Artificial Intelligence Based Methods for Retrofit Projects: A Review of Applications and Impacts

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Abstract

The Architecture, Engineering and Construction (AEC) sector faces severe sustainability and efficiency challenges. In recent years, various initiatives have demonstrated how artificial intelligence can effectively address these challenges and improve sustainability and efficiency in the sector. In the context of retrofit projects, there is a continual rising interest in the deployment of Artificial Intelligence (AI) techniques and applications, but the complex nature of such projects requires critical insight into data, processes, and applications so that value can be maximised. This study aims to review AI applications and techniques that have been used in the context of retrofit projects. A review of existing literature on the use of artificial intelligence in retrofit projects within the construction industry was carried out through a thematic analysis. The analysis revealed the potential advantages and difficulties associated with employing AI techniques in retrofit projects, and also identified the commonly utilised techniques, data sources, and processes involved. This study provides a pathway to realise the broad benefits of AI applications for retrofit projects. This study adds to the AI body of knowledge domain by synthesizing the state-of-the-art of AI applications for Retrofit and revealing future research opportunities in this field to enhance the sustainability and efficiency of the AEC sector.

Keywords

Artificial intelligence, Retrofit, Digital Twin, Sustainability, Construction Industry

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Abstract

The Architecture, Engineering and Construction (AEC) sector faces severe sustainability and efficiency challenges. In recent years, there are many efforts that illustrate the application of artificial intelligence as an effective solution to enhance the sustainability and efficiency of the AEC sector. In the context of refurb projects, there is a continual rising interest in the deployment of Artificial Intelligence (AI) techniques and applications, but the complex nature of such projects requires critical insight into data, processes, and applications so that value can be maximised. This study aims to review AI applications and techniques that have been used in the context of retrofit projects. A thematic analysis of available literature on AI applications for retrofit projects in the construction industry was conducted. The review identified the opportunities and challenges of AI applications for retrofit projects in construction highlighting most common techniques applied, data used, and processes followed. This study provides a pathway to realise the broad benefits of AI applications for retrofit projects. This research contributes to the existing knowledge on AI by combining the latest advancements in AI technology with Retrofit applications. It also identifies opportunities for further research in this area to improve the sustainability and effectiveness of the AEC industry.

Keywords

Artificial intelligence

Retrofit

Digital Twin

Sustainability

Construction Industry

1. Introduction and Background

Buildings are responsible for over 48% of the world's energy and heat production as well as about 19% of all energy-related CO2 emissions [1]. To overcome this issue, a decrease in the energy consumption must be sought globally. Approximately 75% of the buildings expected to exist in 2050 have already been constructed, according to [2]. In [3], the European Commission established ambitious objectives for cutting greenhouse gas (GHG) emissions by 50-55% relative to 1990 levels by 2030 and achieving climate neutrality by 2050. This can only be achieved by improving the already built buildings, the term being called retrofit process. Experts view retrofitting of current buildings as a cost-effective approach to reducing energy usage and decreasing carbon emissions [4,5]. According to Granade et al. [6], retrofitting existing buildings for energy efficiency could result in a reduction of primary energy use and related carbon footprint of up to 25%. In comparison to conventional methods, recent years have seen Artificial Intelligence (AI) make substantial advancements in enhancing business operations, service processes, and industrial productivity [7].

The Industry 4.0 or fourth industrial revolution concentrates on automating processes, incorporating data-driven technology, and utilizing advanced AI applications in manufacturing [13]. This revolution has resulted in notable enhancements in processes, reduced production times, and increased cost-efficiency [14]. To handle complex problems and support decision-making throughout the asset's entire lifecycle, the AEC sector has incorporated AI subfields like machine learning, natural language processing, robotics, computer vision, optimisation, automated planning, and scheduling [14]. Resource and waste optimization [15, 16, 17] and waste generation minimization [18.19] are a few of the identified subdomains [20], value-driven services like scheduling and estimation [20,21], supply chain management [22-25] and the incorporation of 4D and 5D BIM to enable better planning at an early design stage [26], health and safety [27-30] and AI-driven construction contract analytics construction site [31-33]; voice user interfaces [34-36] and AI-driven audit system for construction financial [37-40]. Job creation, AI and BIM integrations with other industry 4.0 tools such as internet of things (IoT) and smart cities, augmented reality [41,42] are also being developed [43-45]. Previous research has used AI for building performance to improve the AEC industry's sustainability and effectiveness [47,48], such as achieving LEED credits [49,50] and gauging occupant happiness with LEED certified residential buildings [40], ranking sustainability of materials [51], assessing eco building indicators [52], assessing the cost and price prediction of sustainable design [53], optimised indoor air quality [38], life cycle costs and life cycle environmental impact assessment [54,55], building energy optimisation [44, 56, 57] energy efficient design making and optimisation at early design stages [58-60]. As most of the buildings are already existing, the focus should be driven towards applying AI techniques for Retrofit complexities.

In the context of retrofit projects, it is argued that finding a sensible approach to choose retrofit options is considerably complex [8, 9, 10]. Modelling techniques, data capturing, and data processing are highly demanded due to the intricacy, dynamics, and nonlinearity of retrofitting a single building or building cluster [11]. Despite efforts to support decision-making on building retrofits, especially for large scale structures, retrofit analysts still face significant challenges [61,62] due to the unbounded solution space. Several studies have been conducted in this regard. In order to identify the optimal retrofit solutions for current buildings, a comprehensive review was conducted on essential topics such as energy audits, building performance evaluation, measurement of energy savings, economic analysis, risk assessment, and verification [9, 10, 63]. This review was conducted with a state-of-the-art approach. For retrofit projects, datasets from building operations systems, operations and maintenance information can be continuously collected with the implementations of AI applications, building automation systems and Internet of Things (IoT) [11]. This provides good opportunities to develop data-driven models for data resources when looking at retrofit scenarios. It is likely that the adaptation of artificial intelligence (AI) to retrofit projects can help overcome some complexities related to data capturing, data processing and optimal retrofit outcome. However, very little studies focused on AI applications for retrofit projects such as support sustainable retrofit decision using AI [64,40, 37], when compared to AI for AEC. According to several studies, there are a variety of challenges preventing the wide use of AI, including cultural barriers, a lack of skills, high start-up costs for implementing AI-based solutions, a lack of talent, security concerns, a lack of computer capacity, and poor internet access [65]. To understand the current state of AI applications for Retrofit, it is important to discuss the major subfields of AI to retrofit projects, as shown in Fig. 1 AI components bellow.

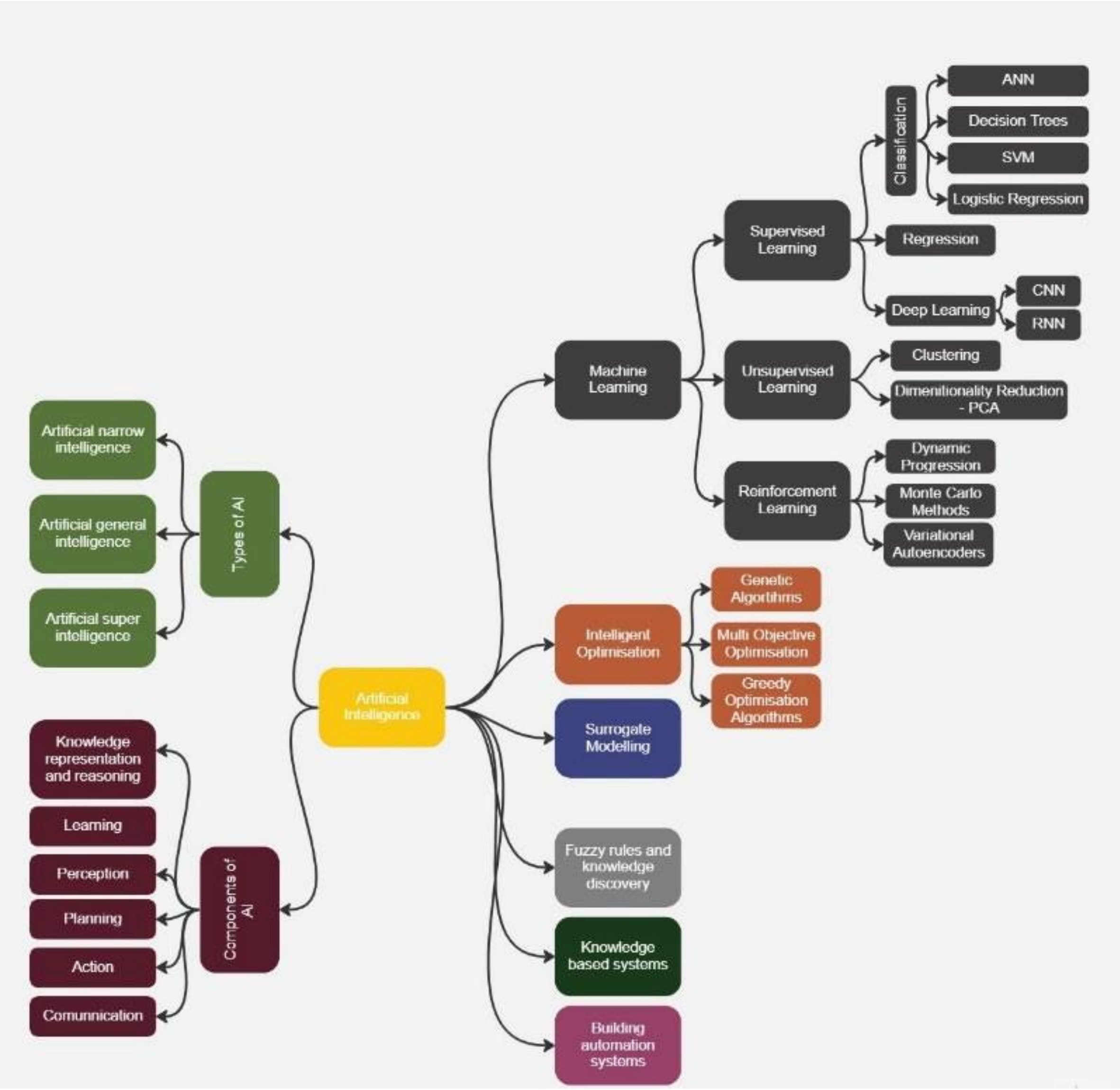

Fig. 1 - AI Components

Although previous studies have applied AI applications for Retrofit has increased over the past few years and the applications are applied over different retrofit actions and areas [8, 9, 12], it is complex to assert how AI can benefit retrofit projects, as this requires critical insight into AI applications, processes applied, and data used. This study aims to review AI applications and techniques that have been used in the context of retrofit projects. The research reviews the impact of AI in overcoming many of the complexities faced within Retrofit scenarios. This will be addressed by thematically analysing the existing studies that apply AI techniques to retrofit projects. This will also discuss the key AI subfields for retrofit, key AI Datasets used for retrofitting process and key Retrofit outcomes. This study seeks to answer the following research questions:

Q1. What are the existing applications of AI within the context of retrofit scenarios? (3.1)

The objective was to determine how were the AI technologies applied and evaluated within the context of retrofit scenarios, what study areas within the various uses were present, which projects were it applied to, and what current challenges are associated with its use?

Q2. How AI has supported overcoming complexities associated with Retrofit scenarios, and the potential future directions? (3.2 and 3.3)

The objective is to evaluate the present limitations and determine the course of future research based on the documents that have been examined and the response to the first question.

2. Research Methodology

The aim of this study is to synthesise the domain knowledge and to identity how artificial Intelligence applications can improve the Retrofit Process. Fig 2 shows frequency of papers on the applications of AI for retrofit process from 2005 to 2023, showing an increase in the last two years. This is mainly due to the recent innovations and the applications of Artificial Intelligence.

The review was conducted utilising the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) technique. The objective of the PRISMA statement is to guide authors in enhancing the reporting of systematic reviews and meta-analyses. PRISMA primarily concentrates on systematic reviews and meta-analyses of randomised trials. For this purpose, the study employed a mixed-method literature review comprising a qualitative systematic review and a thematic analysis of subfields related to AI for Retrofit. Additionally, the study examined the essential characteristics of datasets utilised while deploying AI for Retrofit and the key objectives/outcomes of retrofitting. This study involved three stages: Stage 1 – search for publications, Stage 2 – assessing quality of results (exclusion criteria), Stage 3 – data cleansing, Stage 4 – thematic analysis. The outcomes led to the identification of knowledge gaps and prospects for future research, which are presented subsequently. The research approach is summarised in Figure 3: Flowchart of the literature review selection process provides an overview of the research methodology; details of which are discussed next.

2.1. Stage 1 – Searching Strategy

The extensive inclusion of peer-reviewed journals and conference materials related to AI applications for retrofit situations across the AEC industry justifies the use of the SCOPUS database. SCOPUS also allows to look for document titles, abstracts, and keywords with relevance to areas of research from database of over more than 41,000 research publications. As a result, this database enables deeper study into research outputs related to AI for Retrofit and permits increased focus on the selected AI subfields. In order to conduct informative search, two steps were taken. Firstly, SCOPUS search tool was used to look for document titles, abstracts and keywords that relate to the AI subfields identified in literature and Retrofit process. Simultaneously, it was investigated Renovation and Refurbishment. Below are the SCOPUS queries used to conduct the search:

- (TITLE-ABS-KEY (retrofit) AND TITLE-ABS-KEY (Artificial Intelligence) = 85 results
- (TITLE-ABS-KEY (retrofit) AND TITLE-ABS-KEY (AI) = 26 results
- (TITLE-ABS-KEY (retrofit) AND TITLE-ABS-KEY (machine learning) = 122 results
- (TITLE-ABS-KEY (retrofit) AND TITLE-ABS-KEY (Deep learning) = 39 results
- (TITLE-ABS-KEY (retrofit) AND TITLE-ABS-KEY (intelligent optimisation) = 62 results
- (TITLE-ABS-KEY (retrofit) AND TITLE-ABS-KEY (smart cities) = 84 results
- (TITLE-ABS-KEY (retrofit) AND TITLE-ABS-KEY (IoT) = 74 results
- (TITLE-ABS-KEY (retrofit) AND TITLE-ABS-KEY (computer vision) = 54 results
- (TITLE-ABS-KEY (retrofit) AND TITLE-ABS-KEY (digital twin) = 22 results
- (TITLE-ABS-KEY (retrofit) AND TITLE-ABS-KEY (semantic web) = 15 results

A total of 583 papers were found. Secondly, a manual search for records that directly correlated with the above-mentioned AI subfields and retrofit, and the above-mentioned AI subfields and Refurbishment has been conducted. Also, keywords such as CNN, RNN, SVM, MOO and <retrofit> have been used as part of this manual search. The objective of the final step was to gain a comprehensive comprehension of the proposed AI methodology for the retrofit process. Moreover, this enabled the authors to offer a more informative analysis of the validity of each proposed AI subfield in the retrofit process. A total of 68 papers were identified in the second step, bringing the total number of papers to 651.

