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Review

Artificial Neural Network Application in Construction and the Built Environment: A Bibliometric Analysis

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Abstract: Over the past decade, there has been a dramatic increase in the use of various technologies in the Architecture, Engineering, and Construction sector. Artificial intelligence has played a significant role throughout the different phases of the design and construction process. A growing body of literature recognizes the importance of artificial neural network applications in numerous areas of the construction industry and the built environment, presenting a need to explore the main research themes, attributes, benefits, and challenges. A three-step extensive research method was utilized by conducting a bibliometric search of English language articles and conducting quantitative and qualitative analyses. The bibliometric analysis aimed to identify the current research directions and gaps forming future research areas. The scientometric analysis of keywords revealed diverse areas within the construction industry linked to ANNs. The qualitative analysis of the selected literature revealed that energy management in buildings and construction cost predictions were the leading research topics in the study area. These findings recommend directions for further research in the field, for example, broadening the application ranges of ANNs in the current Construction 4.0 technologies, such as robotics, 3D printing, digital twins, and VR applications.

Keywords: artificial neural network; built environment; bibliometric analysis; scientometric analysis; energy efficiency

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1. Introduction

Over the past decade, the Architecture, Engineering, and Construction (AEC) sector has witnessed radical change due to new technologies as part of the Industry 4.0 revolution. The fourth industrial revolution is part of the "cyber-physical systems" age that includes a multitude of technologies, including the Internet of Things (IoT), robotics, blockchain systems, 3D printing, and artificial intelligence (AI) [1]. AI implies using machines to model intelligent behavior, such as reasoning, learning, and knowledge, with minimal human intervention [2]. AI is a vast computer science area, including artificial neural networks (ANNs). ANNs simulate some of the data-processing capabilities of the human brain [3]. They are systematic models that consist of a set of computational elements called neurons that are organized into layers [4]. The most frequently used architecture of ANNs consists of the input layer, which receives the data. The data are processed in the hidden layer, and the output layer produces the results [5]. They have been making considerable technological progress in several industries. They have also become a powerful tool in the construction industry. ANNs have exhibited abilities to learn through examples, identify and classify patterns in the data, and consequently deduce predictions when fed new information [6]. An advantage of these applications over traditional prediction methods is that ANNs give more accurate predictions and are proven to be original models for problem-solving and machine learning [7], ultimately becoming practical decision-support tools [8].

A considerable amount of the literature has been published regarding the application in numerous areas of the construction industry. Typical examples include achieving sustainability in the energy conservation sector [9], and prediction and estimation problems in construction [8]. Further studies have delved into the confines of cost [10] and the application of ANNs in construction materials [11], and a considerable amount of the literature has been conducted on the use of ANNs in structural analysis [12].

The applications of ANNs in the construction industry have been reviewed in the literature from specific aspects, such as the applications of ANNs in energy systems [13], the optimization of building thermal consumption [14], building energy use [15,16], the performance of building material through the use of ANNs [17], the application of ANNs in tunnel engineering [18], and the use of ANNs in construction management [19] and civil engineering [20]. However, those reviews are limited to one aspect; they do not explore the current research in applying ANNs in construction and built environments and fail to include all the grounds and knowledge areas within the built environment. Thus, the specific objectives of this bibliometric analysis are as follows:

1. A quantitative analysis identifies the critical authors and journal articles from emerging regions that have had the most significant influence on ANNs in construction and the built environment over the past two decades.
2. Identify the key growth areas in research on ANNs in the built environment.
3. Recognize the structure of the knowledge base on ANNs in the built environment.
4. Reveal the areas that need further investigation by identifying the gaps in knowledge.
5. Identify the directions of future research.

