potential savings; see the work of Geraldi et al. [30], Marasco et al. [31].

Energy Modeling: Building energy modeling involves the use of simulation software to predict energy consumption and savings associated with retrofit measures. Models can simulate a range of scenarios based on different retrofit strategies, allowing for the evaluation of potential impacts on energy performance before implementation. Energy modeling is crucial for planning and optimizing retrofit interventions, as it provides predictive insights into how changes will affect overall energy use. This approach supports decision-making by forecasting the potential benefits and costs of various retrofit options; see the work of He et al. [32].

Digital Twins: Digital Twins are virtual replicas of physical buildings that use real-time data to simulate and analyze building performance. They integrate data from sensors, BMS, and other sources to create a dynamic model that mirrors the real-world conditions of the building. Digital twins enable the comprehensive monitoring and simulation of building systems, allowing for predictive analysis and optimization of energy use. They offer a powerful tool for assessing retrofit impacts, testing scenarios, and refining strategies by providing detailed insights into how changes will affect building performance; see the work of Jradi et al. [20].

The combination of different data sources allows for a thorough evaluation of energy performance and the effectiveness of retrofit measures. In particular, the integration of data-driven approaches in building energy retrofitting is increasingly supported by a growing body of research that utilizes diverse datasets and objectives to enhance energy efficiency. The detailed analysis of these selected studies, extracted through a rigorous database search, reveals the breadth of data sources and methods applied across different contexts, highlighting the versatility and potential of data-driven methodologies in retrofitting processes. To provide a clearer picture of how these studies align with various objectives and datasets, we summarize the reviewed studies in Table 2. This table offers an overview of the study titles, their objectives, and the datasets used, showcasing the diversity and scope of research in this area.

Table 2. Overview of reviewed studies in data-driven approaches to building energy retrofitting.

Study	Objective	Dataset
[10]	Create a data-driven AI model to predict building energy performance for different retrofit scenarios	EPC dataset for residential buildings in the UK.
[11]	Develop a model for predicting Building Emission Rate (BER) to estimate non-domestic building energy efficiency	records of non-domestic buildings in the UK, sourced from the arbnco Consult platform.
[18]	Urban-scale energy modeling with hybrid approaches.	Electricity consumption, weather, building geometry.

Table 2. *Cont.*

Study	Objective	Dataset
[19]	Optimize urban-scale energy retrofits with cost-effective recommendations.	EPC data, building census data, retrofit cost data.
[20]	Digital twin for non-residential retrofits.	Building operational data, sensor data.
[21]	Address incomplete retrofit data with fusion methods.	EPC data, PCA-imputed variables.
[23]	Develop a model to evaluate the impact of retrofit technologies on stakeholder expectations.	Survey data from owners and energy auditors.
[25]	Agent-based modeling for retrofit rate and CO_2 impact analysis.	Building geometry, census sources, retrofit scenarios.
[26]	Enhance deep learning for large-scale retrofit impacts.	Electricity consumption data, building geometry, weather data.
[27]	Explainable AI for energy conservation measures.	UNICON dataset (multi-campus energy data).
[28]	Evaluate energy savings potential in retrofitting high-performance buildings.	EMS and BAS monitored data.
[29]	Assist users in designing and selecting building retrofitting actions by leveraging real-time data	Real-time energy consumption data.
[30]	Propose energy benchmarking using ANN models.	Energy audit data, electricity bills, surveys.
[31]	Assess ECM opportunities with machine learning models.	Energy audit data from NYC Local Law 87.
[32]	Normative simulations for climate-specific retrofits.	Simulation data from EPC tools.
[33]	Efictive retrofitting decision support for EU decarbonization goals.	Building energy performance, geometry, installed technologies.
[34]	Develop and evaluate a data-driven approach for city-wide building retrofitting,	Heat energy consumption, EPC data, climate data, standardized building details.
[35]	development of the LuminLab AI-powered building retrofit platform, which help users in the retrofit process.	Energy Performance Certificates (EPC)
[36]	Implement and evaluate XAI to assess their prediction accuracy and explainability.	Total energy consumption, monitoring data.
[37]	Develop an ANN model to directly classify building EPC labels and use explainable AI thereby increasing trust in the model.	The CENED database, buildings' energy consumption information
[38]	Apply machine learning and XAI to classify building retrofits, validate findings.	EPC data, socio-demographic data, property prices.
[39]	Optimize retrofitting with GA and ANN models.	Simulation-generated retrofit scenarios.
[40]	Develop an intelligent decision support system for home energy retrofits.	Energy reports, online housing data.
[41]	Optimize energy retrofit levels for building portfolios.	Case study portfolio data from 25 buildings.

Table 2. *Cont.*

Study	Objective	Dataset
[42]	Improve energy efficiency in this building stock.	Swedish database of Energy Performance Certificates (EPCs).
[43]	Develop a surrogate retrofit model that balances accuracy and computational cost.	Data on residential buildings from GIS and census sources.
[44]	Develop a multi-source data fusion deep learning framework to predict building energy efficiency ratings.	Energy Performance Certificate (EPC) data, the UK Buildings dataset and Google Street View (GSV) images
[45]	Improved retrofit ranking with machine learning pipelines.	Building characteristics data (Lombardy region).
[46]	Predict energy savings using ensemble learning.	De-risking Energy Efficiency Platform (DEEP) database.
[47]	Predict urban-scale energy performance with ensemble models.	EPCs, census data, weather, construction data.
[48]	Develop a data-driven framework to assess and optimize residential building retrofits.	Simulation data (HOT2000, HTAP).
[49]	Develop a fast multi-objective optimization method for building retrofits that accounts for future climate conditions	Metered energy use data.
[50]	Identify key building variables for clustering and retrofitting.	Energy audit reports for office buildings.
[51]	Comprehensive retrofitting framework for tropical climates.	Energy simulation data.
[52]	Develop different building archetypes for addressing various urban energy challenges	EPC data, heat energy use, climate data.
[53]	Predict building energy consumption using CatBoost.	Seattle Energy Benchmarking Program data.
[54]	Multi-objective optimization for industrial retrofits.	Simulation data, thermal characteristics, schedules.
[55]	Develop database for SME building retrofits.	EnergyPlus simulation database (DEEP).
[56]	Calibrated simulations for retrofitting strategies.	Energy audit and operational data.
[57]	Multi-model fusion for energy prediction.	Chicago building energy Performance data.
[58]	Develop a generalized methodology for multi-scale GIS-based mapping of building energy performance.	Energy Performance Certificate (EPC) dataset, the Irish Census dataset, the GeoDirectory database, the Irish retrofit housing scheme dataset.
[59]	Determine the optimal investment strategy for energy efficiency retrofits.	Data on 27 NGO buildings in Delaware, USA, including energy savings, emissions reductions, and investment costs.
[60]	Develop methodologies to assess building energy use and create retrofit models	Hourly wireless sensor network (WSN) data.
[61]	Develop a method to assess the energy performance under future climate conditions.	EnergyPlus building energy simulation data.

Table 2. *Cont.*

Study	Objective	Dataset
[62]	Create a data-driven methodology to verify energy efficiency savings in commercial buildings.	EnergyPlus simulations, monitoring data.
[63]	Assess retrofitting impacts in residential buildings.	Energy consumption, indoor temperature, occupant surveys.
[64]	Conduct a holistic cost–optimal retrofit analysis	Measured values of various temperature sensors and energy consumption.
[65]	Predict energy savings from retrofitting decisions.	GSA building portfolio data.
[66]	Life-cycle optimization for retrofit planning.	Energy consumption, thermal property, life-cycle data.
[67]	Enable market actors to assess, forecast, and quantify energy efficiency opportunities and performance risks	The DOE Buildings Performance Database (BPD).
[68]	Provide energy advising using systematic frameworks.	Survey data, building stock data.

Table A1 presents a more detailed overview of the reviewed studies in data-driven approaches to building energy retrofitting.

Overview of the key insights from Table 2:

- Diverse Objectives: The studies aim to address a wide range of goals, from optimizing retrofit decisions on a large urban scale to developing decision support systems and AI models for enhancing building energy efficiency. Some research focuses on specific aspects, such as life-cycle optimization, real-time data utilization, or integrating explainable AI to improve model transparency and trust.
- Varied Datasets: The datasets utilized across these studies are equally varied as seen in Figure 3, reflecting the different scales and contexts of the research. Commonly used datasets include Energy Performance Certificates (EPCs) from various countries (e.g., Ireland, Sweden, and the UK), building energy consumption data, and simulation-generated datasets. Several studies also incorporate weather data, socio-demographic information, and other contextual data such as building geometry or historical data.
- Geographical Diversity: The research spans multiple geographic regions, including Europe (Ireland, Sweden, Germany, Italy, and the UK), North America (California and New York), and China, among others. This highlights the global relevance of energy retrofitting research and the need to tailor approaches to specific regional conditions.
- Integration of Advanced Technologies: A significant number of studies focus on the integration of advanced technologies like AI, machine learning, and digital twins into the retrofitting process. These technologies are employed to enhance predictive accuracy, optimize retrofit solutions, and enable more informed decision-making processes.
- Policy Implications: Some studies aim to support policy-making by providing data-driven tools and indices, such as the Energy Retrofit Index (ERi) or frameworks for policy impact analysis. This suggests an increasing emphasis on aligning research outcomes with practical applications in energy policy and building regulations.