2.2. Stage 2 - Assessing Quality of the Results

To ensure the quality of the findings, several procedures were carried out to identify literature that was appropriate for the research's scope, as shown in Figure 3: Flowchart of the literature review selection process. The diagram illustrates the methodological choices, which are elaborated on below.

2.3 Stage 3 – Data Cleansing

The first step in evaluating the quality of the records involved the elimination of non-article or irrelevant proceedings. Furthermore, publications that were not in the English language were excluded from consideration. After the removal of non-article or irrelevant proceedings, 125 duplicate results were also eliminated. The next screening phase involved evaluating the remaining records by examining their titles or abstracts to identify those that had undergone a validation process as part of their proposed framework. A total of 56 papers were selected for analysis.

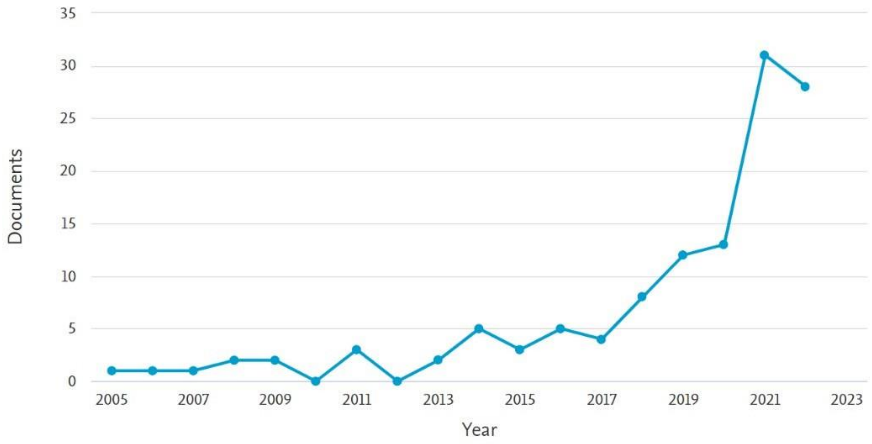

Fig 2 – Frequency of Papers From 2005 – 2023

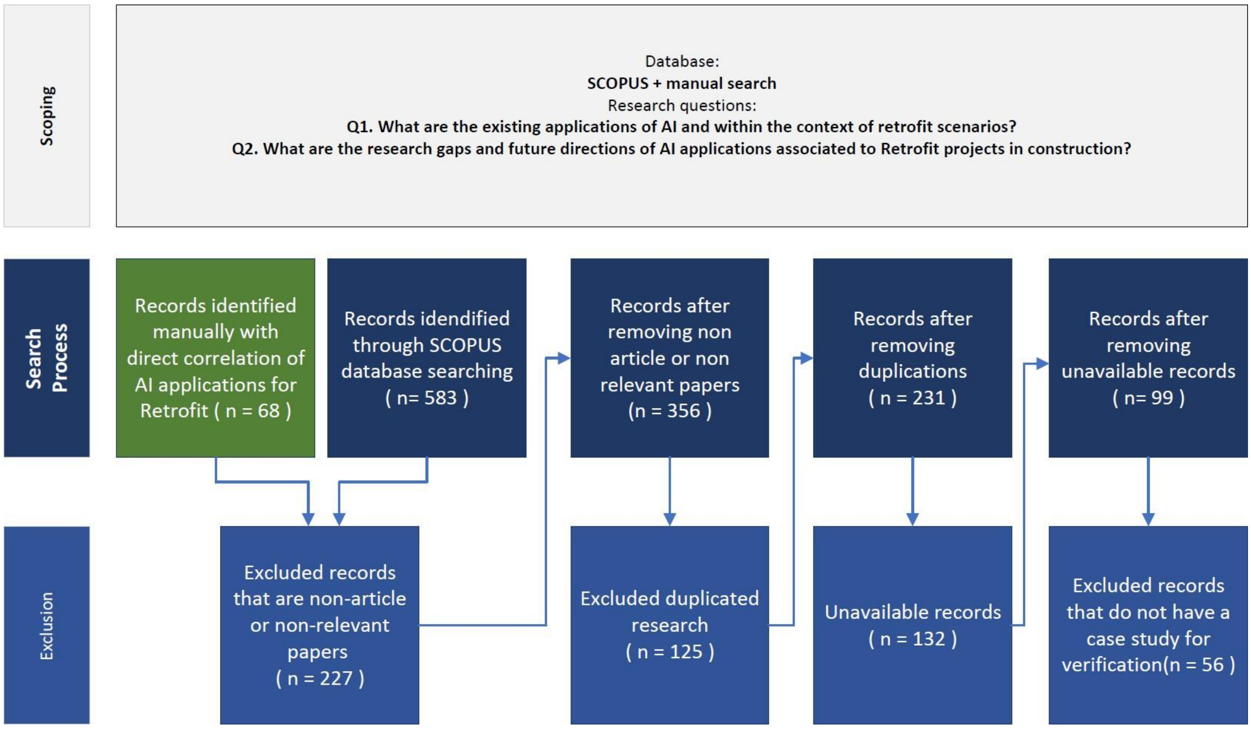

Figure 3 - Flowchart of the literature review selection process

3. Thematic Analysis and Discussion

This paper uses thematic analysis to categorise and classify the findings from the reviewed research on AI applications for Retrofit scenarios. Thematic analysis is a qualitative research method used to identify, analyse, and report patterns or themes within a dataset. It involves systematically organizing and coding data to identify patterns or themes, which are then interpreted and analysed in order to gain insights into the underlying meanings and concepts. Thematic analysis can be applied to a wide range of data sources, including interviews, focus groups, surveys, and documents. The process typically involves multiple rounds of coding and refinement to identify and develop the themes, and it can be conducted manually or with the assistance of specialised software It reports on the patterns observed (key AI subfields for retrofit – section 3.1), applications conducted, and datasets used (section 3.2), strengths and limitations of the applications and the retrofit objectives(outcomes) taxonomy (Section 3.3). Additionally, future recommendations and a proposed framework for retrofit approach are also presented. The process behind analysing each paper is described in Fig 4. The manuscripts selected were analysed thematically. A careful read-through the methodology and the results of each paper was executed where the AI applications themes were then identified. Thereafter, within those themes the key datasets used on for the retrofit process were identified and discussed. Moreover, a taxonomy for the retrofit approach has been discovered based on the retrofit approach taxonomy similarities discovered in the selected manuscripts. After the paper examinations, 6 themes were identified, categorised as <Key AI Applications for Retrofit>. Within these identified themes, the datasets characteristics of each were discussed as wells the retrofit target approach discovered within those themes.

3.1. Key AI applications for Retrofit Projects

Following a careful examination of the papers, six AI applications (themes) were identified as the most common AI techniques applied in the context of retrofit projects. Within these themes, specific datasets (section 3.2) and a set retrofit outcome (section 3.3) has been recognised and discussed. These papers also compared different algorithms and reflected on the challenges faced as well as the opportunities and future trends, discussed further. As shown in Fig 5, it was identified that Machine Learning techniques are most used for Retrofit Process, primarily since it can manage large datasets and it can save time whilst having accurate results. It was followed by Intelligent Optimisation algorithms and Surrogate Modelling. Fuzzy rules and knowledge discovery algorithms were also applied and building automations systems seem to be more adopted due to the new IoT/Smart buildings approach. Knowledge base systems were also applied but limited case studies were validated. The next sections expand on these AI applications in retrofit projects highlighting the data utilised as well as different retrofit outcomes obtained.

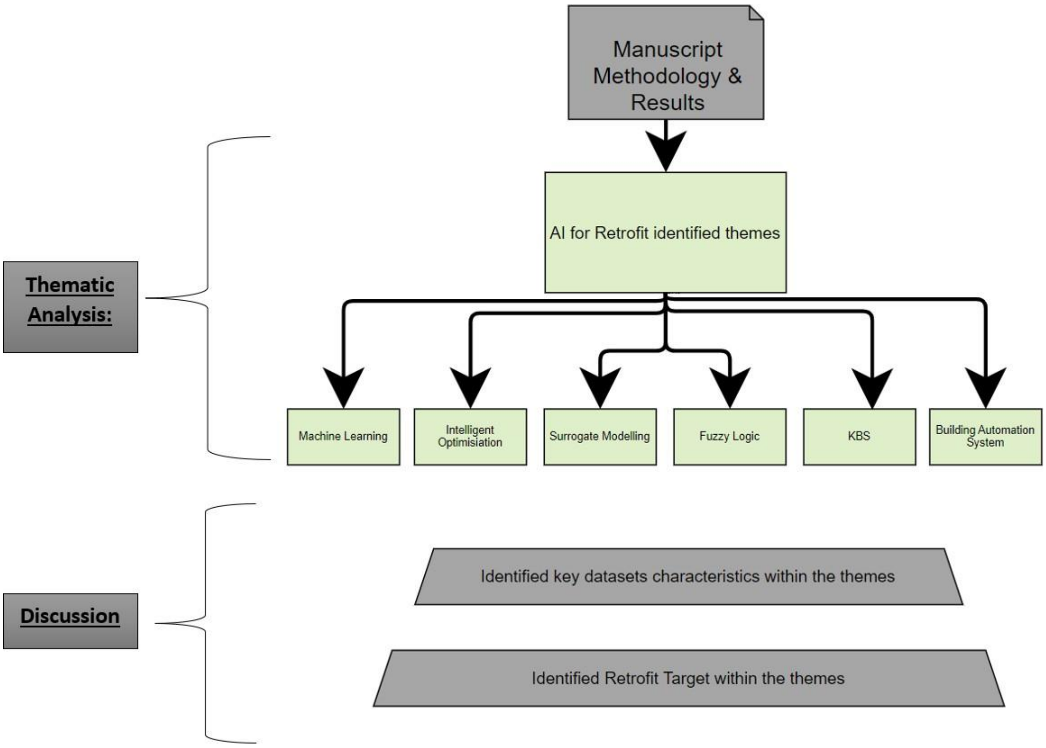

Fig 4 - Process Behind Each Paper Examination

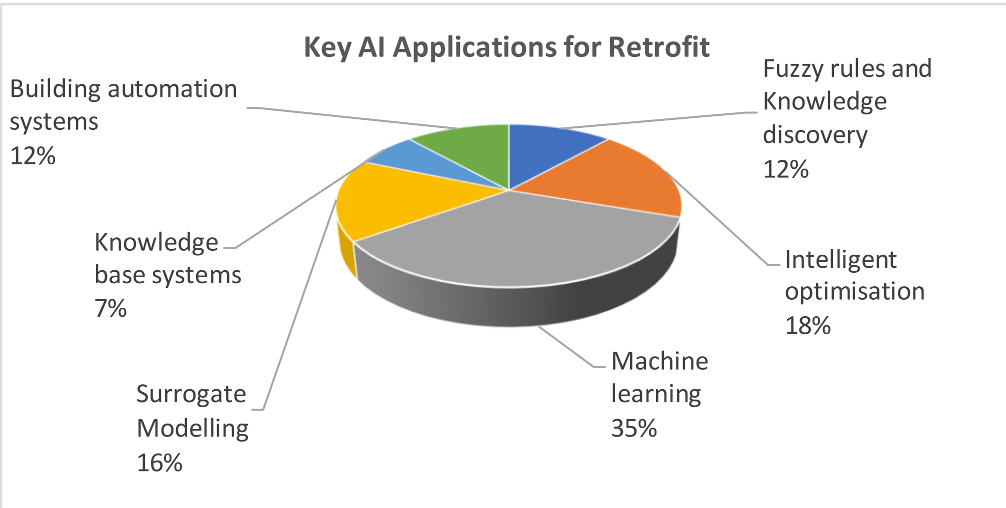

Fig 5 – Key AI Applications for Retrofit Chart

3.1.1. Machine Learning

Amongst the reviewed studies, machine learning was identified as a major contributor to retrofit projects. Whilst there exist a variety of machine learning techniques, most frequently applied methods in the context of retrofit projects were ANNs (Artificial Neural Networks), Deep learning, support vector machine (SVM), naïve Bayes (NB), Gaussian mixture (GM), and reinforcement learning (RL). Table 1 and Fig 6 shows some of the relevant application of machine learning applications to retrofit projects.

It was identified that supervised machine learning methods were most used and adopted for Retrofit projects. This approach was proven to help speed up the process of data collection [66] and data processing (ANN in particular) [66], helping to retrofit similar types of buildings [76,75,68, 106]. On the other hand, some studies adopted SVM as a supervised ML technique. This approach was adopted as SVM can handle both linear and nonlinear classifiers and, SVM has low bias and high variance [83] and [78]. Other studies have shown the effectiveness of using linear decision lists as a supervised ML technique as by focusing on the most crucial elements affecting retrofits, it made it easier for building stakeholders to undertake efficient audits of building systems and identify possible ECM (Energy Conservation Measures) opportunities [81]. As supervised ML relies on human interaction when processing the data captured, it has been proved to be reliable and with a very high accuracy whilst remaining less computational than other AI methods [68, 76, 83]. Therefore, it's implementation in the retrofit process is favourable. Also, some supervised ML techniques (such as SVM) can handle both training and testing when simulating retrofit scenarios, saving time and computational cost. However, a common limitation was identified in the above-mentioned cases: obtaining measured retrofit data is extremely difficult, and typically, such data are erroneous and subjective. It was identified that supervised ML methods such as deep learning methods were implemented to discover the significant features that produce the cost-optimal retrofit strategy in an optimised way without having to undergo an exhaustive search process [73, 74]. Additionally, the adaptation of transfer learning, a deep learning technique, helped with identifying potential sources of uncertainty that may arise in building energy simulations [77]. This approach employs a recurrent neural network (RNN), which enables it to rapidly generate new predictions for energy consumption incorporating proposed retrofits [77]. Nevertheless, a significant impediment to replicating this research is the challenge of gathering highly detailed energy consumption data, primarily due to concerns over privacy.

The research revealed that unsupervised machine learning methods enhance retrofit decision-making by capturing and communicating significant high-level insights regarding the intricate and extensive design space for renovations. This is accomplished by means of qualitative KPI (Key Performance Indicators) profiles, which may indicate factors such as low privacy or exorbitant costs [90, 91]. Additionally, by employing the Clustering K-means method, the analysis is carried out instantaneously in the high-dimensionality KPI-space. Users can investigate the retrofit by analysing the design choices instead of analysing the design spaces of the actual retrofit because the analysis is directly displayed in the high-dimensional KPI-space [86]. It was acknowledged that this represents an important distinction from current retrofit methods. However, a major drawback attached to this ML technique is that retrofit actions regarding the structure of the building were not included and it also relied on extensive data, privacy [86].The study's findings in [86] demonstrate that by integrating box plots and scatterplots, unsupervised machine learning techniques like scenario sampling (2-ary coverage), clustering (k-means), and dimensionality reduction (PCA) can be used to visually communicate high-level information about KPI trade-offs across renovation scenarios. However, there are limitations on the number of scenarios that can be evaluated directly against KPIs within a feasible amount of time, which means that only a fraction of the full scenario space can be evaluated. It should also be noted that the specific workflow used in the study was only tested on data from Danish databases, making it limited to the Danish context.