The manuscript is organized into several vital sections to provide a comprehensive overview of the application of artificial neural networks (ANNs) in the construction and built environment. Following this introduction, the Methodology section details the multi-stage critical literature review process, encompassing the data collection, quantitative analysis, and qualitative analysis. The Quantitative Analysis & Scientometrics section presents the results of the bibliometric search, highlighting the publication trends, the authorship patterns, and the influential research articles. This is followed by the Quantitative Analysis & Scientometrics section, which delves into the main research themes identified: energy management in buildings, occupant comfort, design, and construction optimization, cost prediction, health and safety, and soil mechanics. The Results section presents the findings from the quantitative and qualitative analyses, including the authorship analysis, the citation analysis, and the thematic clusters. The Discussion section synthesizes the insights from the analysis, identifies the research gaps, and suggests future research directions. The Future Perspectives section outlines the potential advancements and applications of ANNs in Construction 4.0 technologies and emphasizes the importance of extending research to developing countries and addressing model improvement challenges. Finally, the Conclusions section summarizes the key findings and highlights the transformative potential of ANNs in the construction industry.

2. Methodology: Multi-Stage Critical Literature Review

A bibliometric analysis was first introduced by [21] as it was identified as "the application of mathematical and statistical methods to books and other media of communication". This method replaced the statistical bibliography and expanded as a scientific technique for conducting scientific research [22]. This study implemented a mixed-method approach combining quantitative and qualitative research methodologies, enhancing the strengths and minimizing the weaknesses of the monomethod research [23]. The three phases of the research methodology are: (1) Data Collection, (2) Quantitative Analysis, and (3) Qualitative Analysis, as shown in Figure 1.

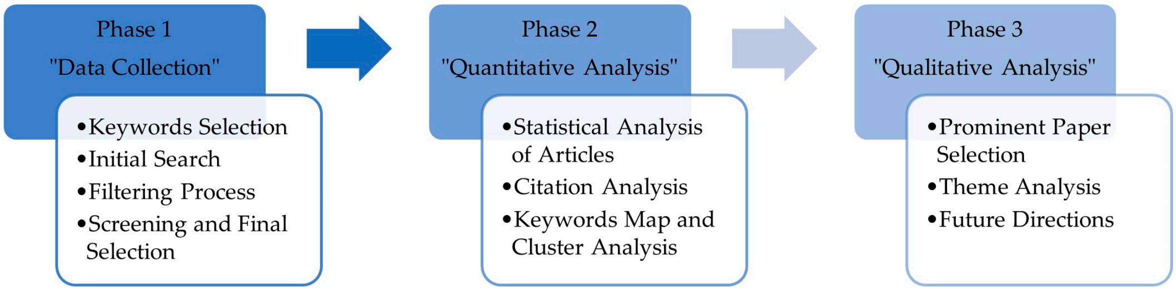

Figure 1. Phases of research methodology.

2.1. Phase 1: Data Collection

This phase started with the keyword selection. The search query used for the data collection was "(ANN OR "Artificial Neural Network" OR "Artificial Neural Networks") AND ("Building Construction" OR "Built Environment" OR ((construction OR building) AND management)) AND NOT (infrastructure)". The keywords were chosen to help focus the search on the artificial neural networks in construction and the built environment, including the planning, design, execution, construction, operation, and post-occupation phases.

The initial search was conducted using the Scopus database and resulted in 1865 documents, as displayed in Figure 2. The resulting articles were filtered by choosing the "journal" articles, excluding all the other conference papers and books to ensure the quality of the study, and limiting the search to articles in the English language, thus resulting in 1265 articles. Further manual screening was performed by reading the title and the abstract and skimming through the paper to remove the unrelated research articles. This process resulted in 689 articles saved in CSV format through the export option in Scopus, preparing the results for further statistical analysis.