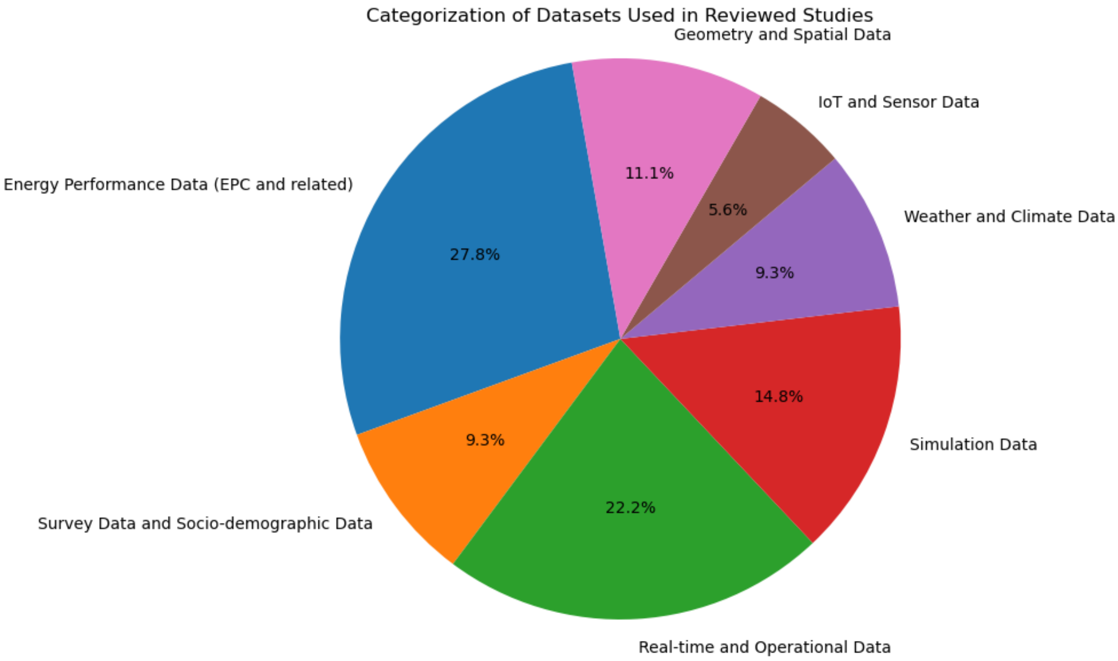

Figure 3. Categorization of datasets used in reviewed studies.

Overall, the reviewed studies collectively advance the field of building energy retrofitting by employing data-driven methods to optimize retrofitting strategies, enhance energy efficiency, and support policy and decision-making processes. The research underscores the importance of integrating diverse data sources, employing cutting-edge technologies, and considering regional contexts to achieve sustainable retrofitting outcomes.

While data-driven approaches have shown significant promise in advancing building energy retrofits, several limitations remain evident in the reviewed studies. Many works lack a consideration of the urban-scale retrofitting challenges, such as integrating inter-building energy dynamics and broader urban context effects. For example, while Pasichnyi et al. [34] explore city-scale retrofit strategies using district heating data, their methodology could be expanded to include multi-building interactions and energy-sharing opportunities. Additionally, the long-term impacts, such as life-cycle energy and carbon assessments, remain underexplored. Ali et al. [47] present a promising urban-scale model using ensemble learning techniques, yet the approach would benefit from life-cycle analysis integration to enhance decision-making.

The scalability of models across diverse building types and regions is another key challenge. Nutkiewicz et al. [26] demonstrate the adaptability of deep learning models for large-scale retrofits but highlight the need for more comprehensive datasets to ensure model generalizability. Furthermore, data quality and gaps in building information compromise the predictive accuracy of machine learning models. Jradi et al. [20] leverage digital twins to address these challenges, offering real-time operational insights, but more studies are needed to integrate this approach at scale. These examples underscore the importance of future research in developing adaptable, data-rich, and life-cycle-oriented models that can address these limitations. Incorporating explainable AI techniques and real-time data sources could further enhance the robustness and applicability of retrofit strategies,

5. AI and Machine Learning Algorithms in Energy Retrofitting

It is very well demonstrated that energy retrofitting plays a crucial role in improving the energy efficiency of existing buildings, which is essential for reducing overall energy consumption and minimizing greenhouse gas emissions. Traditionally, retrofitting approaches have relied on empirical guidelines and generalized methods, which may not always consider the unique attributes of each building or provide optimal results. The advent of artificial intelligence (AI) and machine learning (ML) represents a transformative shift in this field. AI encompasses the development of systems that perform tasks requiring human-like intelligence, such as problem-solving, decision-making, and learning. Within AI, machine learning (ML) is a subset that focuses on creating algorithms capable of learning from data and making predictions or decisions without explicit programming for each specific task. ML algorithms can be categorized into supervised learning, which involves training models on labeled data to predict outcomes; unsupervised learning, which identifies patterns in unlabeled data; reinforcement learning, which learns optimal strategies through interactions and feedback; and deep learning, which uses complex neural networks to model intricate data patterns. By leveraging these advanced technologies, AI and ML enable more precise, data-driven approaches to energy retrofitting. They offer significant advantages over traditional methods, such as enhanced accuracy in predictions, real-time monitoring, and dynamic adjustments, ultimately leading to more effective and efficient energy upgrades in buildings.

Types of Artificial Intelligence and Machine Learning Algorithms in Building Retrofitting

The rapid evolution of AI and ML technologies has introduced a diverse range of algorithms, each uniquely suited to different aspects of energy retrofitting. The application of these algorithms in the built environment enables more precise energy consumption modeling, the accurate prediction of retrofit outcomes, and the effective optimization of energy conservation measures. Understanding the variety and capabilities of these algorithms is essential for leveraging their full potential in energy retrofitting.

Each type of AI and ML algorithm presents distinct advantages and trade-offs, making them more or less suitable for specific retrofitting tasks. The choice of algorithm depends on various factors, including the nature of the data, the complexity of the retrofitting problem, and the specific objectives of the project. The subsequent sections delve into the most widely used AI and ML algorithms in energy retrofitting, emphasizing their distinctive contributions and specific applications within this domain.

Supervised Learning:Algorithms such as Linear Regression, Decision Trees, and Support Vector Machines (SVMs) are frequently employed to predict energy consumption and evaluate the impact of retrofitting measures. These models require labeled datasets to learn the relationships between input features and output predictions. The authors in Nutkiewicz et al. [26] use LSTM to understand the relationship between simulated and metered energy consumption and improve prediction accuracy. LSTMs bring significant advantages to energy retrofitting projects, especially in scenarios involving time-series data and complex, dynamic systems. Their ability to learn from past data and predict future trends makes them a powerful tool for optimizing energy efficiency in buildings, ensuring that retrofitting efforts are both effective and sustainable in the long term. Ali et al. [47] develop machine learning models to predicts building energy performance on a large scale using an ensemble or segregation method, and then they compare the performance of ten supervised learning techniques for each of the methods (the algorithms include XGBoost (XGB), LightGBM (LGBM), Gradient Boosting (GB), Histogrambased Gradient Boosting (HGB), Random Forest (RF), Neural Network (NN), Decision Tree (DT), Linear Regression (LR), K-Nearest Neighbors (KNN) and Support Vector Machine (SVM)), and the results indicate that incorporating segregation in the analysis improves the performance of most models, particularly XGB, LGBM, and HGB. These findings highlight the importance of considering segregation in the machine learning process to obtain more accurate predictions.

Unsupervised Learning: Clustering algorithms like K-means and hierarchical clustering are utilized to segment buildings or components based on energy consumption patterns, which can identify retrofit opportunities. These methods do not require labeled data, making them useful for exploratory analysis. Looking at Feng et al. [21], the authors propose an innovative approach from the perspective of being data driven to support retrofitting selection under incomplete information through performance modeling and data imputation based on the already available BPDs' big data. In their approach, Isolation Forest (IF) is chosen for the data-cleaning process of building performance datasets (BPDs) because it is an effective unsupervised learning technique for anomaly detection. As an unsupervised method, IF does not require labeled data to identify outliers. Instead, it works by isolating data points that differ significantly from the rest. This is particularly valuable in BPDs, where detecting and removing anomalies is crucial to ensure the reliability of the data and the accuracy of performance modeling. By using IF, the process can effectively filter out invalid, duplicated, or anomalous entries, leading to cleaner, more dependable data for analysis. They also utilize hybrid models like the BRBNN–FCM integrated method (this model integrates Belief Rule-Based Neural Networks (BRBNNs) with Fuzzy C-Means (FCM) clustering, combining both supervised and unsupervised machine learning techniques) to model the building's retrofitting performances based on the available building properties. It models the retrofitting performance by establishing the relationship of retrofitting and performances' prediction intervals, without being supported by generally missing data. Ali et al. [19] develop a generic methodology to optimize urban-scale energy retrofit decisions for residential buildings using data-driven approaches. They implement the LOF (Local Outlier Factor) algorithm for outlier detection to processes large datasets more efficiently than the distance-based and density-based outlier detection techniques.

Reinforcement Learning: This approach involves learning optimal retrofit strategies through simulation, where the model interacts with an environment and learns from the outcomes of different actions. Reinforcement learning is particularly useful for dynamic and complex systems, where traditional optimization methods may fall short. While reinforcement learning (RL) is a powerful approach for optimizing complex systems, its application in energy retrofitting is currently limited in the literature. However, RL has found significant use in optimizing building operations and systems to enhance energy efficiency. For example, RL algorithms are effectively employed in controlling heating, ventilation, and air conditioning (HVAC) systems to ensure that energy usage is minimized while maintaining comfort levels [69]. These systems learn optimal strategies by interacting with the building environment, receiving feedback in the form of energy consumption data, and adjusting their actions accordingly. Although RL is not yet widely adopted for retrofitting decisions, its potential for dynamic and real-time optimization makes it a promising tool for future applications in this area.

Optimization Algorithms: Optimization algorithms play a critical role in the energy retrofitting process, especially when it comes to selecting the most cost-effective and energy-efficient retrofitting measures. These algorithms are designed to explore a vast space of potential solutions, balancing multiple objectives such as cost, energy savings, and environmental impact. The use of optimization techniques ensures that retrofit strategies are not only effective in reducing energy consumption but also feasible within the constraints of budget, time, and operational requirements. The authors of Seyedzadeh et al. [11] present an energy performance prediction model using machine learning to assist in multi-objective optimization of retrofit planning and they use the SMAC (Sequential Model-Based Algorithm Configuration) algorithm, an advanced evolutionary algorithm that provides a reliable tool for building analysts to explore the large solution space of retrofit options. Zhang et al. [48] present a data-driven framework that integrates machine learning, multi-objective optimization, and multi-criteria decision-making techniques to streamline this process. A Pareto optimization algorithm is employed to identify the most effective retrofit strategies for the selected building. By integrating this optimization approach with a well-trained Artificial Neural Network (ANN) model within a Python environment, the process efficiently handles multiple objectives, such as energy efficiency, emissions reduction, and cost. The ANN model predicts the building's energy performance before and after retrofits, and these predictions are then used as input for the optimization. The Pareto algorithm systematically evaluates the trade-offs among various retrofit strategies, ultimately identifying optimal solutions that balance the competing objectives, ensuring the most efficient and cost-effective outcomes are selected.

Table 3 below presents a detailed overview of the key studies reviewed, categorized by the type of machine learning algorithm utilized. This categorization illustrates the breadth of applications within the energy retrofitting process, highlighting the diverse approaches taken to optimize energy efficiency, predict consumption, and support decision-making. By examining the specific algorithms employed and their impacts, this summary provides insights into the current state of research in AI-driven energy retrofitting.