According to research, the combination of Reinforcement Learning techniques such as VAE and SBMO leads to improved efficiency in terms of accuracy and time, as cross-validation is not required during the training process. This is due to the use of Bayesian regularization backpropagation, which uses regularization through Bayesian inference. Additionally, Cecconi et al. [105] use Montecarlo simulation (RL) to compute energy savings for multiple clusters based on different retrofit scenarios. However, this method of ML relies on large amounts of accurate data and dataset preparation and expert knowledge in RL is essential. Perhaps this can be overcome by gathering more data from different buildings with the use of smart technologies, IOT, digital twins. Furthermore, the more data about the building's characteristics there is, the more the MLM (Machine Learning Models) can be improved and generalised, therefore be able to help the MLMs to provide more detailed recommendations for retrofit. This approach can help with developing a framework that looks at retrofit approaches in a holistic manner, without having a set objective in mind such as cost/energy optimal retrofit.

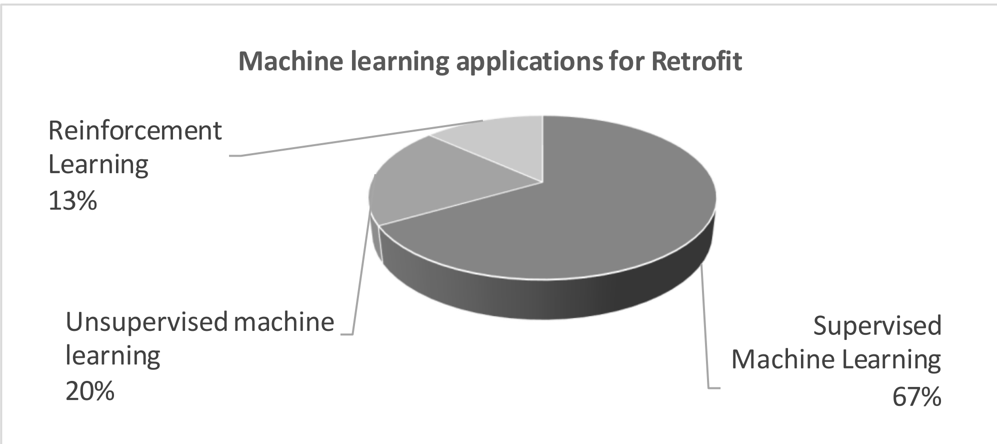

Fig 6 – Machine Learning Applications for Retrofit Chart

Table 1 – Reviewed Studies on Machine Learning for Retrofit

Ref.	Purpose	Main AI	Method	Building Type, Location	Retrofit Apprch.
Supervised Machine Learning					
[106]	Development of a statistical model for estimating energy savings.	Linear Regression	To predict energy use intensity, a multivariate linear regression model was used, which included both numerical predictors (such as working hours and occupant density) and categorical indicator variables (such as climate zone and heating system type).	Unknown	Energy optimal retrofit
[75]	To predict the performance of heat pump systems in retrofit residential housing.	ANN	Machine learning algorithms using Artificial Neural Network (ANN).	Six 2/ 3bedroom rowhouse Canada	Energy optimal retrofit
[68]	Provided a rapid energy performance estimation engine for assisting multi objective optimisation of non-domestic buildings energy retrofit planning	ANN	8 Artificial Neural Networks are implemented along with an open database and data-drive collection of techniques to assess the potential for energy savings.	Single floor from a non-domestic building, Glasgow	Energy optimal retrofit
[83]	To improve national estimations of energy savings potential.	SVM	Machine learning - SVM was used to predict the building characteristics (i) building type and (ii) suitability for additional façade insulation.	Multifamily buildings in Sweden from 1945 - 1975	Energy optimal retrofit
[91]	Develop a deep renovation scheme.	Decision Trees	Diagnosis and design optimisation within retrofit using As-Built BIM models as input for the application of ML (decision tree base tables, rule-based systems and expert systems) to deal with problems in specific elements of buildings.	Multiple: Spain, France, Germany, Poland	Energy optimal retrofit
[81]	Reducing building GHG- Greenhouse gas emissions.	FRL	A user-facing falling rule list (FRL) classifier for machine learning based on binary characteristics extracted from the Local Law 87 data in New York City was created.	Buildings in NYC	Green retrofit

Table 1 – continued

[86]	Seek to reduce the dimensions of the evaluating KPIs for the sake of designers	BIM tool and clustering k-means	Combines renovation scenario sampling with k-means clusterring in terms of KPIs evaluations, which is based on the nova-dm semantic domain model.	Large apartment block, Denmark	Green retrofit
[90]	To create and assess optimum and comprehensive renovation scenarios suited for home improvement in Denmark	BIM tool + Clustering +PCA	A decision-support tool built on BIM (BIM-based DSS) - incorporated utility PARADIS (Process Integrating Renovation Decision Support) evaluates decisions based on sustainability criteria that the user specifies (KPIs).	Large apartment block, Denmark	Green retrofit
Unsupervised Machine Learning Clustering and Dimensionality Reduction					
[73]	To assist in identifying the building characteristics that have the greatest influence on remodelling.	Deep Learning and PCA	ML and SHAP (shapley Additive explanations) values to determine the most significant features, principle component analysis (PCA) is used to examine the data distribution.	Single-family house, Eastern Switzerland	Energy optimal retrofit
[77]	To determine whether it would be practical to use an integrated data-driven urban energy simulation model to analyse various large-scale retrofits.	RNN	Updating models for retrofit scenarios by combining physics-based building simulation techniques with data-driven machine learning techniques and a trained RNN.	Buildings, Californian City	Energy optimal retrofit
Deep Learning					
[107]	To create a load prediction algorithm for residential buildings based on machine learning.	Multiple ML	Five ML models were used for domestic annual heating and cooling load intensity prediction to choose the most accurate ML model for predicting heating and cooling load intensity, models were examined and compared.	Residential buildings, China	Energy optimal retrofit
[74]	To offer a data-driven approach to retrofit analysis applicable to portfolio-wide retrofit plans.	ML casual forest	Data driven methods - application of machine learning method with causal forest for the prediction of retrofit savings.	Commercial building	Energy optimal retrofit

Table 1 – continued

[78]	To support the stakeholders in taking decisions on refurbishments options when not all of physical information is available	SVM-FCM	SVM and Fuzzy C-means clustering (SVM-FCM) used to extract the case-specific knowledge from EPC big data regarding building characteristics and energy saving of retrofit measures.	Sweden, homes built between 1965-1975	Energy optimal retrofit
Reinforcement Learning					
[105]	To reduce building components thermal transmittance and energy consumption.	Clustering techniques and Montecarlo simulation	The method is based on: i) clustering techniques to divide building assets into groups with similar characteristics and energy consumption, and ii) Montecarlo simulation to compute each cluster' s energy savings.	Unknown	Energy-cost optimal retrofit
[85]	To overcome the time-consuming stamp attached to the use of SBMO in previous research.	VAE Bayesian method	Propose a generative deep learning building energy model using Variational Autoencoders (VAEs) Bayesian regularization backpropagate on method for train.	Residential buildings, Montreal.	Energy optimal retrofit

3.1.2. Intelligent Optimisation

The core concept of intelligent optimisation is the capacity to identify pareto-optimal solutions for retrofit scenarios using AI techniques rather than conventional methodology. In retrofit scenarios, the multi-objective optimization approach is favoured. This could be because of the difficulties and time limits connected with optimization challenges Retrofit Projects entail. As a result, in recent years, time-efficient intelligent optimisation methods have been developed and used to simulate the best retrofit scenarios, as shown in Fig 7 and Table 2. Most frequently, MOO has been adopted as intelligent optimisation method for retrofit scenarios [72, 7, 26, 69]. Ascione et al., [72] helped finding a constrained cost-optimal solution permitting a strong reduction in the GHG emissions, Li et al., [7] focused on delivering green building standards optimal retrofit, studies in [109] and [110] focused on using MOO to define cost optimal retrofit whilst minimising the GHG emission. Similarly, GA (NSGA-II) was adopted to optimise retrofit outcomes. Sharif et al., [92] used Non-dominated Sorting Genetic Algorithm (NSGA-II) optimization method as NSGA II were proven to calculate the pareto front that minimised the TEC, LCC and the environmental effects of the building at once. Similarly, Rosso et al., [104] adopted GA towards multi objective optimisation as the benefits of the retrofit actions were the specific objectives established using an active archive NSGA II (a NSGA II). When using Genetic Algorithms for a retrofit project, several retrofit solutions were optimised by Calama-Gonzales et al. [94] while considering three predetermined goals: yearly overheating hours (%), annual undercooling hours, and investment costs. Moreover, Nutkeiwics et al.'s research [71] demonstrates how an adaptable urban energy prediction model like DUE-S and greedy optimisation algorithms can assist in directing energy-related decisions for a variety of urban-minded stakeholders, including architects, engineers, planners, and legislators [71]. Overall, when looking at finding the best retrofit scenarios, intelligent optimisation was a popular method. Several crucial factors or components were left out because there was not a lot of data used during the data collection stage, as can be seen. Due to this, the results are only applicable to similar buildings and the framework developed using intelligent optimisation sems to be subjective and only applicable on small scale. Furthermore, intelligent optimisation relies on mathematical algorithms that require expert mathematical knowledge.

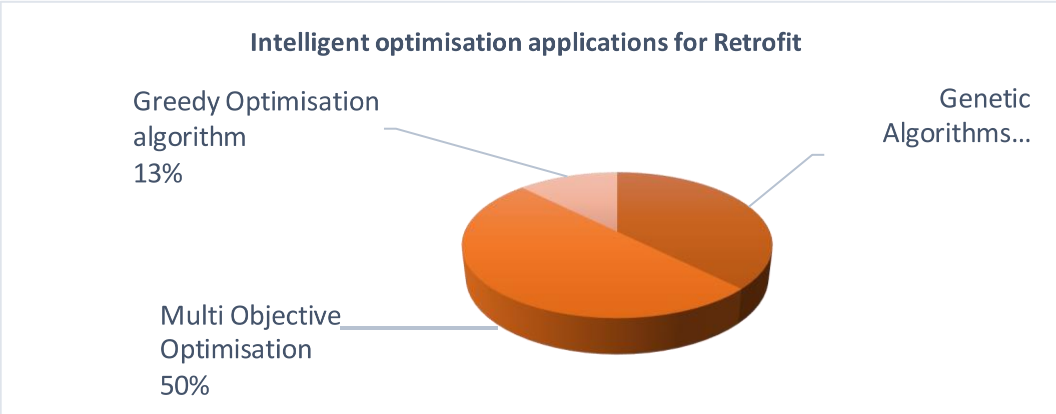

Fig 7 – Intelligent Optimisation Applications for Retrofit

Table 2 – Researched Studies on Intelligent Optimisation

Ref	Purpose	AI	Method	Building Type, Location	Retrofit Apprch.
[92]	Find the optimal scenario for the renovation of institutional buildings considering energy consumption and LCA	GA	Genetic algorithm and an energy simulation tool for simultaneously minimizing the LCC, and environmental impact of a building.	Multipurpose university building, Canada	Energy optimal retrofit
[94]	Proposes calibrated building stock models to assess thermal comfort of the social housing stock of southern Spain	GA	Using a genetic algorithm to obtain the best retrofit solutions, considering three objectives: annual overheating hours (%), annual undercooling hours (%) and investment costs (€/m2).	Four different climatic areas in southern Spain	Cost optimal retrofit
[71]	Minimise the number of required retrofits needed to achieve maximal energy savings across	Greedy optimisation	A previously data-driven urban energy simulation model with a greedy optimisation algorithm technique used when analysing the output of the simulation.	downtown, California, USA	Energy optimal retrofit
[72]	To highlight that the optimization of building energy design is fundamental for solving the climatic issues of contemporary society.	Moo + ga using pareto front	A multi-objective optimisation method: multi-stage approach - genetic algorithm, using pareto front.	1970s office, Italy	Cost optimal retrofit
[7]	To facilitate evaluating various design alternatives and balancing multiple objectives in building green retrofit	Moo	Multi-objective optimization method is employed to identify critical building parameters to generate set of alternative plans for building retrofit based on green building.	school building, Wuhan , China	Green retrofit
[26]	Find the best energy retrofitting strategy	MOO	A simulation-based multi-objective optimization framework using parallel processing structure and results.	Family residence, Iran	Energy optimal retrofit
[69]	Find cost optimal green retrofit	MOO	A multi-objective optimisation process was developed, aiming to minimise the operating GHG emissions and the life-cycle cost.	Multi residential building, Greece	Green retrofit
[104]	To facilitate the selection of the optimal retrofit actions	GA - NSGA-II	An active archive non-dominated sorting genetic algorithm (a NSGA-II) towards multi-objective optimization is used.	Unknown, Italy	Energy optimal retrofit

3.1.3. Surrogate Modelling

Surrogate modelling coupled with Machine learning applications or Intelligent optimisations is a hybrid method applied to retrofit scenarios, as shown in Table 3. Studies revealed that for the majority of the retrofit dimensions, the suggested hybrid approaches can significantly reduce computational cost without compromising accuracy [80,79,88]. The surrogate model and ML methods such as ANN operates on a smaller input set and the time required to develop retrofit solutions is significantly reduced when compared to energy simulation-based tools [84]. Ascione et al. [67] employed a similar strategy to make sure that the project took into account predictions of energy usage and occupant thermal comfort for any participant in the building category. A more sustainable approach to retrofit was developed with the use of Surrogate modelling and PCO ML method in [93] where the technique allowed for the development of an energy management implementation as a non-destructive retrofit process. On the other hand, MOO helped identify the retrofit designs that balance energy consumption and capital cost whilst surrogate modelling helped speed up the process whilst being accurate in [80, 89]. To conclude, it seems that when using the surrogate modelling and ML/Intelligent optimisation hybrid approach, a large number of simulations are required for the evolution process to reach optimal case. Also, it seems to be an accurate approach but time consuming and perhaps mixed with intelligent optimisation algorithms, the process can be quicker also, it seems that this approach works best with BIM authoring tools which makes this approach favourable despite its lengthy process.

3.1.4. Fuzzy Rules and Knowledge Discovery

Table 4 summarises some relevant studies in the use of Fuzzy rules and Knowledge Discovery for Retrofit, where mathematical modelling such as fuzzy logic [99,100,101] and Bayesian calibration [97, 87, 70] are adopted. Mathematical modelling has been found to be a useful technique for determining the best building energy retrofit strategy that considers both environmental goals, such as energy efficiency and the use of clean and renewable energy sources, and economic factors, such as profit, initial cost, and payback period [99]. For building energy retrofits, Ruuparathna et al. [100] used a life cycle cost analysis approach based on fuzzy logic to assess the total costs of different energy retrofit alternatives and to help choose those with the lowest costs. In addition, the authors in [101], with the use of a mixed-integer problem (MIP/pl. MIPs) and fuzzy logic optimisation develops a model for energy retrofit measures in single-family homes. To estimate energy demand profiles for various retrofit scenarios, Yuan et al. [87] used the Gaussian process as a meta-model. A cost- effectiveness analysis was then used to rate the different retrofit scenarios. When overcoming complex decisions and uncertainties, the retrofit process has benefited from the use of fuzzy rules and knowledge discovery, but the results may not be generalizable to larger projects [97, 99, 87]. Additionally, this approach has been found to be time-consuming and requires expert mathematical knowledge, as well as having limitations such as small sample sizes and sampling biases.