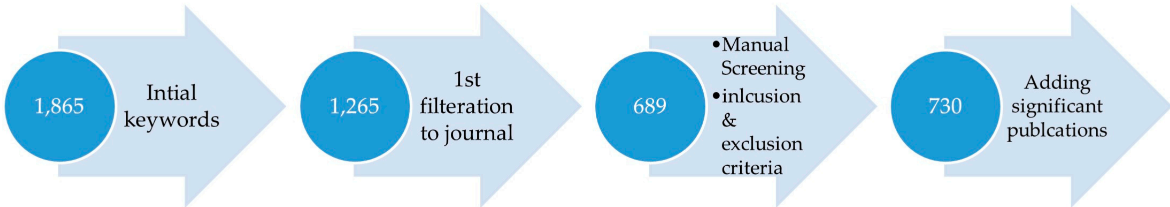

Figure 2. Keywords database results.

2.2. Phase 2: Quantitative Analysis Stage

The second phase started with applying bibliometric techniques to conduct a quantitative analysis of the 730 papers extracted from Scopus that are closely related to the application of ANN in the built environment. Bibliometric mapping was used in this section to refine the most influential articles and identify the research trends and direction. Text mining software was used to conduct a scientometric analysis. It uses bibliometric data to create knowledge maps and present new perceptions of the research area built on the previous research strengths [24]. Several data mining software tools, such as CiteSpace, Gephi, and HistCite, are available to conduct scientometric analyses. Nevertheless, VOSviewer was chosen for this study because it is widely available and most suitable for visualizing more extensive networks [25].

2.3. Phase 3: Qualitative Analysis Stage

Following the data collection and the scientometric analysis, a qualitative analysis was conducted to identify the knowledge areas in applying ANN in construction and the built environment. Gaps in knowledge were explored and identified, providing recommendations for future research.

3. Quantitative Analysis and Scientometrics

After applying the exclusion criteria described in the previous section, a quantitative analysis was performed on the skimmed 730 papers. This section introduced an overview of the publication rate within the field. A co-authors analysis, co-words analysis, and cluster analysis were performed to determine the publication frequencies and the shift in the study aims over the years. The impact analysis referred to the strengths and research gaps for future reference.

The number of articles on ANNs increased steadily until 2008. The first peak line between 2010 and 2013 refers to the development phase of the ANN's contribution to information technology beforehand [26]. Figure 3 shows an evident increase in the publication rate within the past five years (2019–2023). The volume of publications has almost doubled between 2018 and 2020.

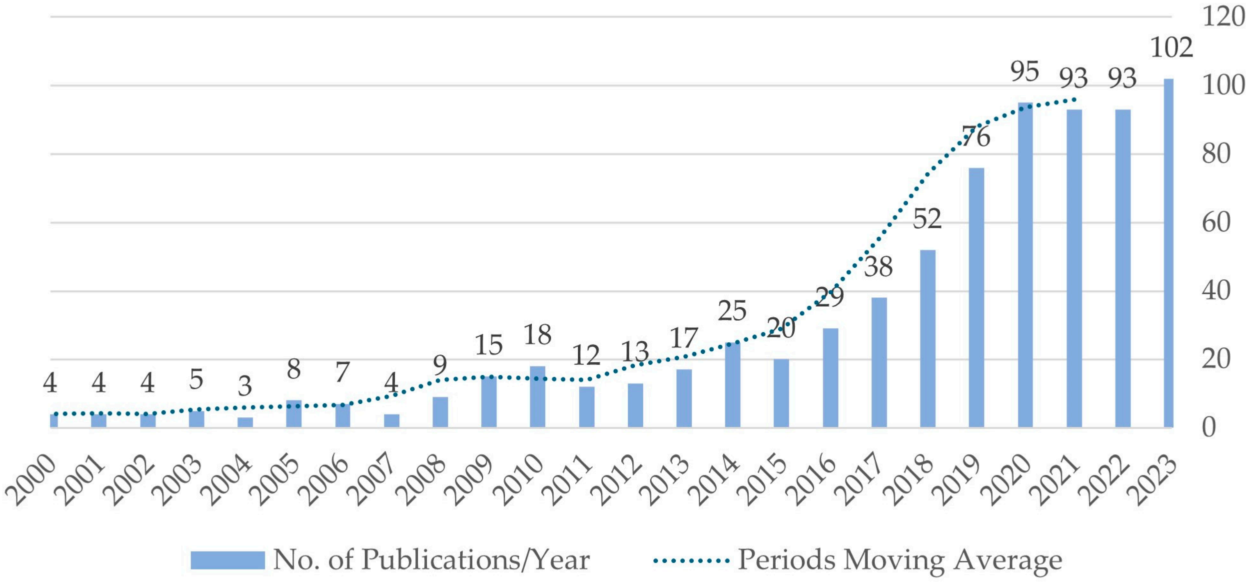

Figure 3. No. of publications per year (2000–2023).