Table 3. Overview of key studies on AI and machine learning applications in energy retrofitting.

Study	ML Algorithm Type	Specific Algorithm and Application
[10]	Supervised Learning	• Random Forest (RF) for energy prediction. • Extreme Gradient Boosting (XGBoost) for energy prediction. • Extra Trees (ET) for energy prediction. • Ensemble learning methods for energy prediction. • Artificial neural network with a multilayer perceptron (MLP) for energy prediction.
[11]	Supervised Learning, Optimization Algorithm.	• Optimized Gradient Boosted Regression Tree (GBRT) using the SMAC algorithm to predict Building Emission Rate (BER).
[18]	Supervised Learning, Deep Learning.	• Recurrent Neural Network (RNN) to capture the sources of uncertainty that arise in building energy simulation.
[19]	Unsupervised Learning, Supervised Learning, Optimization Algorithm	• Local Outlier Factor (LOF) algorithm for outlier detection. • Greedy Optimization algorithm to determine optimal features. • Deep Learning to compute and predict the energy rating. • Rule Induction to compute and predict the energy rating. • Neural Network to compute and predict the energy rating. • Naive Bayes to compute and predict the energy rating. • Decision Trees to compute and predict the energy rating. • Random Forest to compute and predict the energy rating. • Gradient Boosted Trees to compute and predict the energy rating. • Learning Vector Quantization (LVQ) to compute and predict the energy rating. • K-Nearest Neighbors (KNN) to compute and predict the energy rating. • Deep Learning to compute and predict the energy rating.
[21]	Unsupervised Learning, Supervised Learning	• Isolation Forest (IF) for Data Cleansing. • Bidirectional Recurrent Bayesian Neural Network with Fuzzy C-means Clustering (BRBNN-FCM) for performance modeling. • Principal Component Analysis with Trimmed Score Regression (PCA-TSR) for data imputation.
[25]	Supervised Learning.	• Extreme Gradient Boosting (XGBoost) to estimate building energy performance (BEP) before and after retrofits.

Table 3. *Cont.*

Study	ML Algorithm Type	Specific Algorithm and Application
[26]	Supervised Learning	• Long Short-Term Memory network (LSTM) for energy prediction.
[30]	Supervised Learning.	• Artificial Neural Network (ANN) for bottom–up energy benchmarking.
[31]	Supervised Learning.	• User-facing falling rule list (FRL) to predict ECM eligibility based on building characteristics.
[35]	Supervised Learning, Deep Learning.	• Multi-layer perceptron (MLP) using random feature corruption (SCARF) for building energy classification.
[42]	Supervised Learning.	• Logistic Regression (LR) to predict building-specific suitability for specific energy conservation measures. • Support Vector Machine (SVM) to predict building-specific suitability for specific energy conservation measures.
[43]	Supervised Learning.	• Artificial Neural Network (ANN) to evaluate necessary building retrofit measures, balancing accuracy and computational cost.
[44]	Supervised Learning.	• Multi-branch deep learning model using two branches one with Dense Convolutional Network (DenseNet) and the other uses Artificial Neural Network (ANN) the two branches work to predict building energy efficiency rating from image or descriptive features
[46]	Supervised Learning.	• Random Forest (RF) to predict energy savings from retrofitting. • Extreme Gradient Boosting (XGBoost) to predict energy savings from retrofitting. • Light Gradient Boosting Machine(LGBM) to predict energy savings from retrofitting. • Ensemble learning methods using the three previous models to further improve the accuracy of the final predictions.
[47]	Supervised Learning	• Extreme Gradient Boosting (XGBoost) for energy prediction. • Light Gradient Boosting Machine (LGBM) for energy prediction. • Gradient Boosting (GB) for energy prediction. • Histogram-based Gradient Boosting (HGB) for energy prediction. • Random Forest (RF) for energy prediction. • Neural Network (NN) for energy prediction. • Decision Tree (DT) for energy prediction. • Linear Regression (LR) for energy prediction. • K-Nearest Neighbors (KNN) for energy prediction. • Support Vector Machine (SVM) for energy prediction.
[48]	Supervised Learning, Optimization Algorithm	• Artificial Neural Network (ANN) as a surrogate model to predict the energy performance of a wide range of retrofit packages. • Genetic Algorithm (GA) to optimize the structure and hyperparameters of the ANN model. • Pareto optimization approach coupling the well-trained ANN model with a Pareto optimization approach developed in the Python coding environment to find the Pareto optimal retrofit solution.
[66]	Optimization Algorithm	• Particle Swarm Optimization (PSO) for determining the optimal retrofitting plan.

Table 3 underscores the diverse application of machine learning (ML) techniques in enhancing building energy efficiency and optimizing retrofit decisions. Predominantly, studies employ supervised learning methods, such as Random Forest (RF), XGBoost (XGB), and Artificial Neural Networks (ANNs), which are effective in handling complex datasets and predicting energy performance. The integration of deep learning approaches, including multi-layer perceptron (MLP) and recurrent neural networks (RNNs), further improves prediction accuracy and simulation capabilities. Optimization algorithms, notably genetic algorithms (GAs) and multi-objective genetic algorithms (MOGAs), are used in conjunction with ANNs to refine retrofit solutions, while ensemble methods enhance prediction accuracy by combining multiple models. The application of these techniques spans from predicting energy savings and retrofit opportunities to improving energy databases and decision support systems, utilizing real-world data for practical relevance. Collectively, these methods reflect a comprehensive and promising strategy for optimizing energy management and supporting sustainable building practices. The integration of different ML algorithms from the reviewed studies in the building energy retrofitting process can be seen in Figure 4.

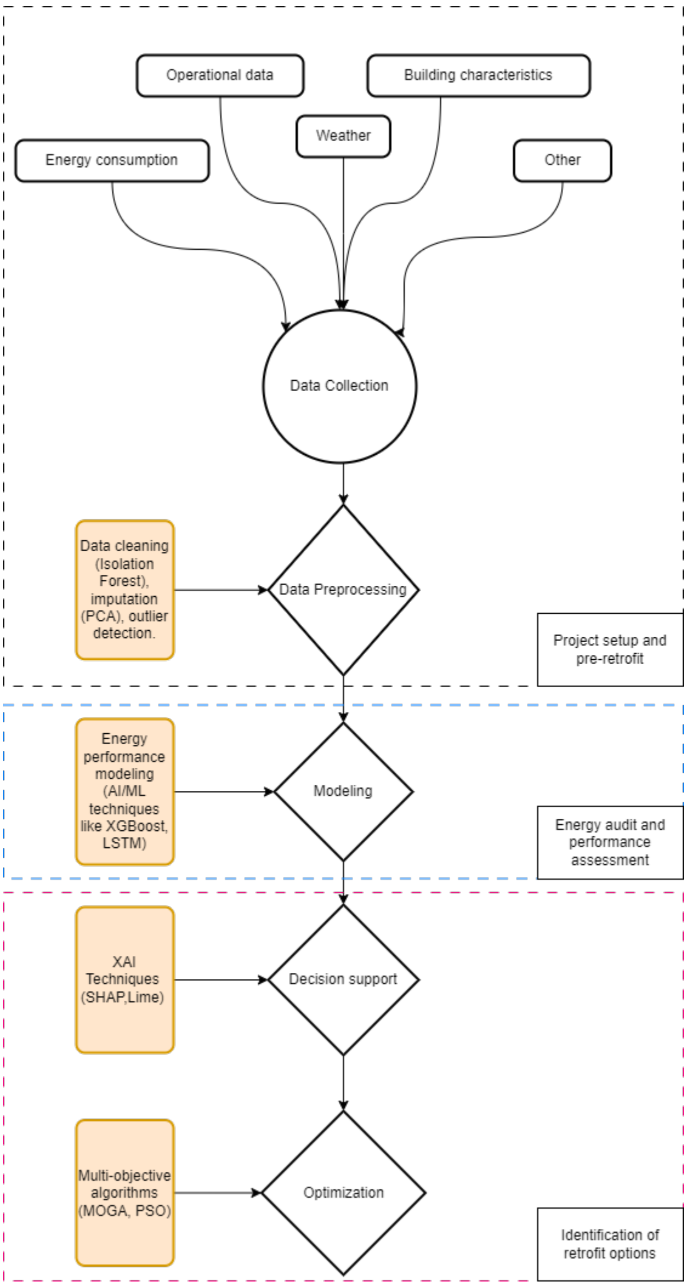

Figure 4. Example of different ML algorithms integration in retrofitting process.

Despite the growing adoption of AI and machine learning techniques in building energy retrofitting, significant challenges remain. Seyedzadeh et al. [11] demonstrate the potential of supervised learning algorithms, such as random forests and gradient boosting, for predicting energy performance, yet these models are often constrained by the quality and quantity of the available training data. Thrampoulidis et al. [43] employ surrogate models based on artificial neural networks (ANNs) to optimize retrofit strategies, but their approach lacks robustness when applied to diverse building types and regions, limiting scalability. Marasco and Kontokosta [31] apply machine learning to identify retrofit opportunities using large-scale building audit data; however, their methods highlight the challenges of integrating heterogeneous datasets and accounting for real-world uncertainties. Furthermore, explainability remains a key limitation, as most studies focus on predictive accuracy without providing insights into the underlying decision-making processes, which is critical for stakeholder trust. These shortcomings underscore the need for future research to develop more generalizable, interpretable, and data-efficient models that can adapt to diverse retrofit scenarios and support informed decision-making.

6. Explainable AI for Energy Retrofitting

Explainable AI (XAI) is an emerging field within artificial intelligence that focuses on making the decision-making processes of AI systems more transparent and understandable to humans. In the context of building energy retrofitting, XAI is crucial for ensuring that stakeholders, including building owners, engineers, and policymakers, can trust and effectively use AI-driven insights to make informed decisions Figure 5 shows Explainaple AI in th retrofit decision process. By providing clear explanations of how AI models arrive at their conclusions, XAI helps bridge the gap between complex algorithms and practical application, enhancing both the adoption and impact of AI technologies in energy retrofitting.

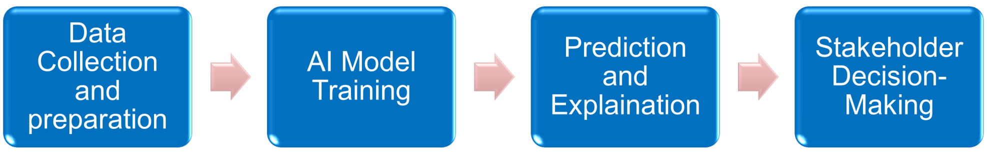

Figure 5. Explainable AI in retrofit decision-making.