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Table 3 – Reviewed Studies on Surrogate Modelling for Retrofit

Ref	Purpose	AI	Method	Building Type, Location	Retrofit Apprch.
[79]	Develop a ML model to predict near-optimal retrofit solutions validated with a conventional building simulation-optimization.	ANN + Surrogate modelling	Adopting surrogate modelling with ANN that replaces both building simulation and optimisation part.	Residential buildings, Zurich, Switzerland	energy optimal retrofit
[88]	Developing a low-cost model that can quickly assess the thermal behaviour of any communal housing stock component in southern Spain.	ANN + Surrogate modelling	A surrogate model that accelerates the prediction of a building's thermal comfort while assuring high reliability using actual measurements.	Social housing, southern Spain	cost optimal retrofit
[84]	Develop a model to select near optimal building energy renovation methods using data from the SBMO - simulation based multi objective optimisation model.	ANN surrogate modelling	Different ANNs were used to model the relationship between the near optimal renovation scenarios of the building's, TEC, LCC, and LCA. The proposed ANN models allow the extension of the traditional Building Energy Models.	One dataset of an institutional building	energy optimal retrofit
[67]	To predict primary energy consumption and occupants' thermal comfort for any member of a building category using surrogate modelling and ANN.	ANN + Surrogate modelling	EnergyPlus simulation results that have been post-processed in MATLAB® are used as targets for training and evaluating two families of ANNs in the MATLAB® environment and building simulation tools can be replaced by the developed ANNs reducing computational time/effort.	Office buildings, South Italy, the period 1920-1970.	green retrofit
[93]	To promote sustainability in the built environment and finally to have a smart green building.	PCO+ Surrogate Modelling	A new generation of adaptable systems developed using surrogate modelling and supervisory PCO.	Low-rise office, Portugal	energy optimal retrofit
[89]	To obtain energy-optimal thermal designs for residential buildings in the urban areas. .	GA+ Surrogate Modelling	A genetic algorithm optimisatio n n technique and gradient boosting machine based surrogate model was developed.	Buildings in urban areas in Turkey	cost optimal retrofit
[80]	To select building retrofit designs that balance energy consumption and the capital cost.	MOO+ Surrogate Modelling	Surrogate modelling and Multi objective optimisation with Pareto optimal design.	Residential apartment, Lisbon, Portugal	cost optimal retrofit

3.1.5. Building Automation Systems

Building automation systems, also referred to as smart systems or smart buildings, offer an extensive quantity of information about how buildings operate. As shown by numerous studies [87, 131], this data allows buildings to be monitored and managed automatically and intelligently in real-time. In [95], it is explained that an automatic building energy management system is essential for monitoring and evaluating a retrofit scenario. Various studies related to building automation systems are listed in Table 5. In order to predict the effectiveness of natural ventilation systems for smart buildings, Chen et al. [102] used systems and reinforcement learning to optimise HVAC and window systems for natural ventilation. In order to predict annual heating demand based on multivariate weather data, Westermann et al. [103] used raw data from building automation systems and a deep temporal CNN, which helped condense hourly values for up to 25 variables from 8760 to a few parameter values. This adaptation of AI applications and building automation systems proves that real life data can be more accessible and more manageable therefore making the retrofit process more accurate.

3.1.6. Knowledge Base Systems

Ali et al., [82], Xu et al., 2021 [74], and Zhao et al., [97] focused on developing the datasets for future retrofitting scenarios using knowledge base systems. The authors in [82], an intelligent knowledge-based RS (Recommendation Systems) development approach is used that uses a predictive model. This approach was beneficial as it was able to prove effective even when there is very limited knowledge of the building dynamics, with a very high accuracy (89%). Authors in [74], a less computational approach that focuses on large scale empirical evaluation of energy efficiency interventions in commercial buildings is implemented using random forest (grf) R package. A methodology developed by Zhao et al. in [97] green retrofit approach is achieved with the use of case-based reasoning (CBR), this approach includes represent, retrieve, reuse, revise, and retain [97]. Table 6 presents a list of some studies on retrofit that utilise Knowledge Base Systems.

Table 4 - Reviewed Studies on Knowledge Discovery and Fuzzy Logic For Retrofit

Ref	Purpose	Main AI	Method	Building Type, Location	Retrofit Approach
[100]	Propose a framework to support building energy retrofits.	Fuzzy logic	A fuzzy logic-based life cycle cost analysis approach for building energy retrofits to estimate the overall costs of energy retrofit alternatives and to facilitate the selection of those with lowest costs.	A public office Columbia	Energy optimal retrofit
[101]	Propose an economic optimization model for energy retrofit measures for single-family houses	Mixed integer problem, fuzzy logic	Use mathematical modelling, fuzzy logic - as a mixed-integer problem (MIP/pl. MIPs).	German buildings	Energy optimal retrofit
[99]	Find the best strategy for building energy retrofit	Mathematical model	Use mathematical modelling to find the best strategy for building energy retrofit that considers economic criteria such as profit, initial cost, and payback period, as well as environmental objectives.	A seven-story building at the University of Tehran in Iran	Energy optimal retrofit
[70]	To find the optimal combination of energy retrofit interventions on a building portfolio consisting of historic buildings.	Mathematical model	Mathematical modelling and decision optimisation based on score driven.	Historic building, Italy	Energy optimal retrofit
[87]	Help identify trade-offs among building retrofit options	Metamodel-based method using the Bayesian method	A metamodel-based method using the Bayesian method to estimate the unknown parameters including the calibration parameters based on the proposed Gaussian process model is used to evaluate the life cycle cost of implementing each measure.	Singapore building	Energy and cost optimal retrofit

Table 5 - Reviewed Studies on Building Automation Systems for Retrofit

Ref	Purpose	Datasets	Method	Building Type and Location	Retrofit Approach
[95]	Implement a protocol using IOT and sensors for a large-scale building retrofit.	Smart metering data historical training data that includes details on the environment, holidays, and energy use.	Using smart building data -placement of the sensors and devices for data capturing - IoT Sensors and wireless sensor network.	20-year old six-storey academic building in Malayasia	Energy optimal retrofit
[87]	Improve the prediction performance for Natural ventilation rate.		Performances of eight machine learning algorithms were compared for predicting natural ventilation rate (NVR) with Deep Neural Network showing best prediction performance.	Office on the fifth floor of a research building in Daejeon, Republic of Korea	Energy optimal retrofit
[103]	Develop e retrofit framework that looks into building performance.		To analyse annual multivariate weather data with hourly resolution, create a single surrogate model that spans arbitrarily many locations using a deep temporal convolutional neural network.	Canada case study	Green retrofit
[102]	Advance the control strategy of natural ventilation and to achieve greater comfort and energy efficiency.		A reinforcement learning control method that uses model-free Q-learning to make the best possible decisions on how to operate HVAC and window systems in order to reduce energy use and discomfort.	Miami and LA case studies	Green retrofit
[131]	Point and context anomaly detection of energy consumption.		Using smart metering data to quantify building daily load profiles (i.e. energy consumption patterns) with a set of statistics using ML.		Energy efficient

Table 6 - Reviewed Studies on Knowledge Base Systems				
Ref	**Purpose**	**Method**	**Building Type, Location**	**Retrofit Apprch.**
[82]	To predict the energy rating and recommend a list of retrofit measures.	An intelligent knowledge-based RS (Recommendation Systems) development approach is used that uses a predictive model.	Dwellings in Dublin, Ireland	green retrofit
[74]	To offer a data-driven alternative approach to retrofit analysis that could be more easily applied to portfolio-wide retrofit plans.	Data driven methods - application of machine learning method with causal forest for the prediction of retrofit savings.	unknown, commercial building	cost optimal retrofit
[97]	Guide decision makers in making improved decisions on new green retrofit projects.	A synthetic optimisation weighting method using case base reasoning approach was adopted based on both expert opinion and the attribute characteristics.	Shanghai building	green retrofit

3.2. Key datasets of AI applications for Retrofit process

AI has proved useful in increasing or automating the decision-making process through prediction, optimization, digitization, risk management, and monitoring and analysing the health of construction projects. Multiple AI based methods and software tools (as shown in Table 10 from the Appendix) have made this possible as it helped managing large datasets obtained through a variety of techniques such as interviews data, experimental tests, surveys data, as well as data captured with use of sensors, smart systems and wearable systems. All of this data was data related to building performance, energy related data such as EPC Rating certificate, open-source data from the government website. An overview of the types of datasets required in the specified AI subfields for the Retrofit process is given in Table 7 (Table 7 - Summary of datasets characteristics, strengths, and limitations of AI for Retrofit). The following section discusses the types of datasets and sample sizes used in the various artificial intelligence (AI) applications for retrofit.

Machine learning applications have mostly been used to analyse large sample sizes of building data such as 1,500 datasets – ANN, 2,915 datasets [76] -Surrogate models, 4900 records in [68], 12,806 census/EPC audit data [79] - surrogate model, 52 buildings representing 105,216 observations in the data [77] - RNN. Intelligent optimization algorithms were proved to be capable of handling both small and big datasets [69, 94]. It has been noted that the development of Retrofit multi-objective optimization models accepts and frequently uses data based on BIM and experimental simulation. In multi-criteria decision-making techniques, such as knowledge-based fuzzy logic, it is observed that competence and experience in the field are more significant than the amount of data used [70]. This is possible as fuzzy rules and knowledge discovery needs expert knowledge (mathematical model method) for training and applying the technologies to the issues in question, so such approaches.

will become reliant on human expertise [58] and the data used for the framework is not necessarily relevant. Building automation systems rely upon real-time data gathered by smart technologies like wearables, smart meters, and sensor-based technologies. Studies demonstrate that when used in the retrofit process, this method can use any datasets size. For instance, 144 daily samples of smart metering data were collected [87] to characterise building load profiles. On the other hand, temporal convolutional networks were employed by Westermann et al. [103] to handle 150,000 hourly weather time series data collected from building automation systems each year. Notably, the majority of the research used case studies to verify the developed models or results.

To conclude, there is a similar approach on which datasets are used based on the above mentioned. However, the importance of datasets size in retrofit scenarios cannot be underestimated as they have the potential to influence the design and analysis of a proposed system. papers [85, 90] reviewed the data side of AI application, arguing that a reliable testing platform and high-quality, representative, and real-world collected testing data are lacking, or the framework developed can only be applied to similar buildings. It is discussed in some papers that these limitations can be overcome by having access to larger and more accurate datasets. It is fair to say that there are similarities when it comes to what types of datasets are needed and used, regardless of the AI applications applied to retrofit projects but it is important to highlight the importance of the datasets size needed to the process as well as the importance of what impact the datasets have on the retrofit process. However, it is still unclear what the ideal sample size should be, particularly for AI algorithms, and these findings are often underreported in the literature, but the need of linked building data is proven to have great potential.

3.3. Key retrofit outcome taxonomy

Decision making on optimal retrofit options mostly relied on mapping outcomes using AI technologies aimed to achieve energy efficiency. Others focused on cost or sustainable retrofit and very little took a holistic approach. Most optimal retrofit options were directed toward energy efficiency parameters, and this could perhaps be reasoned to the availability of data but also it can be related to avoiding the complexities from integrating different stakeholders' inputs to achieve a holistic retrofit solution. To emphasise on this, Table 8 shows Retrofit Target taxonomy, elaborates the parameters and retrofit focus and outcome undertaken by previous researchers in detail. Based on the selected studies, it can be noted that when the retrofit project was simulated, particular retrofit actions were considered in order to achieve the set result (see Fig 8 - Retrofit Target Taxonomy chart). From the studies, it is important to highlight that by only focusing on one or some retrofit outcome, retrofit action has been disregarded (as shown in Fig 9 – existing retrofit approach and in Table 8 – Retrofit Target). It is evident that regardless of the AI application choice, the Retrofit outcome is mostly depended on the already set objectives. These objectives could be cost effective, energy efficient, sustainable retrofit. Therefore, the more objectives are set, the broader the retrofit outcome can be, a more holistic retrofit can be achieved. It is important to understand that there is a need of having more than one or two sets of objectives, therefore looking at developing a framework for retrofit that includes.

multiple stakeholders, occupants' comfort, building structure, energy performance, indoor air quality, building performance is vital (as shown in Fig 10 – Proposed retrofit approach). The proposed framework relies on the premises of having data availability, as discussed below in Section 4. It is essential that once the retrofit target is identified, the AI applications can be chosen based on the availability of data. If there is a large amount of data available and accessible, applications such as ML can be adopted during retrofit process. However, little amount of data will mean looking into trying to develop the optimal outcome using intelligence optimisation, this technique relies on expert knowledge, high computational cost. we should identify the retrofit target; the data sets available/requirements.

3.3.1. Optimal Energy Efficient Retrofit

In studies such as [76], [74], [83], and [79], the use of supervised machine learning techniques was investigated in order to enrich building databases with novel building characteristics important for energy efficiency optimal retrofit. The energy cost was reduced by either repairing the envelop [79], improving the performance of the envelop [76] or reconfiguring the building envelop [74] [83] respectively. Other actions considered when executing the retrofit simulation were improving the HVAC system, the Lighting system and gas system [74] or integration of solar renewable technologies [79].

Big Data Driven approach to deliver optimal energy efficient retrofit has also been adopted by the authors when running retrofit simulations in studies [75], [81], and [78]. Precisely, authors in [75] focused on reinstalling or air source heat pumps, authors in [81] focused on developing a BIM Tool with the use of supervised learning (SVM) to develop an efficient workflow for deep renovation projects aimed at optimal energy efficiency. On the other hand, authors in study [78] employed the use of big – data, available from the Swedish Energy Agency' transfer big data from Swedish Energy Performance Certificates for building retrofitting database to support energy efficient retrofit when not all physical information is available regarding building characteristics and energy saving of retrofit measures.

The use of supervised machine learning (SMAC in [68] study, Deep Learning CNN in [71] study, Deep Learning RNN in [77] study) and the use of IoT and BIM [95] where running retrofit simulations led to optimal urban large scale retrofit. Particularly, authors in [95], [71] and [68] proposed to improve the energy performance in terms of energy rating whereas authors in [77] proposed to improve the lighting system and reinstallation of the windows.

3.3.2. Optimal Cost-efficient Retrofit

The use of supervised learning such as Deep Learning - RNN by authors in [73] focused on simulating the cost optimal retrofit. This is achieved by integrating smart sensors for the building systems as well as replacing the building envelop and heating systems.

3.3.3. Energy and cost optimal retrofit

Furthermore, the use of supervised machine learning such as SMBO and ANN by the authors in [84] study or Evolutionary algorithms such as Multi objective optimisations in [87] study, and Genetic Algorithms in study [92] focused on simulating the cost optimal retrofit scenario considering life cycle cost, total energy consumption whilst keeping the cost of the retrofit optimal as well.