The importance of explainable AI (XAI) in building energy retrofitting lies in its ability to foster trust and transparency by clarifying how AI models make decisions, thus enabling stakeholders to understand and rely on AI-driven recommendations. XAI enhances decision-making by providing detailed insights into how various factors influence energy performance, allowing for more tailored and effective retrofit measures. It also supports regulatory compliance by ensuring that AI decisions are transparent and meet legal and funding requirements. Furthermore, XAI facilitates error diagnosis and model improvement by enabling engineers to identify and correct issues, refine algorithms, and improve overall model accuracy and robustness.

In this review, we found five studies from the total reviewed studies that leverage explainable AI (XAI) to enhance various aspects of building energy retrofitting. Each study employs different XAI methods and models, showcasing the broad applications and benefits of XAI in this domain.

In the work of Leuthe et al. [36], the authors explore a range of XAI techniques, including Partial Dependency Plots (PDPs), Accumulated Local Effects (AMEs), Local Interpretable Model-Agnostic Explanations (LIMEs), and Shapley Additive Explanations (SHAPs), applied to Linear Regression, Decision Trees, and QLattice models for predicting energy consumption in residential buildings. This investigation underscores the inherent trade-off between prediction accuracy and explainability, revealing how the choice of XAI method can mitigate this trade-off and improve decision-making processes for building retrofits. They also conduct an online survey to evaluate the explainability of the models and model–XAI–method combinations from the perspective of non-ML and non-energy experts (i.e., property owners).

In contrast, Tsoka et al. [37] focus on the classification of building energy performance certificates (EPC) using an Artificial Neural Network (ANN), enhanced by LIME and SHAP. This research demonstrates the utility of XAI in simplifying complex ANN models by clarifying feature contributions, thus fostering greater trust and understanding of the model's classifications. The emphasis here is on improving transparency and trust in the predictive capabilities of ANN models.

Wenninger et al. [38] integrate supervised learning with XAI by applying Extreme Gradient Boosting (XGBoost) and SHAP to analyze retrofitting practices within the UK's residential sector. This study illustrates how XAI can validate and interpret predictive models, providing valuable insights for policy development and improving retrofit strategies. It highlights the role of XAI in transforming qualitative insights into quantitative analyses and policy recommendations.

Looking at Moraliyage et al. [27], the authors present a comprehensive AI framework for the measurement and verification (M&V) of energy conservation measures (ECMs), using XGBoost and SHAP for predictive modeling and explanation. This research emphasizes the development of robust and transparent methods for evaluating energy savings, with practical applications in real-world settings. The focus is on creating a systematic approach for assessing the impact of energy conservation efforts and supporting sustainability goals.

On the other hand, Sun et al. [44] advance the field by proposing a deep learning-based multi-source data fusion framework to estimate building energy efficiency. By incorporating Energy Performance Certificate (EPC) data and Google Street View (GSV) images, and utilizing SHAP for feature interpretation, this research demonstrates significant improvements in model accuracy and offers insights into urban energy efficiency. The study's methodology includes a deep convolutional neural network that integrates both image and descriptive features, showcasing the potential of XAI to enhance city-level energy efficiency understanding. Collectively, these studies reveal the broad applicability and benefits of XAI in building energy retrofitting. They illustrate how XAI techniques can enhance model transparency, improve prediction accuracy, and facilitate better decision-making across various applications. The integration of XAI into machine learning frameworks not only bridges the gap between complex models and practical insights but also supports the development of more effective and informed retrofit strategies.

While explainable AI (XAI) holds significant potential in building energy retrofitting, key limitations remain. Tsoka et al. [37] highlight scalability issues when applying XAI techniques to diverse datasets and building stocks. Gabrielli et al. [41] note the trade-off between model accuracy and interpretability, particularly in heterogeneous building contexts. Moraliyage et al. [27] reveal challenges in adapting XAI frameworks to varying operational and climatic conditions. Additionally, most existing XAI implementations focus on post hoc explanations rather than embedding interpretability into the model design, limiting their effectiveness in real-time decision-making. These gaps underscore the need for further research to enhance the adaptability, scalability, and integration of XAI into dynamic retrofit processes.

7. Discussion and Challenges

7.1. Discussion

The evolution of data-driven decision support systems for energy retrofitting has seen significant advancements, particularly through the integration of artificial intelligence (AI) and machine learning (ML) techniques. These innovations have enabled more accurate energy performance predictions, streamlined retrofit processes, and addressed several longstanding challenges, such as incomplete data, scalability, and generalizability. However, despite these strides, notable research gaps still require further exploration.

A primary challenge in energy retrofitting is managing incomplete or inconsistent data. In many cases, as shown in the work by Wiethe et al. [25], the absence of granular data—such as real-time occupant behavior and operational anomalies—hampers the precision of energy-saving estimates and post-retrofit performance evaluations. Feng et al. [21] use isolation forests for data cleansing and advanced ML techniques like Bayesian Ridge Building Networks (BRBNNs) and Principal Component Analysis (PCA) to impute missing data, highlighting how hybrid models can overcome gaps in datasets. Similarly, Ali et al. [47] employ ensemble learning models, such as XGBoost and LightGBM, which combine multiple model predictions to deliver reliable forecasts, even when faced with incomplete datasets. This reflects an increasing trend toward developing sophisticated algorithms to handle the incomplete or inconsistent data that pervades retrofitting projects.

Beyond handling incomplete data, ML models have also helped address issues of data integration. As highlighted by studies such as that of Sarmas et al. [46], which uses ensemble learning to predict energy savings, ML algorithms can process heterogeneous data sources—such as sensor data, energy performance certificates, and weather information—combining them into cohesive inputs for retrofit planning.

One of the most significant innovations in the field is the use of artificial neural networks (ANNs) and time-series models to optimize retrofit strategies. Zhang et al. [48] develop a surrogate ANN model that integrates real-time sensor data and historical energy consumption records to predict retrofit outcomes, demonstrating how data-driven techniques can provide cost-effective solutions even when high-resolution data are unavailable. Time-series forecasting techniques, such as weighted support vector regression (SVR) used by Zhang et al. [69], allow for short- and medium-term energy consumption predictions, effectively addressing the challenge of incomplete or inconsistent time-series data. These advancements make real-time monitoring and optimization a reality, allowing for more responsive and dynamic retrofit strategies.

Explainable AI (XAI) has emerged as another innovation that addresses the transparency issues associated with traditional black-box ML models. Moraliyage et al. [27] use XAI techniques to make AI-driven decisions in energy retrofitting more transparent, allowing stakeholders to understand the reasoning behind the predictions. This is crucial in energy retrofitting, where building owners, policymakers, and investors need to trust the system's recommendations. XAI provides an essential bridge between sophisticated ML algorithms and their practical adoption by making the decision-making process clear and interpretable.

Despite these advancements, scalability remains a persistent challenge in large-scale retrofit efforts. While models developed by Nutkiewicz et al. [26] demonstrate how data-driven urban energy simulations (DUE-S) can predict energy savings across multiple buildings, they also highlight the difficulties of scaling these solutions to broader urban environments. Pasichnyi et al. [52] emphasize the need for archetype-based models tailored to specific building stocks and regional conditions, noting that more generalized ML models often lack the precision needed for localized retrofitting efforts. Thus, while ML models can offer scalable solutions, they must be adaptable to specific building and environmental contexts to fully realize their potential.

Optimization algorithms are also proving essential in retrofitting projects. For instance, Zhang et al. [48] use multi-objective optimization techniques to reduce retrofit costs while maintaining energy efficiency. These algorithms balance competing objectives, such as cost and energy performance, providing stakeholders with optimized solutions that meet both financial and environmental goals.

Moreover, Piira et al. [29] develop a decision support system that integrates real-time building operational data, improving retrofit strategy responsiveness and energy savings. These tools allow stakeholders to adapt retrofit measures dynamically, ensuring that real-time building performance informs retrofitting decisions, which increases overall effectiveness.

Another critical area in energy retrofitting is the consideration of life-cycle cost analysis and environmental impact. Luo and Oyedele [66] develop a life-cycle optimization framework that not only predicts energy savings but also accounts for the economic and environmental benefits of retrofits over time. This shift toward life-cycle thinking is crucial in aligning retrofitting efforts with broader sustainability goals, ensuring that energy efficiency improvements also contribute to long-term environmental and economic gains.

7.2. Challenges and Research Gaps

The analysis of the selected papers on data-driven energy retrofitting has revealed several critical research gaps that need to be addressed to advance the field. These gaps span a wide range of topics, from data quality and modeling challenges to practical application barriers, and they underscore the complexity of implementing effective energy retrofitting strategies on a large scale.

Data Availability and Quality: A significant challenge identified in the literature is the lack of comprehensive and accurate data in existing building stock databases. Many databases suffer from outdated information, poor data quality, and insufficient physical descriptions of buildings. Moreover, there is a notable absence of detailed information on the existing and potential retrofit measures. This lack of data limits the ability to perform accurate energy performance assessments and hinders the development of reliable models for predicting retrofit outcomes.

Urban-Scale Retrofitting and Contextual Considerations: The literature reveals a gap in studies focusing on urban-scale retrofitting, particularly for residential buildings. Most existing research is limited to commercial buildings or specific climates, resulting in a lack of generalized solutions applicable across different urban contexts. Furthermore, simulation-based models often struggle to account for the complex inter-building energy dynamics and the broader urban environment, leading to challenges in accurately predicting the performance of large-scale retrofits.

Modeling and Simulation Challenges: There is a clear need for more adaptable and robust models that can better simulate the effects of energy retrofits. Existing models often face difficulties in capturing the interaction between multiple retrofitting measures, and the optimization objectives are frequently limited to the operating energy or life-cycle cost, rather than a more comprehensive evaluation that includes life-cycle energy and carbon impacts. Additionally, current models tend to separate the tasks of predicting energy consumption and assessing the influence of urban context, which limits their effectiveness.

Practical Application and Decision-Making: The transition from theoretical models to practical applications remains a significant hurdle. There is a lack of decision support tools that can effectively incorporate decision-makers' preferences and account for the uncertainties inherent in retrofit projects, such as savings estimation and cost fluctuations.

Moreover, the existing tools often rely on pre-simulated data or fixed assumptions, which may not be adaptable to the dynamic nature of building retrofitting projects.

Addressing Uncertainties and Enhancing Predictive Accuracy: Many studies have highlighted the uncertainties in building energy performance evaluations, particularly when using data-driven models. The accuracy of these models is often compromised by the limited availability of high-quality data, missing data, and noise in the datasets.