3.3.4. Sustainable / Green Retrofit

The use of supervised learning such as ANN by the authors in [67], Decision trees & NN in studies [82], Falling Rule List in studies by [81] or evolutionary algorithms such as MOO in [72] studies have been adopted when retrofitting the building systems with renewable energy to improve energy consumption and reduce CO2 emission. Some renewable resources strategies such as installing photovoltaic panels in [67] studies have been proposed as a retrofit action. The main goal of studies developed by author's in [72] research was to reduce greenhouse gas emission by retrofitting the HVAC system, restoring the building envelop and implementing renewable energy sources whereas [82] focused on predicting the overall Energy Conservation Measures (ECMs) eligibility given a specific set of building characteristics.

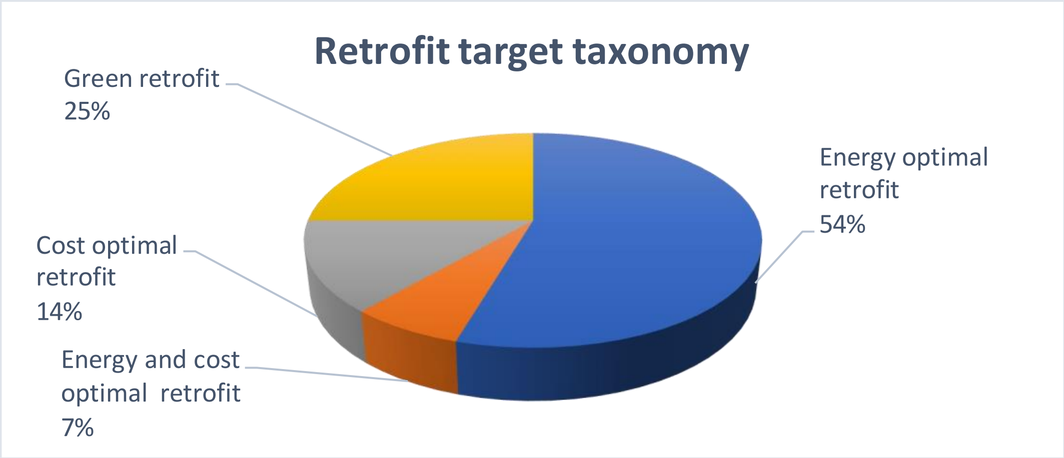

Fig 8 – Retrofit Target Taxonomy Chart

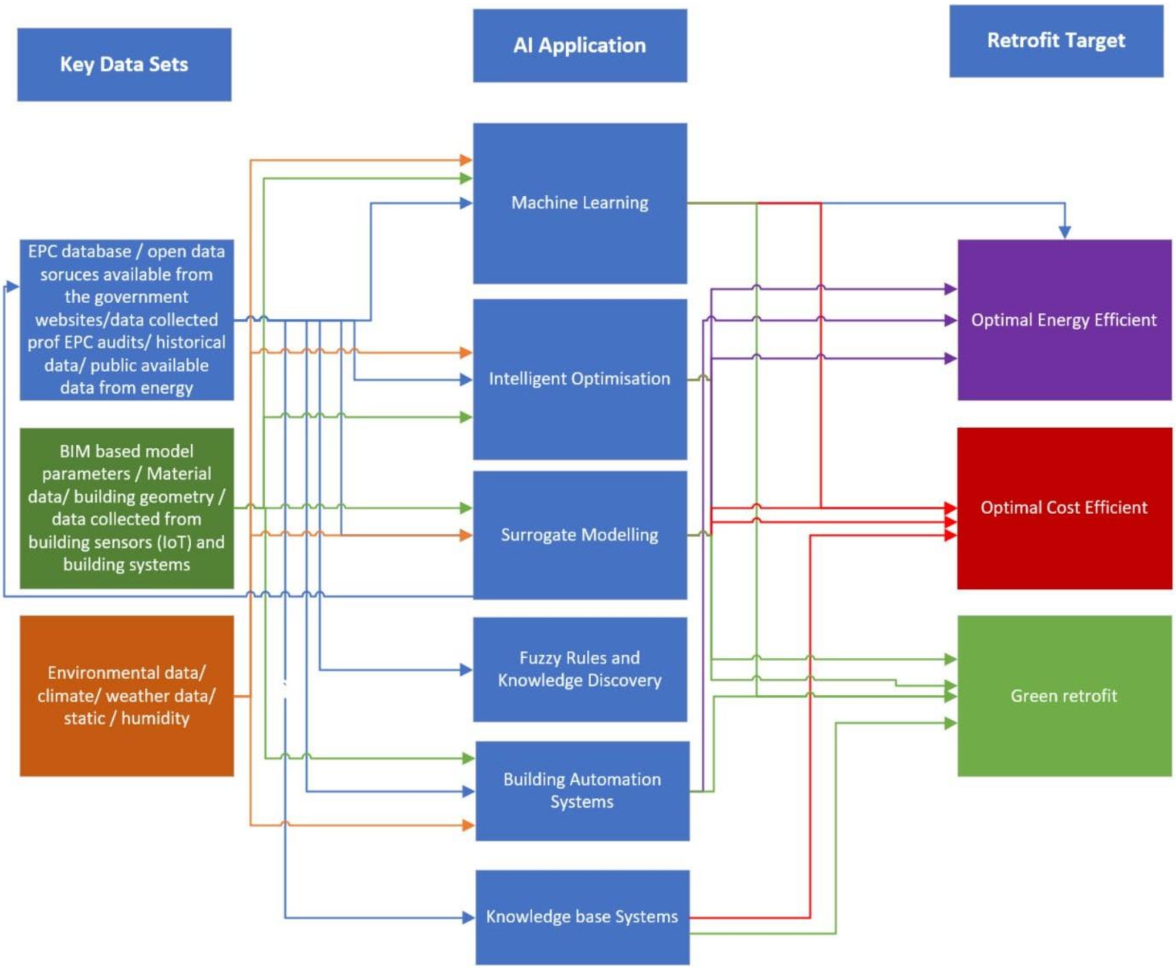

Fig 9 – Existing Retrofit Approach

Table 7 - Summary of datasets, characteristics, strengths and limitations of AI applications for Retrofit datasets characteristics of AI applications for Retrofit process

Ref	AI	Datasets	Strengths	Limitations
[106] [75] [68] [83] [81] [74] [107] [77] [73] [90] [86] [78] [105] [85]	Machine learning	-open data sources available in Zurich -reliable data from government sources -historic data -statical data on retrofit -simulated energy consumption data -real life energy consumption data -BIM models and data -material data -data collected from EPC -existing databases on building pathologies -energy audit data -sensor data --green building data and green building materials data	-able to predict even when there is very limited knowledge of the building dynamics -very high accuracy -less computational -not having to undergo an exhaustive search process -not having to rely on time intensive recalibration process -enables more accurate results -less time consuming than energy simulation tools -feasible for complex buildings on a large scale -generalisation ability -reliability	-considerable amount of reliable data is needed -lack of effective and convenient tools to perform the large dataset analysis -large number of accurate datasets and expertise when preparing the data -very challenging to obtain measured retrofit data and usually, such data are subjective and not optimal -small sample size and sampling biases -black box problem -data unavailability -cannot be applied on many other scenarios as it is bespoke -difficult to collect high granular energy consumption -unable to collect data due to privacy concerns -only suitable for similar buildings -difficulty to collect large quantities of useful real-life data from sensors etc -users and other parameters (fire safety codes, flexible spaces) were not taken into account
[92] [71] [72] [7] [69] [104] [94]	Intelligent optimisation	-BIM Based model parameters and materials -LCC and TEC data -weather data, thermal comfort data, building geometry and real time energy consumption data -thermal energy demand for heating, building geometry -building structure, data from building energy audit report -environmental data (Temperature statics, humidity, weather)	-stronger and better optimisation -reduce the computational time associated with simulation tools	-high computational cost -expert knowledge in the field -not all components needed for retrofit were included in the optimisation -inaccurate results due to exclusion of certain parameters -applicability to other buildings -only applied to Singapore climate and regulations

Table 7 Continued

[79] [88] [84] [67] [93] [89] [80]	Surrogate Modelling	-materials, building geometry, climate conditions, and market prices BIM models and data -material data -data collected from EPC	-very high accuracy	large number of simulations are required for the evolution process when applied to a cluster of buildings accurate but time consuming -level of complexity of the problem makes it difficult to understand which approach is the most strategic - challenging to get adequate building operational energy consumption datasets
[99] [100] [94] [87] [70]	Fuzzy rules and knowledge discovery	-EPC database from Sweden -BIM based model parameters - buildings with a lot of data and in- formation, such as drawings, reports, energy bills, building management system data, or others	-deal with multi criteria decision making problems and uncertainties	-unable to apply on a wider project -absence of reliable big data source - monetary implications -time consuming -expert mathematical knowledge
[82] [74] [97]	Knowledge based systems	-publicly available Irish building energy performance certificate data -energy data and retrofit records form US GSA Portfolio -general building information and energy and cost information of 72 buildings in China	-Less computational -Easily applicable to large scale retrofit -easy to adopt by non-expert of AI field -easy to interpret and share with decision makers	-the system would never recommend any measures outside the available knowledge -relying on huge amount of very high-quality data -only applicable to US climate and regs -only applicable to the exact same buildings
[95] [87] [103] [102] [131]	Building Automation systems	-data collected from building systems and sensors and historical data related to weather, location -BIM Data	- The building model with reinforcement learning control ensures optimal performance by self-advancement on set objectives and cost functions and is capable of adapting to variable occupancy and occupant behaviours, which are challenging to accommodate by heuristic control. -fuzzy set theory has been developed for modelling complex systems under uncertain or imprecise environments	-it requires a sufficiently long learning period before it can make optimal decisions under various conditions -large sample sizes of data is required

Table 8 – Retrofit Approach Taxonomy		
Ref	Aim	AI Used
Energy Optimal Retrofit Approach		
[100] [101] [99] [70] [87] [95] [131] [93] [84] [79] [104] [26] [71] [92] [85] [105] [106] [75] [68] [83] [91] [74] [107] [77] [73] [78]	• propose a framework to support building energy retrofits. • propose an economic optimization model for energy retrofit measures for single-family houses. • find the best strategy for building energy retrofit. • to find the optimal combination of energy retrofit interventions on a building portfolio consisting of historic buildings. • find the optimal scenario for the renovation of institutional buildings considering energy consumption and LCA while providing an efficient method to deal with the limited renovation budget. • minimie the number of required retrofits needed to achieve maximal energy savings across an urban study area model for estimating energy savings. • to predict the performance of heat pump systems in retrofit residential housing. • provided a rapid energy performance estimation engine for assisting multi objective optimisation of non-domestic buildings energy retrofit planning. • to improve national estimations of energy savings potential • develop a deep renovation scheme. • to offer a data- driven alternative approach to retrofit analysis that could be more easily applied. • to portfolio-wide retrofit plans. • to develop machine learning based load prediction model for residential building. • to assess the feasibility in using an integrated Data-driven Urban Energy Simulation (DUE-S) model to quickly evaluate various large-scale retrofits in an urban environment. • to help determine those building features that are most influential in retrofitting. • to support the stakeholders in taking decisions on refurbishments options when not all of physical information is available. • develop a machine learning-based surrogate model to predict near-optimal retrofit solutions validated with a conventional building simulation-optimization model. • to promote sustainability in the built environment • and finally, to have a smart green building • Implement a protocol using IOT and sensors for a large-scale building retrofit. • improve the prediction performance for Natural ventilation rate.	fuzzy logic mixed integer problem, fuzzy logic mathematical model mathematical model GA Greedy optimisation algorithms MOO GA a NSGA-II Linear Regression ANN SVM Decision Trees ML casual forest Multiple ML RNN Deep Learning and PCA SVM-FCM VAE Bayesian method ANN + Surrogate modelling PCO ML + Surrogate Modelling NSGA-II
Cost Optimal Retrofit Approach		
[74], [80], [89], [72],	• proposes calibrated building stock models to assess thermal comfort of the social housing stock of southern Spain (Mediterranean area) • to highlight that the optimization of building • energy design is fundamental for solving the climatic issues of contemporary society. • to determine whether it is possible to develop a surrogate model to evaluate the thermal behaviour. • to obtain energy-optimal thermal designs for • residential buildings in the most urbanised cities in Turkey • propose a retrofitting building information modelling (RBIM) to achieve a trade-off design set between two conflicting objectives, namely. minimizing OTTV (overall thermal transfer value) and minimizing the retrofit cost.	GA MOO + GA using Pareto Front ANN + Surrogate modelling GA+ Surrogate Modelling

Table 8 – Retrofit Approach Taxonomy Continued		
Energy and Cost Optimal Retrofit Approach		
[105] [87]	• to select building retrofit designs that balance energy consumption and the capital cost. • To offer a data- driven alternative approach to retrofit analysis that could be more easily applied. • to portfolio-wide retrofit plans.	MOO+Surrogate Modelling clustering techniques and Montecarlo simulation
Sustainable/Green Retrofit Approach		
[97], [82], [102], [103], [69], [7]	• to facilitate evaluating various design alternatives and balancing multiple objectives in building green retrofit. • find cost optimal green retrofit. • reducing building Greenhouse gas emissions • generates and evaluates optimal and holistic renovation scenarios tailored toward the renovation of dwellings in a Danish context. • seek to reduce the dimensions of the evaluating KPIs for the sake of designers. • to predict primary energy consumption and occupants' thermal comfort for any member of a building category using surrogate modelling and ANN. • to predict the energy rating and recommend a list of retrofit measures. • guide decision makers. • in making improved decisions on new green retrofit projects. • develop e retrofit framework that looks into building performance. • expand the reinforcement learning control in order to advance the control strategy of natural ventilation and to achieve greater comfort and energy efficiency. • to assess the performance level of a green building based on assessment factors of green building rating system	MOO MOO FRL BIM tool + Clustering K Means and PCA BIM tool: PARDIS and KPIs with clustering k-means ANN + Surrogate modelling KBS KBS Building Automation Systems Building Automation Systems Building Automation Systems

4. Strengths, limitations, implications, and future of AI applications for retrofit

4.1 Strengths of AI applications for Retrofit

The application of AI when dealing with the Retrofit process has a number of advantages, as shown in Table 7. With the effective use of AI technologies like machine learning, surrogate modelling, and intelligent optimisation, research shows that the retrofit process has been successful in increasing building efficiency and encouraging sustainability. Increased efficiency, time and money savings, reliability, and greater accuracy when carrying out the retrofit procedure are all common strengths.

4.2 Limitations and Implications of AI for Retrofit

Despite the strengths of AI applications to Retrofit process and its current implementation in the field, there are still several challenges. Table 7 (Summary of datasets characteristics, strengths, and limitations of AI for Retrofit) presents an overview of these. The literature [66, 98] has explored additional restrictions include data complexity, high starting costs, data privacy and security difficulties, high initial costs, computing power and internet connectivity, ethical and legal issues, cultural/heritage challenges, a lack of competence. Furthermore, AI applications were frequently constrained by data accessibility issues, inadequate data, low data quality, a lack of trustworthy databases, short sample sizes, and sampling biases but also the need to better link large datasets to the asset using an open data source environment. A further consideration can be the need to develop models that people can comprehend, trust, and manage, where effects of culture, individual values, and religious beliefs on the acceptability and use of AI [98] should also be further studied.

4.3 Future of AI for Retrofit & Recommendations

The majority of AI applications from research presented seem to disregard the inclusion of a common data environment and involve multiple stakeholders in the retrofit process that can aid develop a holistic retrofit solution. The major limitation deducted is the stakeholder's inclusivity in the retrofit process and the need of implementing building data capture with the use of digital twins and linking it to the retrofit process. When discussing the retrofit process, these haven't been sufficiently studied. The generation and capture of useful data can be accomplished in novel ways with the help of AI technologies, which have the potential to alter the practice and process of retrofitting dramatically. The noted missing links invite further research on the right integration and use of AI applications for optimising and improving cost, building performance and sustainability in the AEC industry by Retrofitting the already existing building stock. However, integrating the various heterogeneous data types gathered using these AI applications is difficult and time-consuming, which consequently restricts the potential of the retrofit process. Complex retrofits can be made possible with the use of open data sources, such as semantic web ontologies. Based on the limitations discussed above and the key retrofit objectives' taxonomy identified through the thematic analysis and discussed in the analysis section (3.3), it is important to emphasise that there is a need of having a holistic approach when looking at the retrofit process. Therefore, looking at developing an inclusive, open data source framework for retrofit process that includes multiple stakeholders, occupants' behaviour, building geometry, energy performance, indoor air quality, achieving net-zero standards with the use of Artificial intelligence is vital (as shown in Fig 10 – Proposed Retrofit Approach).

A robust methodology needs to be in place to capitalise on this data and drive the retrofit approach in a holistic manner. Due to the variety and individuality of buildings, as well as the varied stakeholder goals, assessing the energy performance of buildings during the retrofit process is a complex process. One of the primary causes of ineffective assessments of building energy performance is the varied and fragmented nature of the information that is currently accessible. Exploring the factors that contribute to the complex discrepancy between expected and observed building energy performance has remarkable potential with effective cross-domain information sharing. Information integration has been driven by the semantic web, which has allowed a paradigm shift in the management and sharing of cross-domain information. Semantic web technologies have shown improvements in a variety of industries due to their adaptable and computer-readable model for representing information. As part of the process of creating service-oriented architectures, Web discovery services are made possible by a semantic web-based framework.

The proposed Retrofit Approach (Fig 10) relies on the premises of having data availability gathered from the digital twin of the asset, data from real-life sensors that collects the occupant's behaviour data, and it is using a open data environment that links building data with outcomes. It is essential that once the retrofit target is identified, the AI applications can be chosen based on the availability of data. If there is a large amount of data available and accessible, applications such as ML can be adopted during retrofit process. More importantly, to support more controlled/sensitive/smart decision-making for retrofit projects, data can be defined semantically to support decision making. This can better utilise the large amounts of real-time datasets that can is captured using the digital twin. Although data carries a large but important amount of information, large datasets that are not analysed accordingly can be seen as a downside/negative when generating retrofit process, causing interoperability issues.

A more holistic approach needs to be considered even further that will focus on building performance of retrofit project. Based on the findings and analysis of AI applications for retrofit projects in the AEC sector, the following recommendations are proposed, as shown in Fig 10 – Proposed Retrofit Approach:

a) Establish an open data source framework for retrofit projects: There is a need to develop a comprehensive and inclusive data source framework that includes multiple stakeholders, building geometry, energy performance, indoor air quality, and occupant behaviour. This framework should be designed to facilitate data sharing and enable the integration of different datasets, such as those gathered through digital twins, sensors, and other sources.
b) Embrace semantic web technologies: The integration of semantic web technologies into the retrofit process can help address the issues of heterogeneity and fragmentation of information. By creating a computer-readable and adaptable model for representing information, semantic web technologies can facilitate effective cross-domain information sharing and enable more controlled and smart decision-making.
c) Focus on building performance: More research is needed to develop a more holistic approach to retrofit projects that prioritise building performance. This approach should consider the unique characteristics of individual buildings, as well as the varied stakeholder goals, to enable effective assessment of building energy performance and support data-driven decision-making.
d) Include stakeholders in the retrofit process: The retrofit process involves multiple stakeholders, including building owners, occupants, contractors, and designers. Therefore, it is important to establish inclusive and collaborative processes that enable effective communication, stakeholder engagement, and shared decision-making.
e) Increase the use of AI applications: The use of AI applications can help enhance the sustainability and efficiency of retrofit projects by enabling data-driven decision-making, optimizing building performance, and reducing energy consumption. Therefore, it is recommended that stakeholders in the AEC sector increase their use of AI applications, especially those that have proven to be effective in retrofit projects.
f) Conduct further research: Although significant progress has been made in the application of AI for retrofit projects, more research is needed to explore the potential of emerging technologies, such as machine learning and deep learning,

and to identify new opportunities for improving the sustainability and efficiency of the AEC sector.

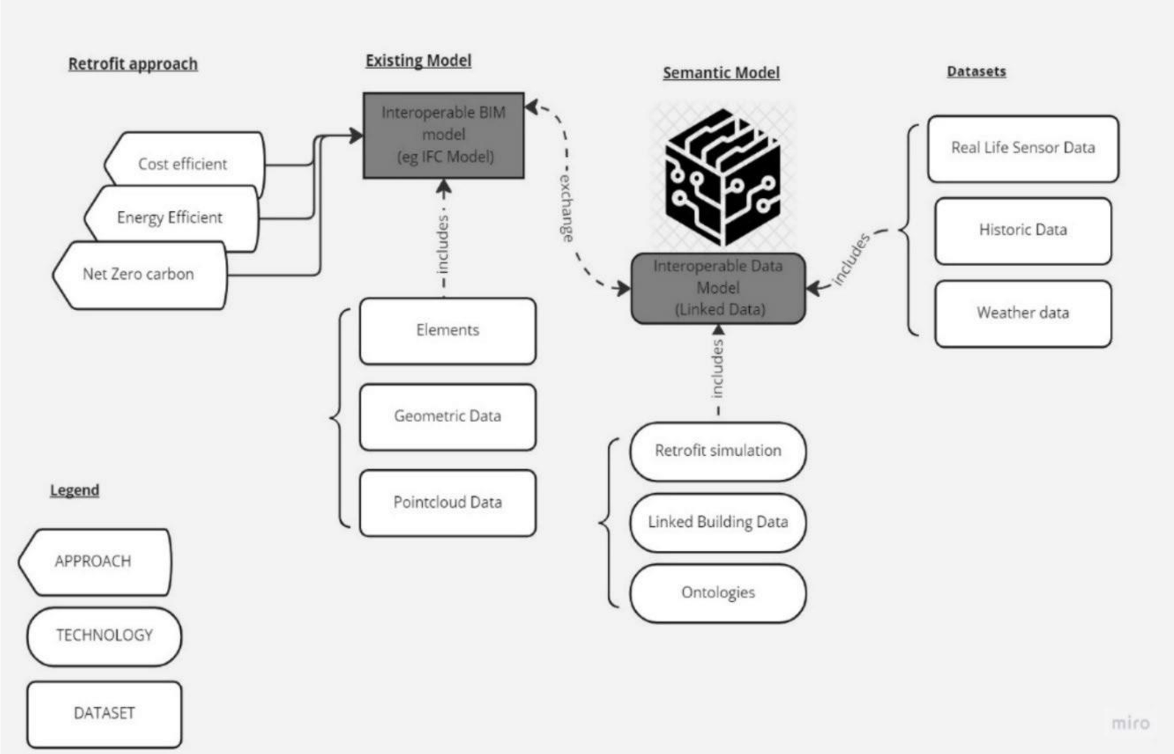

Fig 10 – Proposed Retrofit Approach

5. Conclusion

Based on the results analysed in the study, in conclusion, the Architecture, Engineering and Construction (AEC) sector is facing significant sustainability and efficiency challenges. Artificial Intelligence (AI) has been identified as an effective solution to address these challenges, and there is a growing interest in applying AI techniques and applications to retrofit projects in the construction industry. This study has conducted a thorough review of available literature on AI applications for retrofit projects in construction, identifying the opportunities and challenges of AI applications, and highlighting the most common techniques, data used, and processes followed. This study provides a valuable pathway for realizing the broad benefits of AI applications for retrofit projects and contributes to the AI body of knowledge by synthesizing the state-of- the-art of AI applications for retrofit and revealing future research opportunities in this field. Overall, this study highlights the potential for AI to enhance the sustainability and efficiency of the AEC sector and underscores the need for continued research and development in this area. In conclusion, the Architecture, Engineering and Construction (AEC) sector faces significant challenges in terms of sustainability and efficiency. However, have shown promise in addressing these challenges. The study also identified the limitations associated with the current use of AI applications for retrofit projects, including the need for a more inclusive approach that involves multiple stakeholders in the retrofit process and the integration of building data capture with the use of semantic web technologies. The study proposes a framework for an AI approach to retrofit projects that relies on the availability of data from real-life sensors, the digital twin of the asset, and an open data environment that links building data with outcomes. The framework also emphasises the importance of a holistic approach to the retrofit process that focuses on building performance. Overall, by synthesising the state-of-the-art of AI applications and highlighting potential future research opportunities in this area to improve the sustainability and efficiency of the AEC industry, this work contributes to the body of knowledge on AI applications for retrofit projects.

6. Future Scope

The proposed framework provides a pathway to realise the broad benefits of AI applications for retrofit projects and could help improve decision-making for retrofit projects in the future. Therefore, it is recommended that future research in this area should focus on the right integration and use of AI applications for optimizing and improving the cost, building performance, and sustainability in the AEC industry by retrofitting the already existing building stock. The findings of this study suggest that AI has the potential to significantly enhance the sustainability and efficiency of retrofit projects. However, the complex nature of such projects requires careful consideration of data, processes, and applications to ensure that value can be maximised. The study provides valuable insights into the current state-of-the-art of AI applications in retrofit projects and highlights future research opportunities in this field. It is hoped that the findings of this study will inspire further exploration and experimentation with AI in the construction industry, leading to more sustainable and efficient practices in the AEC sector.

7. Declarations

Conflict of interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

8. Appendix - Supplementary data

Table 9 - Abbreviations	
AI	Artificial Intelligence
AEC	Architecture, Engineering And Construction
PRISMA	Preferred Reporting Items For Systematic Reviews And Meta-Analysis
ML	Machine Learning
NN	Neural Networks
ANN	Artificial Neural Networks
SVM	Support Vector Machine
DL	Deep Learning
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
PCA	Principal Component Analysis
VAE	Value Auto Encoders
GA	Genetic Algorithm
MOO	Multi Objective Optimisation
NB	Naïve Bayes
GM	Gaussian Mixture
RL	Reinforcement Learning
MLM	Machine Learning Methods
ECM	Energy Conservation Measures
KPI	Key Performance Indicators
SBMO	Surrogate-Based Multi-Objective Optimization
IOT	Internet Of Things
GIS	Geographical Information Systems
CENED	CELED Energy Certification Of Buildings (Italian)
SHAP	Shapley Additive Explanations
DSS	Decision Support System
BIM	Building Information Modelling
PARADIS	Process Integrating Renovation Decision Support
SVM	Support Vector Machine
SVM-FCM	Fuzzy C-Means Based Support Vector Machine
NSGA II	Non-Dominated Sorting Genetic Algorithm II
LCC	Life Cycle Cost
LCA	Life Cycle Assessment
TCA	Total Cycle Cost
TEC	Total Energy Cost
BEMs	Building Energy Models
HVAC	Heating, Ventilation And Air Conditioning
GHG	Green House Gas
MATLAB	Matrix Laboratory
SPC	Supervisory Predictive Control
MIP	Mixed-Integer Problem
RS	Recommendation Systems
KBS	Knowledge Based Systems
US	United States
RBIM	Retrofitting Building Information Modelling
OTTV	Overall Thermal Transfer Value
FRL	Falling Rule List

Table 10 – Some AI application datasets and tools/software used for the selected studies

Variables considered	Tools Used	Main AI	Purpose	Ref
Energy saving and retrofitting the energy supply such as HVAC systems and DHQ systems	MOO using TRANSYS - Design Analysis Kit for Optimization and Terascale Applications (DAKOTA)	MOO	find cost optimal green retrofit	[110]
Primary energy efficiency measures	NSGA-II optimization n in MATLAB, EnergyPlus	MOO	Find the best energy retrofitting strategy	[209]
data from drawing files and the gbXML file exported from the BIM model	BIM and MOO inDesign Builder	MOO	to facilitate evaluating various design alternatives and balancing multiple objectives in building green retrofit	[108]
data from Building Energy Model	building performance simulation (BPS), MATLAB, EnergyPlus	MOO + GA	to highlight thatthe optimizationof building energy design is fundamental for solving the climatic issues of contemporary society.	[72]
TEC of the building in detail -thermos- physical properties of the building envelope, data from HVAC system and lighting, and other necessary information about the building.	Revit, ATHENA, DesignBuilder	GA	find the optimal scenario for the renovation of institutional buildings considering energy consumption and LCA while providing an efficient method to deal with the limited renovation budget	[92]
various energy cons various energy conservation measures (ECMs), collected from the National Oceanic and Atmospheric Administration (NOAA). Building geometries were created by merging a 2D building GIS various energy conservation measures (ECMs), collected from the National	EnergyPlus and proposed DUE-S tool developed using RNN	RNN	To assess the feasibility in using an integrated Data-driven Urban Energy Simulation (DUE-S) model to quickly evaluate various large- scale retrofits in an urban environment.	[77]
Typical residential household heating and cooling load intensities	EnergyPlus+ML and data from questionnaires and surveys	Multiple ML	to develop machine learning based load prediction model for residential building	[107]

Table 10 Continued – Some AI application datasets and tools/software used for the selected studies				
building energy performance benchmarking	Ecotect software, TRNSYS and GenOptoptimisation software	ANN	provided a rapid energy performance estimation engine for assisting Multi-objective optimisation of non-domestic buildings energy retrofit planning	[68]
data from EPC sample		SVM-FCM	to support the stakeholders in taking decisions on retrofit when not all of physical information is available	[78]
Energy efficiency, energy consumption, indoor thermal comfort, indoor air quality, occupants,	PARADIS and ICEBear KPI simulator (c++) ML	BIM tool: PARDIS and KPIs	seek to reduce the dimensions of the evaluating KPIs for the sake of designers	[86]
Energy efficiency, energy consumption indoor thermal comfort,	Answer Set Programming (ASP) and a BIM based DSS	BIM tool + Clustering K Means + PCA	generates and evaluates optimal and holistic renovation scenarios	[90]
data from sensors, EPC rating	ML	Deep Learning and PCA	to help determine those building features that are most influential in retrofitting	[73]
ECM (Energy consumption measurements) variables	The GSALink action, a combined energy-use dashboard and fault-detection tool	ML casual forest	To offer a data- driven alternative approach to retrofit analysis that could be more easily applied to portfolio-wide retrofit plans.	[74]
info from energy audit mandates, such as New York City (NYC)' s Local Law	Energy Audit Data Collection Tool, falling rule list ML	FRL	Reducing building GHG-Greenhouse gas emissions	[81]
IfcOpenShell library data	developed Diagnosis Tool using ML	Decision Trees	develop a deep renovation scheme	[91]
The EPC ratings	geographic information software	SVM	to improve national estimations of energy savings potential	[83]
Replace heat pumps to reduce energy consumption	calculations only using a standardised method for evaluating energy savings	ANN	to predict the performance of heat pump systems in retrofit residential housing	[75]

9. References

1 McArthur, J.J. and Jofeh, C.G.H. (2016) "Portfolio retrofit evaluation: A methodology for optimizing a large number of building retrofits to achieve triple-bottom-line objectives," Sustainable Cities and Society, 27, pp. 263–274. Available at: https://doi.org/10.1016/j.scs.2016.03.011.