Expanding the Scope of Retrofit Research: Finally, the scope of current retrofit research is often limited to specific aspects of energy efficiency, neglecting important factors such as the economic feasibility of retrofits, the impact of retrofits on carbon emissions, and the integration of renewable energy systems. There is also a need for more studies that explore the application of data-driven methods in predicting retrofit outcomes at a larger urban scale, beyond individual buildings. Expanding the scope of retrofit research to include these factors will be crucial in developing more comprehensive and effective energy retrofit strategies. To better understand the current challenges and opportunities in data-driven energy retrofit, Table A2 summarizes the research gaps identified across various studies. Each entry includes a reference to the study and the specific research gap(s) it highlights. This compilation provides a clear overview of the areas where further research is needed, helping to guide future efforts in improving data-driven approaches to energy retrofitting.

7.3. Critical Requirements for Advanced Building Energy Retrofit Modeling and Evaluation

In the rapidly evolving field of building energy retrofits, there is an urgent need for more advanced, adaptable, and flexible data-driven approaches. These approaches, powered by machine learning (ML) and artificial intelligence (AI), promise to revolutionize how we predict and implement energy-saving measures. By focusing on creating models that are easily replicable, require specific data inputs, minimize development time, undergo rigorous verification, and maintain high predictive accuracy, we can significantly enhance the efficiency and effectiveness of retrofit projects.

Based on the review conducted in this study, below is a set of critical requirements for advanced building energy retrofit modeling and evaluation.

1. Adaptability and Flexibility The models should be adaptable to a wide range of building types, from residential to commercial and industrial buildings. They should also accommodate different energy systems, including heating, ventilation, air conditioning (HVAC), lighting, and renewable energy systems. Given the variability in building usage patterns and external conditions (e.g., changing weather patterns due to climate change), the models must dynamically adapt to data inputs.
2. Optimized Data Requirements A well-designed data-driven model should clearly specify the essential data required, such as energy usage patterns, building envelope characteristics, occupancy schedules, weather data, and energy system performance metrics. This helps streamline data collection, focusing on the most impactful variables. In cases where complete data are not available, models can employ data enrichment techniques, such as synthetic data generation, interpolation, or the use of similar case studies to fill gaps. This ensures the model remains functional even with incomplete datasets. Furthermore, integration with the Internet of Things (IoT) and smart sensor networks can greatly enhance data collection, providing data on various building parameters such as temperature, humidity, occupancy, and energy consumption. These data can improve model accuracy and enable more precise predictions of energy savings.
3. Efficient and Scalable Development Leveraging automated machine learning tools can significantly reduce the time and expertise required to develop models. These tools can automatically select the most appropriate algorithms, tune hyperparameters,

and even pre-process data, making model development faster and more accessible. Moreover, utilizing pre-trained models or transfer learning techniques can further expedite development. By applying knowledge from models trained on similar buildings or retrofit scenarios, one can reduce the need for extensive retraining, saving time and resources.

4. Rigorous Verification and Validation Models must undergo extensive testing across a range of scenarios and building types to ensure their reliability and accuracy. This could involve back-testing on historical data, cross-validation with different datasets, and pilot projects in real-world settings. In this regard, incorporating uncertainty quantification in the model's predictions can provide a range of potential outcomes, helping stakeholders understand the risk and variability associated with different retrofit measures. This is particularly important in scenarios where data are sparse or highly variable.
5. Enhanced Predictive Accuracy and Insights High predictive accuracy is critical, and models should be capable of making granular predictions, not just at the building level but also at the level of individual systems (e.g., HVAC and lighting). This enables more targeted interventions and maximizes the impact of retrofit measures. The models should support scenario analysis, allowing stakeholders to explore different retrofit options and their impacts. This includes optimizing combinations of retrofit measures for maximum energy savings and cost effectiveness, using advanced techniques such as multi-objective optimization or genetic algorithms.
6. Economic and Environmental Impact Assessment Beyond energy savings, the adopted approach should incorporate comprehensive return on investment (ROI) analysis, considering factors such as upfront costs, maintenance expenses, utility rebates, and potential increases in property value. This helps stakeholders make informed decisions about which retrofit measures offer the best financial return. Additionally, the environmental impact of retrofit measures should be evaluated, including reductions in greenhouse gas emissions, improvements in indoor air quality, and contributions to broader sustainability goals.

8. Conclusions

8.1. Summary of Findings

The integration of machine learning and AI into energy retrofitting processes has made some progress in addressing challenges such as incomplete data, scalability, and generalizability. Techniques such as ensemble learning, artificial neural networks, and explainable AI have improved the accuracy and transparency of energy performance predictions, allowing for more effective and reliable retrofit strategies. Innovations in data imputation, such as those employed by Feng et al. [21], and real-time optimization as demonstrated by Zhang et al. [70], have helped ensure that retrofitting decisions can still be made with confidence, even in the face of inconsistent or incomplete data.

Despite these advancements, the challenge of scaling these solutions to urban or regional levels persists. As emphasized by Pasichnyi et al. [52] and Nutkiewicz et al. [26], more refined archetype-based models and localized data inputs are necessary to ensure that ML-driven retrofit strategies are adaptable to different building types and geographic contexts. Moreover, as the field moves toward more dynamic, real-time retrofit processes, the role of life-cycle assessments, as discussed by Luo and Oyedele [66], will become increasingly important in ensuring that retrofitting efforts align with long-term sustainability goals.

In summary, while machine learning and AI have greatly enhanced the capabilities of energy retrofitting, future research and development must focus on making these technologies more scalable, adaptable, and transparent.

8.2. Future Research Directions

Considering the identified gaps analyzed in Sections 4–6 and 7.2, it seems appropriate to suggest the following directions for further research:

1. Improving Data Quality and Access: The lack of comprehensive, high-quality data on existing building stock remains a fundamental barrier to effective retrofitting. Future work should focus on creating centralized, standardized databases that include detailed building characteristics, historical performance data, and implemented retrofit measures. This includes leveraging advanced data collection methods such as IoT devices and sensor networks to provide real-time, granular data on building performance. Additionally, improving data sharing frameworks and protocols will ensure interoperability and accessibility, enabling the seamless integration of data from diverse sources.
2. Developing Scalable Urban Retrofitting Solutions: Urban-scale retrofitting strategies must move beyond single-building models to account for the complexities of entire districts and cities. Research should focus on developing simulation tools that integrate inter-building energy dynamics and the effects of urban environments, such as shading, heat islands, and shared resources. These tools must be scalable and adaptable to varying building typologies and climate zones, enabling the formulation of retrofit strategies that maximize energy savings while minimizing costs and disruptions.
3. Advancing Modeling and Simulation Techniques: The limitations of current models, including their inability to capture interactions between multiple retrofit measures, must be addressed. Future research should focus on creating integrated simulation frameworks that combine energy, environmental, and economic metrics. Incorporating life-cycle analyses into these models will provide a more comprehensive understanding of the long-term impacts of retrofitting measures, including operational energy savings, carbon emissions, and cost effectiveness. Real-time adaptable models, such as digital twins, should be further explored to enable continuous optimization and monitoring of retrofit strategies.
4. Enhancing Practical Decision-Making Tools: To bridge the gap between theoretical models and practical implementation, there is a need for decision-support tools that are intuitive, adaptive, and transparent. These tools should integrate real-time data inputs, incorporate stakeholder preferences, and account for uncertainties such as cost fluctuations and performance variability. explainable AI (XAI) methods should be embedded within these tools to ensure that decision-making processes are transparent and understandable to non-expert stakeholders, fostering trust and encouraging broader adoption of data-driven approaches.
5. Addressing Uncertainties and Boosting Predictive Accuracy: Uncertainties in data and model predictions hinder the reliability of retrofit strategies. Hybrid modeling approaches that combine machine learning with physics-based simulations offer a promising solution. These approaches can leverage ensemble methods to synthesize predictions from multiple models, improving accuracy and robustness. Future work should also focus on quantifying and communicating uncertainties to stakeholders, enabling more informed decision-making and reducing the perceived risks of retrofitting projects.

6. Expanding Research to Include Economic and Environmental Metrics: Retrofitting research must expand its scope to address economic feasibility, carbon reduction, and the integration of renewable energy systems. Future studies should evaluate the financial impacts of retrofit measures over their life-cycle, including operational savings and long-term value enhancements. Additionally, integrating renewable energy technologies such as solar panels, heat pumps, and energy storage systems into retrofitting strategies will support broader sustainability goals and align with climate change mitigation efforts. Policymakers and researchers should also explore the role of incentives and regulatory frameworks in promoting holistic retrofitting solutions.

By systematically addressing these directions, future research can overcome the current limitations and pave the way for scalable, efficient, and sustainable data-driven energy retrofitting practices.

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Appendix A

Table A1. Overview of reviewed studies in data-driven approaches to building energy retrofitting.

Study	Objective	Dataset
[10]	Create a data-driven AI model to predict building energy performance for different retrofit scenarios, using four machine learning models (XGBoost, random forest, Extra Trees, and ANN-MLP) and develop an interface for analyzing retrofit impacts.	Energy Performance Certificate dataset for residential buildings in the UK
[11]	Develop a model for predicting Building Emission Rate (BER) to estimate non-domestic building energy efficiency in the UK, provide a rapid tool for the multi-objective optimization of retrofits, use a comprehensive dataset of existing buildings, and perform sensitivity analysis to identify the impact of each input parameter on building performance.	The dataset used in the study included 4900 records of non-domestic buildings in the UK, sourced from the arbnco Consult platform. To expand the dataset for machine learning training, an additional 80,000 samples were generated by mutating the original 4900 records.
[18]	Evaluate the feasibility of a Data-driven Urban Energy Simulation (DUE-S) model for rapid large-scale retrofit assessments and demonstrate the benefits of integrating data-driven and physics-based approaches for urban energy modeling.	The dataset used in the study encompasses three years (2015–2017) of 15-minute interval electricity consumption data for 52 buildings, historical hourly weather data from NOAA for the same period, building geometries derived from GIS data, and non-geometric building properties based on the DOE's Commercial Reference Buildings.