2 Iea (2022) World energy outlook 2022 shows the global energy crisis can be a historic turning point towards a cleaner and more secure future - news, IEA. Available at: https://www.iea.org/news/world-energy-outlook-2022-shows-the-global-energy-crisis-can-be-a-historic-turning-point-towards-a-cleaner-and-more-secure-future (Accessed: November 19, 2022).

3 2030 climate target plan (no date) Climate Action. Available at: https://climate.ec.europa.eu/eu-action/european-green-deal/2030-climate-target-plan_en (Accessed: November 19, 2022).

4 Luddeni, G. et al. (2018) "An analysis methodology for large-scale deep energy retrofits of existing building stocks: Case study of the Italian office building," Sustainable Cities and Society, 41, pp. 296–311. Available at: https://doi.org/10.1016/j.scs.2018.05.038.

5 Zuhaib, S. and Goggins, J. (2019) "Assessing evidence-based single-step and staged deep retrofit towards nearly zero-energy buildings (NZEB) using multi-objective optimisation," Energy Efficiency, 12(7), pp. 1891–1920. Available at: https://doi.org/10.1007/s12053-019-09812-z.

Panagiotidou, M., Aye, L. and Rismanchi, B. (2021) "Optimisation of multi-residential building retrofit, cost-optimal and net-zero emission targets," Energy and Buildings, 252, p. 111385. Available at: https://doi.org/10.1016/j.enbuild.2021.111385.

6 Choi Granade, H. et al. (2009) "Unlocking the full potential of energy efficiency in the United States." Available at: https://doi.org/10.2172/1219302.

7 Li, X. and Yao, R. (2020) "A machine-learning-based approach to predict residential annual space heating and cooling loads considering occupant behaviour," Energy, 212, p. 118676. Available at: https://doi.org/10.1016/j.energy.2020.118676

8 Nutkiewicz, A., Choi, B. and Jain, R.K. (2021) "Exploring the influence of urban context on Building Energy Retrofit Performance: A hybrid simulation and data-driven approach," Advances in Applied Energy, 3, p. 100038. Available at: https://doi.org/10.1016/j.adapen.2021.100038.

9 Asadi, E., da Silva, M.G., Antunes, C.H., Dias, L., Glicksman, L.: Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application. Energy Build. 81, 444–456 (2014)

10 Kong L, Liu Z, Jianguo W (2020) A systematic review of big data-based urban sustainability research: State-of-the-science and future directions. J Clean Prod 273:123142

11 Zhang, L. et al. (2021) “A review of machine learning in building load prediction,” Applied Energy, 285, p. 116452. Available at: https://doi.org/10.1016/j.apenergy.2021.116452.

12 Debrah, C., Chan, A.P.C. and Darko, A. (2022) “Artificial Intelligence in green building,” Automation in Construction, 137, p. 104192. Available at: https://doi.org/10.1016/j.autcon.2022.104192.

13 Yao, X. et al. (2017) “From intelligent manufacturing to Smart Manufacturing for Industry 4.0 driven by Next Generation Artificial Intelligence and further on,” 2017 5th International Conference on Enterprise Systems (ES) [Preprint]. Available at: https://doi.org/10.1109/es.2017.58.

14 Rao, T.V. et al. (2021) “Reliance on artificial intelligence, machine learning and deep learning in the era of industry 4.0,” Smart Healthcare System Design, pp. 281–299. Available at: https://doi.org/10.1002/9781119792253.ch12.

15 Dahlbo, H., Bachér, J., Lähtinen, K., Jouttijärvi, T., Suoheimo, P., Mattila, T., Sironen, S., Myllymaa, T. and Saramäki, K. (2015). Construction and demolition waste management – a holistic evaluation of environmental performance. Journal of Cleaner Production, [online] 107, pp.333–341. doi:10.1016/j.jclepro.2015.02.073.

16 Shan, N.L., Wee, S.T., Wai, T.L. and Chen, G.K. (2018). Construction Waste Management of Malaysia: Case Study in Penang. Advanced Science Letters, 24(6), pp.4698–4703. doi:10.1166/asl.2018.11684.

17 Bilal, M., Oyedele, L.O., Akinade, O.O., Ajayi, S.O., Alaka, H.A., Owolabi, H.A., Qadir, J., Pasha, M. and Bello, S.A. (2016). Big data architecture for construction waste analytics (CWA): A conceptual framework. Journal of Building Engineering, 6, pp.144–156. doi:10.1016/j.jobe.2016.03.002.

18 Xu, J. et al. (2019) “A BIM-based construction and demolition waste information management system for greenhouse gas quantification and reduction,” Journal of Cleaner Production, 229, pp. 308–324. Available at: https://doi.org/10.1016/j.jclepro.2019.04.158.

19 Liu, Z. et al. (2015) “A bim-aided construction waste minimisation framework,” Automation in Construction, 59, pp. 1–23. Available at: https://doi.org/10.1016/j.autcon.2015.07.020.

20 Niska, H. and Serkkola, A. (2018) “Data Analytics approach to create waste generation profiles for Waste Management and Collection,” Waste Management, 77, pp. 477–485. Available at: https://doi.org/10.1016/j.wasman.2018.04.033.

21 Shafiq, M.T., Matthews, J. & Lockley, S.R. 2013, "A study of BIM collaboration requirements and available features in existing model collaboration systems", Journal of Information Technology in Construction, vol. 18, pp. 148-161

22 Azhar, S., Khalfan, M. and Maqsood, T. (2015) “Building Information Modelling (BIM): Now and beyond,” Construction Economics and Building, 12(4), pp. 15–28. Available at: https://doi.org/10.5130/ajceb.v12i4.3032.

23 Luo, X. et al. (2018) “Recognizing diverse construction activities in site images via relevance networks of construction-related objects detected by convolutional neural networks,” Journal of Computing in Civil Engineering, 32(3). Available at: https://doi.org/10.1061/(asce)cp.1943-5487.0000756.

24 Oyedele, L.O. and Tham, K.W. (2007). Clients’ assessment of architects’ performance in building delivery process: Evidence from Nigeria. Building and Environment, 42(5), pp.2090–2099. doi:10.1016/j.buildenv.2005.06.030.

25 Ajayi, S.O., Oyedele, L.O., Bilal, M., Akinade, O.O., Alaka, H.A. and Owolabi, H.A. (2017). Critical management practices influencing on-site waste minimization in construction projects. Waste Management, 59, pp.330–339. doi:10.1016/j.wasman.2016.10.040.

Tsang, Y.P., Choy, K.L., Wu, C.H., Ho, G.T.S., Lam, C.H.Y. and Koo, P.S. (2018). An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks. Industrial Management & Data Systems, 118(7), pp.1432–1462. doi:10.1108/imds-09-2017-0384.

26 Tavakolan, M. et al. (2022) “A parallel computing simulation-based multi-objective optimization framework for Economic Analysis of Building Energy Retrofit: A Case Study in Iran,” Journal of Building Engineering, 45, p. 103485. Available at: https://doi.org/10.1016/j.jobe.2021.103485

27 Winge, S., Albrechtsen, E. and Mostue, B.A. (2019) “Causal factors and connections in construction accidents,” Safety Science, 112, pp. 130–141. Available at: https://doi.org/10.1016/j.ssci.2018.10.015.

28 Oyedele, A. et al. (2021) “Deep learning and boosted trees for injuries prediction in power infrastructure projects,” Applied Soft Computing, 110, p. 107587. Available at: https://doi.org/10.1016/j.asoc.2021.107587.

29 Zhang, S., Sulankivi, K., Kiviniemi, M., Romo, I., Eastman, C.M. and Teizer, J. (2015). BIM-based fall hazard identification and prevention in construction safety planning. Safety Science, 72, pp.31–45. doi:10.1016/j.ssci.2014.08.001.

30 Kelm, A., Meins-Becker, A. and Helmus, M. (2019) “Improving occupational health and safety by using advanced technologies and bim,” Proceedings of International Structural Engineering and Construction, 6(1). Available at: https://doi.org/10.14455/isec.res.2019.92.

31 Lin, Z.-H., Chen, A.Y. and Hsieh, S.-H. (2021). Temporal image analytics for abnormal construction activity identification. Automation in Construction, 124, p.103572. doi:10.1016/j.autcon.2021.103572.

32 Lin, J.J. and Golparvar-Fard, M. (2018) “Visual Data and predictive analytics for proactive project controls on construction sites,” Advanced Computing Strategies for Engineering, pp. 412–430. Available at: https://doi.org/10.1007/978-3-319-91635-4_21.

33 Muhammad, K., Saoula, O., Issa, M.R. and Ahmed, U. (2019). Contract management and performance characteristics: An empirical and managerial

implication for Indonesia. Management Science Letters, [online] pp.1289–1298. doi:10.5267/j.msl.2019.4.012.

34 Picard, C., Smith, K.E., Picard, K. and Douma, M.J. (2020). Can Alexa, Cortana, Google Assistant and Siri save your life? A mixed-methods analysis of virtual digital assistants and their responses to first aid and basic life support queries. BMJ Innovations, p.bmjinnov-2018-000326. doi:10.1136/bmjinnov-2018-000326.

35 Xia, S., Nie, J. and Jiang, X. (2021) “CSafe,” Proceedings of the 20th International Conference on Information Processing in Sensor Networks (co-located with CPS-IoT Week 2021) [Preprint]. Available at: https://doi.org/10.1145/3412382.3458267.

36 Yao, X. et al. (2017) “From intelligent manufacturing to Smart Manufacturing for Industry 4.0 driven by Next Generation Artificial Intelligence and further on,” 2017 5th International Conference on Enterprise Systems (ES) [Preprint]. Available at: https://doi.org/10.1109/es.2017.58.

37 Alaka, H., Oyedele, L., Owolabi, H., Akinade, O., Bilal, M. and Ajayi, S. (2019). A Big Data Analytics Approach for Construction Firms Failure Prediction Models. IEEE Transactions on Engineering Management, 66(4), pp.689–698. doi:10.1109/tem.2018.2856376.

38 Jang, Y., Jeong, I. and Cho, Y.K. (2021). Identifying impact of variables in deep learning models on bankruptcy prediction of construction contractors. Engineering, Construction and Architectural Management, ahead-of-print(ahead-of-print). doi:10.1108/ecam-06-2020-0386.

39 Alaka, H.A., Oyedele, L.O., Owolabi, H.A., Bilal, M., Ajayi, S.O. and Akinade, O.O. (2017). Insolvency of Small Civil Engineering Firms: Critical Strategic Factors. Journal of Professional Issues in Engineering Education and Practice, 143(3), p.04016026. doi:10.1061/(asce)ei.1943-5541.0000321.

40 Bilal, M., Oyedele, L.O., Kusimo, H.O., Owolabi, H.A., Akanbi, L.A., Ajayi, A.O., Akinade, O.O. and Davila Delgado, J.M. (2019). Investigating profitability performance of construction projects using big data: A project analytics approach. Journal of Building Engineering, 26(100850), p.100850. doi:10.1016/j.jobe.2019.100850.

41 Tuan Le, Q., Pedro, A. and Lim, C.R. (2015) “A Framework for Using Mobile Based Virtual Reality andAugmented Reality for Experiential Construction SafetyEducation,” International Journal of Engineering Education , 31(3), pp. 713–725. Available at: https://doi.org/31(3):713-725.

42 Tan, Y., Xu, W., Li, S. and Chen, K. (2022). Augmented and Virtual Reality (AR/VR) for Education and Training in the AEC Industry: A Systematic Review of Research and Applications. Buildings, 12(10), p.1529. doi:10.3390/buildings12101529.

43 Eadie, R., Browne, M., Odeyinka, H., McKeown, C. and McNiff, S. (2015). A survey of current status of and perceived changes required for BIM adoption in the

UK. Built Environment Project and Asset Management, 5(1), pp.4–21. doi:10.1108/bepam-07-2013-0023.

44 Uhm, M., Lee, G. and Jeon, B. (2017). An analysis of BIM jobs and competencies based on the use of terms in the industry. Automation in Construction, 81, pp.67–98. doi:10.1016/j.autcon.2017.06.002.

45 Walasek, D. and Barszcz, A. (2017). Analysis of the Adoption Rate of Building Information Modeling [BIM] and its Return on Investment [ROI]. Procedia Engineering, 172, pp.1227–1234. doi:10.1016/j.proeng.2017.02.144.

46 Balaji, B., Bhattacharya, A., Fierro, G., Gao, J., Gluck, J., Hong, D., Johansen, A., Koh, J., Ploennigs, J., Agarwal, Y., Bergés, M., Culler, D., Gupta, R.K., Kjærgaard, M.B., Srivastava, M. and Whitehouse, K. (2018). Brick : Metadata schema for portable smart building applications. Applied Energy, 226, pp.1273–1292. doi:10.1016/j.apenergy.2018.02.091.

47 Chen, C., Tran Huy, D., Tiong, L.K., Chen, I-Ming. and Cai, Y. (2019). Optimal facility layout planning for AGV-based modular prefabricated manufacturing system. Automation in Construction, 98, pp.310–321. doi:10.1016/j.autcon.2018.08.008.

48 Ajayi, A., Oyedele, L., Owolabi, H., Akinade, O., Bilal, M., Davila Delgado, J.M. and Akanbi, L. (2019). Deep Learning Models for Health and Safety Risk Prediction in Power Infrastructure Projects. Risk Analysis, 40(10), pp.2019–2039. doi:10.1111/risa.13425.

49 Araújo, N., Cardoso, L., Brea, J.A.F. and de Araújo, A.F. (2018). Green Jobs: The Present and Future of the Building Industry. Evolution Analysis. Social Sciences, 7(12), p.266. doi:10.3390/socsci7120266.

50 Vigneault, M.-A., Boton, C., Chong, H.-Y. and Cooper-Cooke, B. (2019). An Innovative Framework of 5D BIM Solutions for Construction Cost Management: A Systematic Review. Archives of Computational Methods in Engineering. [online] doi:10.1007/s11831-019-09341-z.

51 Mesaros, P., Cabala, J., Mandicak, T. and Oravec, M. (2020). INTELLIGENT TECHNOLOGY FOR SUSTAINABLE FORMWORK DESIGN AND USE OF 3D ELEMENTS LIBRARIES. SGEM International Multidisciplinary Scientific GeoConference EXPO Proceedings. doi:10.5593/sgem2020v/6.2/s10.39.

52 Ye, Z., Yin, M., Tang, L. and Jiang, H. (2018). Cup-of-Water Theory: A Review on the Interaction of BIM, IoT and Blockchain During the Whole Building Lifecycle. Proceedings of the 35th International Symposium on Automation and Robotics in Construction (ISARC). doi:10.22260/isarc2018/0066.

53 Park, C.-S., Lee, D.-Y., Kwon, O.-S. and Wang, X. (2013). A framework for proactive construction defect management using BIM, augmented reality and ontology-based data collection template. Automation in Construction, [online] 33, pp.61–71. doi:10.1016/j.autcon.2012.09.010.

54 Jang, Y., Jeong, I. and Cho, Y.K. (2021). Identifying impact of variables in deep learning models on bankruptcy prediction of construction contractors. Engineering,

Construction and Architectural Management, ahead-of-print(ahead-of-print). doi:10.1108/ecam-06-2020-0386.

55 Kolodner, J.L. (1992). An introduction to case-based reasoning. Artificial Intelligence Review, 6(1), pp.3–34. doi:10.1007/bf00155578.

56 Winfield, A.F.T. and Jirotka, M. (2018). Ethical governance is essential to building trust in robotics and artificial intelligence systems. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376(2133), p.20180085. doi:10.1098/rsta.2018.0085.

57 Yu, H., Shen, Z., Miao, C., Leung, C., Lesser, V.R. and Yang, Q. (2018). Building Ethics into Artificial Intelligence. Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence. doi:10.24963/ijcai.2018/779.

58 Oyedele, L.O. and Tham, K.W. (2007). Clients' assessment of architects' performance in building delivery process: Evidence from Nigeria. Building and Environment, 42(5), pp.2090–2099. doi:10.1016/j.buildenv.2005.06.030.

59 Alaka, H., Oyedele, L., Owolabi, H., Akinade, O., Bilal, M. and Ajayi, S. (2019). A Big Data Analytics Approach for Construction Firms Failure Prediction Models. IEEE Transactions on Engineering Management, 66(4), pp.689–698. doi:10.1109/tem.2018.2856376.

60 Xia, S., Nie, J. and Jiang, X. (2021). CSafe. Proceedings of the 20th International Conference on Information Processing in Sensor Networks (co-located with CPS-IoT Week 2021). doi:10.1145/3412382.3458267.

61 Ascione F, Bianco N, De Stasio C, Mauro GM, Vanoli GP. A new methodology for cost-optimal analysis by means of the multi-objective optimization of building energy performance. Energy Build 2015;88:78–90. http://dx.doi.org/10.1016/j.enbuild.2014.11.058.

62 Walker, L., Hischier, I. and Schlueter, A. (2022) "The impact of modeling assumptions on retrofit decision-making for low-carbon buildings," Building and Environment, 226, p. 109683. Available at: https://doi.org/10.1016/j.buildenv.2022.109683.

63 Alam, Morshed & Zou, Patrick & Sanjayan, Jay & Stewart, Rodney & Sahin, Oz & Bertone, Edoardo & Wilson, John. (2016). Guidelines for Building Energy Efficiency Retrofitting.

64 Akanbi, L., Oyedele, L., Davila Delgado, J.M., Bilal, M., Akinade, O., Ajayi, A. and Mohammed-Yakub, N. (2019). Reusability analytics tool for end-of-life assessment of building materials in a circular economy. World Journal of Science, Technology and Sustainable Development, 16(1), pp.40–55. doi:10.1108/wjstsd-05-2018-0041.

65 Abioye, S.O. et al. (2021) "Artificial Intelligence in the construction industry: A review of present status, opportunities and future challenges," Journal of Building Engineering, 44, p. 103299. Available at: https://doi.org/10.1016/j.jobe.2021.103299.

66 McAleenan, P. (2020). Moral responsibility and action in the use of artificial intelligence in construction. Proceedings of the Institution of Civil Engineers - Management, Procurement and Law, 173(4), pp.166–174. doi:10.1680/jmapl.19.00056.

67 Ascione, F. et al. (2017) “Artificial neural networks to predict energy performance and retrofit scenarios for any member of a building category: A novel approach,” Energy, 118, pp. 999–1017. Available at: https://doi.org/10.1016/j.energy.2016.10.126.

68 Seyedzadeh, S. et al. (2020) “Machine learning modelling for predicting non-domestic Buildings Energy Performance: A model to support deep energy retrofit decision-making,” Applied Energy, 279, p. 115908. Available at: https://doi.org/10.1016/j.apenergy.2020.115908.

69 Panagiotidou, M., Aye, L. and Rismanchi, B. (2021) “Optimisation of multi-residential building retrofit, cost-optimal and net-zero emission targets,” Energy and Buildings, 252, p. 111385. Available at: https://doi.org/10.1016/j.enbuild.2021.111385

70 Ruggeri, A.G. et al. (2020) “Planning energy retrofit on historic building stocks: A score-driven decision support system,” Energy and Buildings, 224, p. 110066. Available at: https://doi.org/10.1016/j.enbuild.2020.110066.

71 Nutkiewicz, A., Choi, B. and Jain, R.K. (2021) “Exploring the influence of urban context on Building Energy Retrofit Performance: A hybrid simulation and data-driven approach,” Advances in Applied Energy, 3, p. 100038. Available at: https://doi.org/10.1016/j.adapen.2021.100038.

72 Ascione, F. et al. (2018) “A multi-criteria approach to achieve constrained cost-optimal energy retrofits of buildings by mitigating climate change and urban overheating,” Climate, 6(2), p. 37. Available at: https://doi.org/10.3390/cli6020037.

73 Deb, C., Dai, Z. and Schlueter, A. (2021) “A machine learning-based framework for cost-optimal building retrofit,” Applied Energy, 294, p. 116990. Available at: https://doi.org/10.1016/j.apenergy.2021.116990.

74 Xu, Y., Loftness, V. and Severnini, E. (2021) “Using machine learning to predict retrofit effects for a commercial building portfolio,” Energies, 14(14), p. 4334. Available at: https://doi.org/10.3390/en14144334.

75 Ye, K.K. et al. (2020) “The use of Artificial Neural Networks (ANN) in the prediction of energy consumption of air-source heat pump in retrofit residential housing,” IOP Conference Series: Earth and Environmental Science, 463(1), p. 012165. Available at: https://doi.org/10.1088/1755-1315/463/1/012165.

76 Re Cecconi, F., Moretti, N. and Tagliabue, L.C. (2019) “Application of artificial neutral network and geographic information system to evaluate retrofit potential in public school buildings,” Renewable and Sustainable Energy Reviews, 110, pp. 266–277. Available at: https://doi.org/10.1016/j.rser.2019.04.073.

77 Nutkiewicz, A. and Jain, R.K. (no date) “Exploring the integration of simulation and deep learning models for Urban Building Energy Modeling and Retrofit Analysis,”

Building Simulation Conference proceedings [Preprint]. Available at: https://doi.org/10.26868/25222708.2019.210264.

78 Lu, W. and Feng, K. (2020) “Big-data driven building retrofitting: An integrated support vector machines and fuzzy C-means Clustering Method,” IOP Conference Series: Earth and Environmental Science, 588(4), p. 042013. Available at: https://doi.org/10.1088/1755-1315/588/4/042013.

79 Thrampoulidis, E. et al. (2021) “A machine learning-based surrogate model to approximate Optimal Building Retrofit Solutions,” Applied Energy, 281, p. 116024. Available at: https://doi.org/10.1016/j.apenergy.2020.116024.

80 Aijazi Arfa N and Glicksman Leon R (2019) “Symposium on Simulation for Architecure and Urban Design (SimAUD) ” in Application of Surrogate Modeling to Multi-Objective Optimization for Residential Retrofit Design. Atlanta GA, USA.

81 Marasco, D.E. and Kontokosta, C.E. (2016) “Applications of machine learning methods to identifying and predicting building retrofit opportunities,” Energy and Buildings, 128, pp. 431–441. Available at: https://doi.org/10.1016/j.enbuild.2016.06.092.

82 Usman Ali and Mohammad Haris Shamsi (2018) “Building Performance Analysis Conference and SimBuild,” in An Intelligent Knowledge-based Energy Retrofits Recommendation System for Residential Building at an Urban Scale.

83 von Platten, J. et al. (2020) “Using machine learning to enrich building databases—methods for tailored energy retrofits,” Energies, 13(10), p. 2574. Available at: https://doi.org/10.3390/en13102574.

84 Sharif, S.A. and Hammad, A. (2019) “Developing surrogate ann for selecting near-optimal building energy renovation methods considering energy consumption, LCC and LCA,” Journal of Building Engineering, 25, p. 100790. Available at: https://doi.org/10.1016/j.jobe.2019.100790.

85 Sharif, S.A., Hammad, A. and Eshraghi, P. (2021) “Generation of whole building renovation scenarios using variational autoencoders,” Energy and Buildings, 230, p. 110520. Available at: https://doi.org/10.1016/j.enbuild.2020.110520.

86 Kamari, A. and Peter Leslie Schultz, C. (2022) “A combined principal component analysis and Clustering Approach for exploring enormous renovation design spaces,” Journal of Building Engineering, 48, p. 103971. Available at: https://doi.org/10.1016/j.jobe.2021.103971.

87 Yuan, J., Nian, V. and Su, B. (2019) “Evaluation of cost-effective building retrofit strategies through soft-linking a metamodel-based Bayesian method and a life cycle cost assessment method,” Applied Energy, 253, p. 113573. Available at: https://doi.org/10.1016/j.apenergy.2019.113573.

88 Escandón, R. et al. (2019) “Thermal comfort prediction in a building category: Artificial Neural Network generation from calibrated models for a social housing stock in southern Europe,” Applied Thermal Engineering, 150, pp. 492–505. Available at: https://doi.org/10.1016/j.applthermaleng.2019.01.013

89 Yigit, S. (2021) “A machine-learning-based method for thermal design optimization of residential buildings in highly urbanized areas of Turkey,” Journal of Building Engineering, 38, p. 102225. Available at: https://doi.org/10.1016/j.jobe.2021.102225

90 Kamari, A., Kirkegaard, P.H. and Leslie Schultz, C.P. (2021) “Paradis - A process integrating tool for rapid generation and evaluation of holistic renovation scenarios,” Journal of Building Engineering, 34, p. 101944. Available at: https://doi.org/10.1016/j.jobe.2020.101944.

91 Mulero-Palencia, S., Álvarez-Díaz, S. and Andrés-Chicote, M. (2021) “Machine learning for the improvement of deep renovation building projects using as-built BIM models,” Sustainability, 13(12), p. 6576. Available at: https://doi.org/10.3390/su13126576.

92 Sharif, S.A. and Hammad, A. (2019) “Simulation-based multi-objective optimization of institutional building renovation considering energy consumption, life-cycle cost and life-cycle assessment,” Journal of Building Engineering, 21, pp. 429–445. Available at: https://doi.org/10.1016/j.jobe.2018.11.006.

93 Gonçalves, D. et al. (2020) “One step forward toward Smart City Utopia: Smart Building Energy Management based on adaptive surrogate modelling,” Energy and Buildings, 223, p. 110146. Available at: https://doi.org/10.1016/j.enbuild.2020.110146

94 Calama-González, C.M. et al. (2022) “Optimal Retrofit Solutions considering thermal comfort and intervention costs for the Mediterranean social housing stock,” Energy and Buildings, 259, p. 111915. Available at: https://doi.org/10.1016/j.enbuild.2022.111915.

95 Dzulkifly, S. et al. (2020) “Methodology for a large scale building internet of things retrofit,” 2020 8th International Conference on Information Technology and Multimedia (ICIMU) [Preprint]. Available at: https://doi.org/10.1109/icimu49871.2020.9243304.

96 Hu, S. et al. (2021) “Building Energy Performance Assessment Using Linked Data and cross-domain semantic reasoning,” Automation in Construction, 124, p. 103580. Available at: https://doi.org/10.1016/j.autcon.2021.103580.

97 Zhao, X. et al. (2019) “Case-based reasoning approach for supporting building Green Retrofit Decisions,” Building and Environment, 160, p. 106210. Available at: https://doi.org/10.1016/j.buildenv.2019.106210.

98 Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019). Artificial Intelligence for Decision Making in the Era of Big Data – evolution, Challenges and Research Agenda. International Journal of Information Management, 48, pp.63–71. doi:10.1016/j.ijinfomgt.2019.01.021.

99 Pazouki, M., Rezaie, K. and Bozorgi-Amiri, A. (2021) “A fuzzy robust multi-objective optimization model for building energy retrofit considering utility function: A university building case study,” Energy and Buildings, 241, p. 110933. Available at: https://doi.org/10.1016/j.enbuild.2021.110933.

100 Ruparathna, R., Hewage, K. and Sadiq, R. (2017) "Economic Evaluation of Building Energy Retrofits: A fuzzy based approach," Energy and Buildings, 139, pp. 395–406. Available at: https://doi.org/10.1016/j.enbuild.2017.01.031.

101 Mayer, Z., Volk, R. and Schultmann, F. (2022) "Analysis of financial benefits for energy retrofits of owner-occupied single-family houses in Germany," Building and Environment, 211, p. 108722. Available at: https://doi.org/10.1016/j.buildenv.2021.108722.

102 Chen, Y. et al. (2018) "Optimal control of HVAC and window systems for natural ventilation through reinforcement learning," Energy and Buildings, 169, pp. 195–205. Available at: https://doi.org/10.1016/j.enbuild.2018.03.051.

103 Westermann, P., Welzel, M. and Evins, R. (2020) "Using a deep temporal convolutional network as a building energy surrogate model that spans multiple climate zones," Applied Energy, 278, p. 115563. Available at: https://doi.org/10.1016/j.apenergy.2020.115563.

104 Rosso, F. et al. (2020) "Multi-objective optimization of building retrofit in the Mediterranean climate by means of genetic algorithm application," Energy and Buildings, 216, p. 109945. Available at: https://doi.org/10.1016/j.enbuild.2020.109945

105 Re Cecconi, F., Khodabakhshian, A. and Rampini, L. (2022) "Data-driven decision support system for Building Stocks Energy Retrofit Policy," Journal of Building Engineering, 54, p. 104633. Available at: https://doi.org/10.1016/j.jobe.2022.104633.

106 Walter, T. and Sohn, M.D. (2016) "A regression-based approach to estimating retrofit savings using the Building Performance Database," Applied Energy, 179, pp. 996–1005. Available at: https://doi.org/10.1016/j.apenergy.2016.07.087.

107 Li, X. and Yao, R. (2020) "A machine-learning-based approach to predict residential annual space heating and cooling loads considering occupant behaviour," Energy, 212, p. 118676. Available at: https://doi.org/10.1016/j.energy.2020.118676.