Table A1. *Cont.*

Study	Objective	Dataset
[19]	Develop a data-driven methodology to optimize urban-scale energy retrofits for residential buildings by identifying key variables influencing energy performance and providing cost-effective retrofit recommendations.	The Energy Performance Certificate (EPC) dataset for Irish residential buildings, published by the Sustainable Energy Authority of Ireland (SEAI), the building census dataset from the Central Statistics Office (CSO) of Ireland, and the retrofit cost dataset with financial details of retrofit projects, also from SEAI.
[20]	Design, develop, and demonstrate the "DanRETwin" digital twin solution to optimize decision-making, enable retro-commissioning, and enhance performance in energy retrofits for non-residential buildings.	a digital twin solution that will utilize building operational data and sensor data.
[21]	Propose a data-driven approach for building retrofitting decisions under incomplete information, using BRBNN-FCM to model relationships between building properties, retrofitting measures, and performance, and PCA-TSR to impute missing data.	The Energy Performance Certificate (EPC) dataset from Sweden.
[23]	Develop a model to evaluate the impact of retrofit technologies on stakeholder expectations, prioritize these technologies to aid decision-making, and integrate the findings with the existing EPC recommendation report.	The study involved two surveys: the first surveyed Romanian owners and tenants to understand their retrofitting requirements, and the second surveyed experts (Accredited Energy Auditors) to explore the relationship between retrofit technologies and stakeholder requirements.
[25]	Determine how building energy performance prediction accuracy affects retrofit rates and resulting CO_2 emissions in the residential building sector and to design an agent-based building stock model to derive this relationship.	The real-world dataset of 25,000 single and two-family buildings from Germany, with 74 variables related to building characteristics, heating systems, and annual metered thermal energy consumption.
[26]	Enhance the DUE-S model by improving its deep learning architecture for time-series data and expanding its ability to estimate large-scale retrofit impacts across different spatiotemporal scales in a city.	Hourly electricity consumption data for 29 buildings in downtown Sacramento, California, from 2016 to 2018, accompanied by publicly available data on building geometry, characteristics, and local weather for the same period.
[27]	Develop a robust and explainable AI-based framework for measuring and verifying energy conservation measures (ECMs) in buildings and to evaluate it in a real-world multi-campus education institution with diverse buildings and sensor technologies.	The dataset used in the study is the UNICON dataset, sourced from the La Trobe Energy AI/Analytics Platform (LEAP). It includes energy consumption and weather data for over 100 buildings across multiple La Trobe University campuses, covering the period from 2018 to 2020.
[28]	Evaluate energy savings potential in retrofitting high-performance buildings, identify necessary performance data, analyze suitable analytics for retrofit measures, and address challenges in data-driven approaches for HPBs.	The study utilized real-time monitored data from the Energy Management System (EMS) and Building Automation System (BAS) of the CalSTRS building, including hourly energy use data and HVAC operating conditions and environmental data at 15-minute or 1-minute intervals.
[29]	Assist users in designing and selecting building retrofitting actions by leveraging real-time operation data and occupant behavior profiles to propose alternative scenarios, improving existing commercial routines based on predicted energy performance.	Automatic collection of real-time building energy consumption data gathered from the building management systems.
[30]	Propose a reducing-uncertainty framework to obtain a bottom-up energy benchmarking model using Artificial Neural Networks (ANN).	The dataset used in the study is a test-bed dataset from school buildings in Brazil, which was previously presented and analyzed in the authors' previous work. The dataset is composed of data from design analysis, energy audits, electricity bills, and surveys

Table A1. *Cont.*

Study	Objective	Dataset
[31]	Use energy audit data from New York City's Local Law 87 to develop a machine learning model for predicting ECM eligibility, create a user-friendly FRL classifier for assessing ECM opportunities, and provide an actionable tool for building stakeholders to identify potential ECMs.	The first year of reported data from New York City's Local Law 87 (LL87), which requires energy audits of large buildings.
[32]	Present a data-driven retrofitting approach for high-rise residential buildings in China using normative calculation-based simulation, and identify suitable retrofitting measures for various climate zones across the country.	The study employs an Energy Performance Calculator (EPC) developed by the Georgia Institute of Technology. This reduced-order simulation tool uses normative calculation logic and functions as a dynamic simulation program, requiring fewer input parameters than traditional simulations while providing robust, easily reproducible results. Its open framework allows users to modify and select simulation parameters, unlike standard normative models.
[33]	Develop a low-cost, data-driven decision support system to help policymakers select effective energy retrofit strategies that align with the EU's decarbonization goals.	The study utilizes the CENED 1.2 database, which includes data on building energy performance, geometry, and installed technologies for residential buildings in Lombardy, Italy.
[34]	Develop and evaluate a data-driven approach for city-wide building retrofitting, introducing a novel energy modeling framework. Assess changes in total energy demand and supply impacts from large-scale retrofitting, providing city authorities and housing institutions with tailored strategies based on specific criteria.	The study employs various datasets, including heat energy use for 15,068 district heating points in Stockholm (AB Stockholm Exergi, 2012), EPC data for 30,472 buildings, standardized building use and envelope details from the Sveby project, and climate data from the Swedish Meteorological and Hydrological Institute (SMHI).
[35]	Describe the development of the LuminLab AI-powered building retrofit platform, which utilizes an intelligent chatbot agent to integrate stakeholder knowledge and help users understand cost trade-offs in the retrofit process.	Energy Performance Certificates (EPC) dataset from the Sustainable Energy Authority of Ireland (SEAI)
[36]	Implement and evaluate seven XAI models, assess their prediction accuracy and explainability, and analyze the trade-off between these factors to derive implications for the residential building sector.	The dataset comprises 25,000 single- and two-family residential buildings in Germany, collected between 2007 and 2014, featuring 74 variables focused on building characteristics. After processing, the final dataset for analysis includes 20,421 buildings, with 22 input variables and a target variable representing the total energy consumption per square meter per year.
[37]	Develop an ANN model to directly classify building EPC labels and use explainable AI techniques to elucidate the ANN model's classifications, thereby increasing trust in the model.	The CENED database, which contains numerous buildings' energy information in the Italian Lombardy region.
[38]	Apply machine learning and XAI to classify building retrofits, validate findings, and derive policy implications for the UK's residential building stock.	EPC data, house price data from HM Land Registry, and socio-demographic data (age groups, employment rate, gross disposable household income, education level) at the regional level.
[39]	Develop a multi-objective optimization model using GA and ANN to assess technology choices in building retrofits, simultaneously optimizing energy consumption, retrofit cost, and discomfort hours.	The authors generated a database of simulation cases for the purposes of the study.

Table A1. *Cont.*

Study	Objective	Dataset
[40]	Identify the key components of an intelligent decision support system (IDSS) for home energy retrofits, develop rules to incorporate expert knowledge into the system, create the IDSS for retrofit decision-making, and demonstrate its application with a pilot system.	The dataset used in the study comprised two main sources: 20 reports from the Alternative Energy Engineering Technologies Program at Lansing Community College, covering a span of 5 years, and housing information gathered from internet-based sources like Michigan Housing Locator, Zillow, Realtor.com, and Trulia, which were used to complement the energy assessment data from the reports.
[41]	Identify optimal energy retrofit levels that maximize benefits for building portfolios, develop a decision support model for choosing effective efficiency actions, and explore a system to help asset holders evaluate robust actions for enhancing portfolios and optimizing cash flows.	A case study portfolio of 25 buildings from the University of Ferrara.
[42]	Investigate how expert observations from Google Street View and transparent machine learning can enhance EPC data for Swedish multifamily buildings from 1945 to 1975, and refine methods for more accurate national estimations and strategies to improve energy efficiency in this building stock.	The dataset used in this study is the Swedish database of Energy Performance Certificates (EPCs), specifically a snapshot from July 1, 2015 that contains around 130,000 EPCs, of which 50,000 are from the period 1945–1975.
[43]	Develop a surrogate retrofit model that balances accuracy and computational cost, using inputs accessible to decision makers. The model should predict retrofit solutions for residential buildings in Zurich, be easy to apply with reduced complexity, and be scalable for wide-area retrofit analyses.	The dataset used in this study contains data on residential buildings in Zurich, Switzerland, gathered from GIS and census sources. It includes both continuous and categorical building features. From this comprehensive dataset, a subset of buildings meeting specific criteria was selected for the study.
[44]	Develop a multi-source data fusion deep learning framework to predict building energy efficiency ratings using building morphology attributes and street-level imagery. Aim for a comprehensive understanding of building energy efficiency and identify influential factors through explainable AI techniques.	The study used three datasets: Energy Performance Certificate (EPC) data for 168,410 domestic buildings in Glasgow from October 2012 to March 2021, the UK Buildings dataset providing 2D building footprints across Great Britain, and Google Street View (GSV) images for 157,222 properties in Glasgow, obtained via the GSV API.
[45]	Contrast the limitations of the Energy Performance index (EPi) for ranking retrofitable buildings, present a machine learning pipeline for extracting key nonlinear features, and introduce the Energy Retrofit index (ERi) to guide financial aid allocation for regional building retrofits.	The dataset used in the study was extracted from the Lombardy Region database in Italy and included five building characteristics relevant to energy retrofitting: the U-value of walls, windows, roof, and basement, as well as the global efficiency of the heating system.
[46]	Provide a machine learning-based framework for predicting energy savings from efficiency renovations, using advanced ensemble algorithms rather than traditional simulations or physical models, and focus on estimating energy savings rather than financial indicators.	The dataset used in the study is the De-risking Energy Efficiency Platform (DEEP) database, which includes a sample of 4183 anonymized energy efficiency investment projects from nine countries: Belgium, Bulgaria, Denmark, France, Germany, Latvia, Sweden, the United Kingdom, and the United States.
[47]	Integrate parametric simulations, ensemble-based machine learning, and segregation methods to predict urban-scale building energy performance with limited resources, and validate the approach by assessing Ireland's residential building stock.	The dataset used in the study includes building stock data, weather information, census data, reports on energy policies, and construction data.

Table A1. *Cont.*

Study	Objective	Dataset
[48]	Develop a data-driven framework combining machine learning, optimization, and decision-making to assess and optimize residential building retrofits. Validate with data from a British Columbia residential building to show its effectiveness in guiding retrofit decisions.	The dataset used in the study consists of 10,368 retrofit scenarios for a medium single-family detached house with a shallow basement, produced using building energy modeling tools HOT2000 and HTAP, and includes the natural gas and electricity consumption values for each retrofit scenario.
[49]	Develop a fast multi-objective optimization method for building retrofits that accounts for future climate conditions and apply it to a case study of the Towne Building at the University of Pennsylvania. The method will be integrated into a decision-making framework to guide the selection of optimal retrofit options based on the optimization results.	The model is calibrated with its actual energy performance in 2015 by metered hourly and monthly energy use data, which are stored and maintained by Penn Facilities and Real Estate Services (FRES).
[50]	Identify key building variables that influence energy consumption in air-conditioned office buildings and determine the optimal set of variables for clustering buildings to gain insights into their energy-saving potential.	The dataset used in this study consists of energy audit reports for 56 office buildings in Singapore, including both pre-retrofit and post-retrofit information on the buildings' energy consumption, chiller plant efficiency, and other characteristics.
[51]	Propose a comprehensive framework for institutional building retrofits in tropical climates, exemplified through a case study of a real institutional building in Singapore. This includes a detailed energy model calibration, selection of retrofit options, local cost data processing, cost–benefit analysis, and final decision-making. The case study also discusses implications for cost-effective retrofit strategies.	The dataset used in this study was the information and data related to the School of Design and Environment 2 (SDE 2) building at the National University of Singapore (NUS), which the authors used to develop and calibrate an energy simulation model.
[52]	Demonstrate how rich datasets can be leveraged to develop different building archetypes for addressing various urban energy challenges, while identifying the potential for energy savings through building retrofitting in Case 1. Additionally, explore the use of electric heating and its potential to reduce electricity demand in Case 2.	The main datasets used in this study are Energy Performance Certificates (EPC) data, measured heat energy use data from district heating metering points, climate data, and reference data on standardized building use and envelope characteristics.
[53]	Apply the CatBoost model to predict building energy consumption (Site EUIWN) using 12 key features, contributing to knowledge and providing insights to improve energy efficiency for building owners and designers.	The dataset used in this study is the building energy performance data collected in 2015 and 2016 by Seattle's Energy Benchmarking Program (SMC 22.920).
[54]	Optimize the energy retrofit of an office area in an existing industrial building in South Italy by developing a comprehensive methodology that includes model development, calibration, and multi-objective optimization. Apply this approach to a real building, providing guidelines for energy-efficient, cost-effective retrofits in the Mediterranean region while considering occupant thermal satisfaction.	Key factors include the location and weather data file, thermo-physical characteristics of both opaque and transparent envelope elements, building space usage, and yearly schedules for building use, occupancy, and energy system operation.
[55]	Develop a database of energy efficiency performance (DEEP) from 10 million EnergyPlus simulations to facilitate quick and reliable retrofit analysis for small and medium-sized commercial buildings. Integrate DEEP into a web-based retrofit toolkit (CBES) to offer preliminary retrofit analysis and recommendations for building owners and stakeholders.	This study utilizes the Database of Energy Efficiency Performance (DEEP), which includes over 10 million EnergyPlus simulations of prototype small and medium-sized office and retail buildings in California. The dataset encompasses various vintages and climate zones, along with a diverse set of energy conservation measures (ECMs).

Table A1. *Cont.*

Study	Objective	Dataset
[56]	Evaluate various building retrofit strategies using a calibrated simulation approach by replicating the base-case energy performance of an existing building with a simulation tool. Propose energy conservation measures focused on the building envelope and analyze the impact of three different retrofit strategies (RS1, RS2, RS3) on energy efficiency and indoor environmental quality.	Orientation, location, comfort ranges, occupancy, and installed technology are obtained through building audits.
[57]	Develop an adaptive multi-model fusion approach to predict building energy consumption, effectively managing samples in the fuzzy zones between clusters. Create a screening algorithm to enhance the fusion process and provide advanced guidance for analyzing and controlling building energy performance.	The dataset used in this study is the Chicago building energy benchmarking dataset from 2017, which includes information on the energy performance and characteristics of buildings in Chicago. It features data on location, energy use, and building type.
[58]	Develop a generalized methodology for multi-scale GIS-based mapping of building energy performance using a bottom-up, data-driven approach to address data availability, consistency, and privacy challenges. Identify optimal features to enhance prediction accuracy and apply spatial aggregation to map energy performance at the neighborhood, district, city, and county levels.	This study utilizes several datasets, including the Irish Energy Performance Certificate (EPC) dataset, which details over 695,000 residential buildings in Ireland; the Irish Census dataset, providing information on approximately 1.98 million residential buildings; the GeoDirectory database, which includes geocoded addresses for over 2 million residential buildings; and the Irish retrofit housing scheme dataset, which contains data on 265,182 retrofitted residential buildings in Ireland.
[59]	Determine the optimal investment strategy for energy efficiency retrofits in multiple NGO buildings while navigating capital constraints from SEU and the government. The aim is to maximize both economic goals, such as net present value and payback period, and environmental goals, including energy savings and emission reductions.	The dataset used in this study comprises data on 27 NGO buildings in Delaware, USA, detailing the available energy efficiency retrofit measures for each building along with relevant information such as energy savings, emissions reductions, and investment costs.
[60]	Develop methodologies to accurately assess building energy use and create retrofit models within a holistic framework that integrates machine learning with investment and operational costs. Utilize raw time-series data from a wireless sensor network (WSN) for systematic feature selection and model development, and perform a cost–optimal analysis to evaluate the effectiveness of various retrofit strategies.	The dataset used in this study comprises hourly measurements collected from a wireless sensor network (WSN) installed in a single-family house in Switzerland. It includes various building variables such as indoor temperature, humidity, heat flux, CO_2 concentration, and window opening times over a two-month period during the winter of 2018–2019.
[61]	Develop a computationally efficient method to assess the energy performance of various energy conservation measure (ECM) combinations under future climate conditions, evaluating their impacts on life-cycle net present value (NPV) and reducing the computational resources needed for building energy simulations.	EnergyPlus building energy simulation software to model the energy performance of various retrofit options under current and future climate conditions.
[62]	Create a data-driven methodology to verify energy efficiency savings in commercial buildings using typical usage profiles for baseline modeling, analyzing pre- and post-efficiency data, and providing accurate results with limited training data, including insights on load profiles and weather dependencies.	The study uses two datasets: synthetic data generated via EnergyPlus simulations for three building typologies (office, primary care center, and hospital) across three geographical locations and six energy efficiency measures, resulting in 54 unique scenarios, and monitoring data from two offices and a cultural building in Barcelona, Spain.

Table A1. *Cont.*

Study	Objective	Dataset
[63].	Summarize, monitor, and assess a real case of energy retrofitting the building envelope (external opaque walls and roof) of an existing energy-inefficient affordable residential building. Collect quantitative data by monitoring four apartments to compare energy savings before and after retrofitting, alongside qualitative data on occupant behavior to evaluate thermal comfort. Draw conclusions from both the quantitative and qualitative data.	This study uses three data types: 1) energy consumption data (thermal energy and electricity) from sensors in four apartments before and after the retrofit; 2) indoor temperature data from sensors in three rooms (living room, bedroom 1, and bedroom 2) of these apartments; and 3) occupant survey data on daily living behaviors and heating/cooling usage patterns.
[64]	Conduct a holistic cost–optimal retrofit analysis for a Swiss single-family house by identifying and collecting popular retrofit measures along with their investment costs. Combine these measures into various retrofit strategies and assess their cost effectiveness and environmental impact. Finally, determine and discuss the cost–optimal retrofit strategy.	Measured values of room temperature, occupancy, and electricity demand were obtained during winter 2016/2017 using a wireless sensor network in the reference building. The heat demand for domestic hot water (DHW) is calculated according to the SIA 380/1 standard and is assumed to remain constant for each retrofit strategy.
[65]	Evaluate past retrofit savings, predict potential savings from future retrofits, and optimize retrofit decisions based on these predictions.	The dataset used in this study is from the U.S. General Services Administration (GSA) portfolio and includes building energy data and retrofit records for a subset of 552 buildings. Of these, 270 buildings have recorded retrofits, while 282 buildings have no recorded retrofits.
[66]	Propose a data-driven life-cycle optimization approach for building retrofitting, assessing the economic, energy, and environmental performance of options to determine the optimal plan that maximizes cost savings, energy reduction, and carbon reduction.	The dataset used in the study includes a historical energy consumption profile, building thermal property information, historical weather data, and real-world life-cycle inventory data.
[67]	Enable market actors to assess, forecast, and quantify energy efficiency opportunities and performance risks using empirical building data, provide probabilistic risk analysis, and reduce transaction costs for predicting savings across a portfolio.	The DOE's Buildings Performance Database (BPD), which contains over 750,000 existing commercial and residential buildings compiled from over 25 different source datasets
[68]	Provide energy advising services to building owners in the Västerbotten region of Sweden by developing a systematic, data-driven framework and a user-friendly web platform. Integrate quantitative analysis to emphasize relevant factors and supply preliminary information for stakeholders.	The study employs two primary datasets: a questionnaire dataset based on the Theory of Planned Behavior (TPB) and a dataset from Boverket covering 550,000 buildings. It focuses on 12,624 one- and two-family houses in the Västerbotten region, categorized by city, year of construction, number of households, and total floor area.
[70]	Develop a hybrid model combining weighted support vector regression (SVR) and differential evolution (DE) optimization to forecast both short-term (half-hourly) and medium-term (daily) energy consumption. Apply and evaluate the model using half-hourly and daily energy consumption data from an institutional building in Singapore.	The study utilizes two datasets: a daily energy consumption dataset for an institutional building in Singapore from 2013, comprising 261 total data points (209 for training and 52 for testing), and a half-hourly energy consumption dataset for the same building covering a 10-day period in June 2012, consisting of 480 total data points (384 for training and 96 for testing).

Table A2. Research gaps in data-driven energy retrofit as identified in reviewed studies.

Study	Reported Research Gap
[10]	• Integrating additional factors like control systems and occupant behavior into the predictive models to improve the comprehensiveness and precision of energy consumption forecasts.
[11]	• The size and complexity of non-domestic buildings make it challenging to identify optimal retrofit packages. • The vast retrofit solution space and high time complexity of energy simulations inhibit the application of artificial intelligence in the retrofit strategy design process. • Achieving comprehensive retrofit planning considering all available technologies and energy policies is not practically possible without a fast and stable energy performance emulator.
[18]	• Simulation-based methods are limited in their ability to quickly evaluate the effects of various design or retrofit scenarios. • Data-driven methods lack an underlying physics-based engine, limiting their applicability and interpretability for assessing design or retrofit scenarios. • Urban building energy models (UBEMs) have limited ability to estimate the impacts a retrofit made in one building could have on the energy use of surrounding ones. • Developing and calibrating an accurate UBEM requires a considerable amount of time and computational resources. • Data-driven methods require training data to understand how different energy conservation measures (ECMs) will impact future building energy use.
[19]	• Lack of physical descriptions for buildings in existing building stock databases. • Dated information in existing building stock databases. • Lack of data quality in existing building stock databases. • Lack of information on existing and suggested retrofit measures in existing building stock databases. • Limited studies on urban-scale retrofitting for residential buildings, with most focusing on commercial buildings. • Existing studies on urban-scale retrofitting are limited to specific climates or pre-defined scenarios, and a more generalized solution is needed.
[20]	• Lack of systematic design and assessment tools for building energy retrofits in Denmark, especially for non-residential buildings. • Existing tools rely on pre-simulated data, energy certificates, or fixed assumptions, and cannot scale up and expedite the rate of retrofit applications while maintaining accuracy. • Lack of emphasis on commissioning existing buildings after retrofitting, leading to undetected faults and malfunctioning systems.
[21]	• Older buildings often lack complete information for building performance simulation (BPS) methods, such as missing U-values of building components due to incomplete documentation or deterioration over time. • Buildings can also have case-specific incomplete information due to different documentation systems. • Previous studies have tried to address incomplete information by using probability distributions based on macro-level data, but this is challenging because it is difficult to determine an objective probability distribution, and different buildings can have different missing information. • Applying the same probability distribution to all buildings is unreliable, as the actual missing values are heavily influenced by building-specific characteristics.
[23]	• Lack of information on retrofit technologies and their benefits, which triggers stakeholder opposition to retrofit actions. • Need to develop a model that evaluates the impact of different retrofit technologies on stakeholder expectations for retrofit actions. • Need to improve the quality of the Energy Performance Certificate by reflecting stakeholder opinions combined with sustainable concepts to achieve significant energy savings.
[25]	• The relationship between building energy performance (BEP) prediction accuracy and retrofit rates, as well as the resulting CO_2 emission reduction potential, is not yet determined in the literature.

Table A2. *Cont.*

Study	Reported Research Gap
[26]	• Simulation-based models struggle to account for inter-building energy dynamics and urban context effect. • Lack of accurate characterization of how large-scale retrofits may perform in an urban area, leading to unintended consequences. • Purely data-driven approaches to predicting energy consumption and estimating the influence of urban context have been considered separate tasks, requiring more integration.
[27]	• The short time interval for ECM monitoring could contain biased consumption data relating to an event of significance or an outlier, and this needs to be factored in as the time interval is incrementally expanded. • The prediction horizon and prediction uncertainty should be incorporated into the model development as further parameters to be fine-tuned.
[28]	• It is difficult to identify specific energy savings potential and retrofit measures for high-performance buildings that already use energy efficient technologies and design strategies. • Previous studies have lacked comprehensive and detailed monitored data, and have focused on limited aspects of building energy performance or building systems.
[29]	• The CPU time required for the BEBM constructor is long, which may discourage users from using this option. • The optimal simulation length for the BEBM constructor is not known and would require further research. • More advanced stopping criteria for the genetic algorithm used in the BEBM constructor could potentially reduce the execution time, but this would require further research.
[30]	• The knowledge gap between current archetype development methods and obtaining data from the building stock to compose the archetypes. • The uncertainties in archetypes that jeopardize the wide application of benchmarking and limit regional applications like UBEM simulations.
[31]	• Improving the quality of data-driven ECM recommendation models by incorporating new audit data and developing models for more specific ECMs or building types. • Improving the data collection process by restricting numerical fields to numbers, converting open text fields to categorical fields, and defining categories based on ASHRAE standards, energy consultant input, and observed data. • Expanding audit requirements to include tenant spaces, which represent a significant portion of energy use in multi-tenanted buildings. • Expanding the coverage of the Greener, Greater Buildings Plan to include smaller buildings, increasing the sample size for analysis and model performance.
[32]	• Developing deterministic decision models for selecting cost-effective sustainable building retrofit measures for high-rise residential buildings in different climatic zones.
[33]	• Estimating the actual energy savings achieved after implementing various retrofit strategies. • Using more suitable statistical distributions to describe the primal energy demand in clusters, rather than a Gaussian distribution. • Assigning the target primal energy demand to assets in the target cluster, particularly when there are many records, to avoid underestimating the total savings.
[34]	• Improving techniques for handling missing data in the data pre-processing stage. • Shifting from nomenclature-based to data-driven building segmentation to improve the relevance of archetype buildings. • Automating the building energy simulation stage and improving model resolution by accounting for individual building geometry. • Incorporating more advanced urban climate modeling to improve the overall accuracy of the model. • Adopting a more holistic life-cycle perspective on the building retrofitting process, including the embodied energy and emissions of the renovation process itself.

Table A2. *Cont.*

Study	Reported Research Gap
[35]	• Lack of research on contextualizing the use of AI for building retrofits and understanding how AI-driven decision support systems can improve energy efficiency and stakeholder engagement. • Limitations in energy performance prediction models due to missing data and noise in the EPC dataset used for training.
[36]	• Previous work has focused on the perspectives of ML experts and energy experts, but there is a need to investigate XAI from the perspective of decision-makers (e.g., property owners). • Most research articles neglect evaluating XAI methods with potential users, or only emulate user evaluation, leading to inaccurate human-centered insights.
[37]	• Existing literature uses neural networks for regression analysis of annual building energy usage to estimate EPC labels, while this study develops ANN models to directly classify EPC labels. • ANN models are black-box models, so their internal processes and reasons for classifications are unknown, leading to reluctance and distrust in their application. This study uses explainable AI techniques to address this constraint.
[38]	• Lack of large-scale quantitative studies on factors influencing actual building retrofits, rather than just energy efficiency. • Lack of research exploiting the opportunities of digitization and data availability. • Lack of applications and investigations using explainable AI (XAI) techniques in energy research.
[39]	• Incorporating the decision maker's preferences into the decision-making process. • Assessing the uncertainty in factors such as savings estimation, weather forecast, and retrofit action costs.
[40]	• Understanding the information barriers to the adoption of home energy retrofits (HERs). • Developing a system that can assist with overcoming these information barriers.
[41]	• Lack of a complete scientific literature on energy efficiency in wide building stocks. • Lack of a specific approach for property asset portfolios, as opposed to single buildings or urban areas. • Lack of an integrated approach that handles energy assessment, economic feasibility, decision-making, and uncertainty simulation for multiple interventions across a portfolio. • Existing methodologies are limited and heterogeneous, so new portfolio-level techniques are needed. • Need to include multi-criteria strategies to address competing economic, environmental, cultural, and social objectives. • Need to introduce decision support systems and optimization rules.
[42]	• Studies using Google Street View and machine learning to predict building-specific suitability for specific energy conservation measures remain a rather unexplored area of research. • There is limited knowledge on the benefits of expert influence in the generation of machine learning models outside the sphere of deep learning.
[43]	• Improving the performance of the surrogate model by exploring different model architectures, such as deeper neural networks, residual connections, and neural architecture search techniques. • Exploring other machine learning algorithms, such as random forests, to improve the model interpretability. • Checking the confidence of the model predictions and rejecting predictions for outlier buildings. • Extending the surrogate model to be applicable for wide-area retrofit analysis, such as at the neighborhood or city level, by accounting for regional variability and using transfer learning techniques.
[44]	• The uncertainty in the EPC dataset, which can lead to a gap between the estimated and actual energy performance. This can be improved in future work as European countries develop standards for EPC data quality assurance. • The limited availability of detailed building attributes outside of the EPC dataset, which constrains the broader application of the framework. The authors suggest exploring ways to balance data availability and prediction accuracy to extend the framework to buildings without EPC data.

Table A2. *Cont.*

Study	Reported Research Gap
[45]	• The economic aspect of building energy retrofit was not included in the proposed ERi measure, as it is highly dependent on individual owners' perceptions. • The economic aspect of building energy retrofit was not included in the proposed ERi measure, as it is highly dependent on individual owners' perceptions. • The framework could be extended to include the economic aspect by merging the ERi with probability theory to create retrofit scenarios. • The framework could be further validated using EPC databases from other regions/countries that use different methodologies for ranking building energy performance. • The framework could be extended to handle high-dimensional data and reconfigure the energy retrofit labels to cover cooling, lighting, and domestic hot water energy consumption, in addition to heating.
[46]	• Combining physical modeling and data-driven modeling techniques to develop more accurate and comprehensive methods for estimating energy savings. • Organizing a structured process to collect and verify data on EE measures, creating a larger and more diverse database. • Linking forecast error with the potential uncertainty of EE investments to support decision-making. • Developing a predictions-as-a-service, web-based tool to support stakeholders in EE financing.
[47]	• More studies are needed on using data-driven models to predict energy consumption at a larger urban scale, beyond just individual buildings. • There is a lack of high-quality data in sufficient quantities to effectively train prediction models at an urban scale. • Previous research has been limited by considering only a small set of parameters in predicting building energy consumption. • Fewer recent studies have incorporated crucial factors like U-values, HVAC systems, and renewable energy systems into their machine learning models.
[48]	• Previous studies have not considered the carbon emission and cost impacts when making retrofit decisions for Canadian residential buildings. • There is a need for prediction models for retrofit scenarios of existing residential buildings in Canada, as over 50% of Canadian residential buildings are over 30 years old and need energy retrofits to reduce carbon emissions.
[49]	• Challenges in evaluating the objective function during optimization across multiple factors such as energy performance, thermal comfort, and investment. • Difficulty in generalizing results from archetypical buildings to individual cases. • Insufficient decision-making support for users in both deterministic and non-dominated optimization methods. • Need for life-cycle cost analysis that considers future climate uncertainties.
[62]	• Existing methodologies do not use the typical consumption patterns detected in the analyzed facilities as a predictor variable in the energy baseline model. • Existing methodologies only use data that precedes the energy efficiency measure (EEM) implementation to train the energy baseline model, which causes the loss of valuable information about how energy consumption fluctuates due to outdoor climate variables in the post-EEM period.
[65]	• The current literature on using data-driven methods to predict retrofit savings is limited, with the field being dominated by simulation-based methods. • This study extends the existing research on data-driven methods for predicting retrofit effects to the commercial building sector, with a focus on weather and climate factors rather than occupant characteristics.
[66]	• Inaccurate building performance evaluation results from using degree-day or simulation software, rather than actual building data. • Limited consideration of the combined effects of multiple retrofitting measures, with a focus on individual measures. • Optimization objectives focused on operating energy or life-cycle cost, rather than life-cycle energy and carbon.

Table A2. *Cont.*

Study	Reported Research Gap
[67]	• The need for more detailed and comprehensive building data in the BPD, including more information on building assets and characteristics. • The need for longitudinal building performance data, tracking changes over time, in order to analyze the impacts of capital and operational changes while controlling for other factors.

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