3.1. Authorship Analysis

3.1.1. Active Countries

The geographical distribution of the research articles based on the correspondence author's country is shown in Figure 4. China leads the list with 160 publications that have over 6300 citations. This corresponds with the country's drive towards a new generation of artificial intelligence [27]. Research articles originating from the United States were cited slightly as the highest. However, China seems to be catching up on citation numbers, even though it has had this rigorous rise only after 2020. The top 20 active countries listed according to the number of publications as a bar chart with an indication of the number of citations per country are shown in Figure 5. The chart aligns the citations for these publications for the quality indication. This analysis identified China, the United States, the United Kingdom, South Korea, and India as the top five countries for publications on ANNs in construction research. Moreover, the citation numbers of quite a lower number of publications refer to the high-quality research in countries such as Australia, Canada, Malaysia, and Japan.

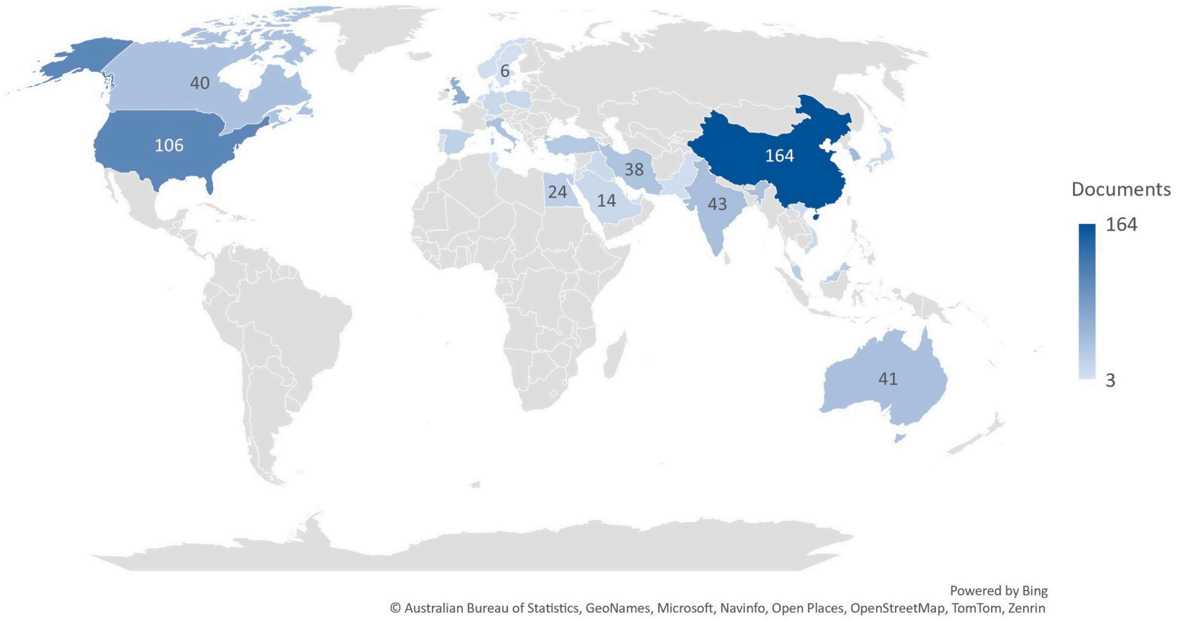

Figure 4. Mapping of publications per country.

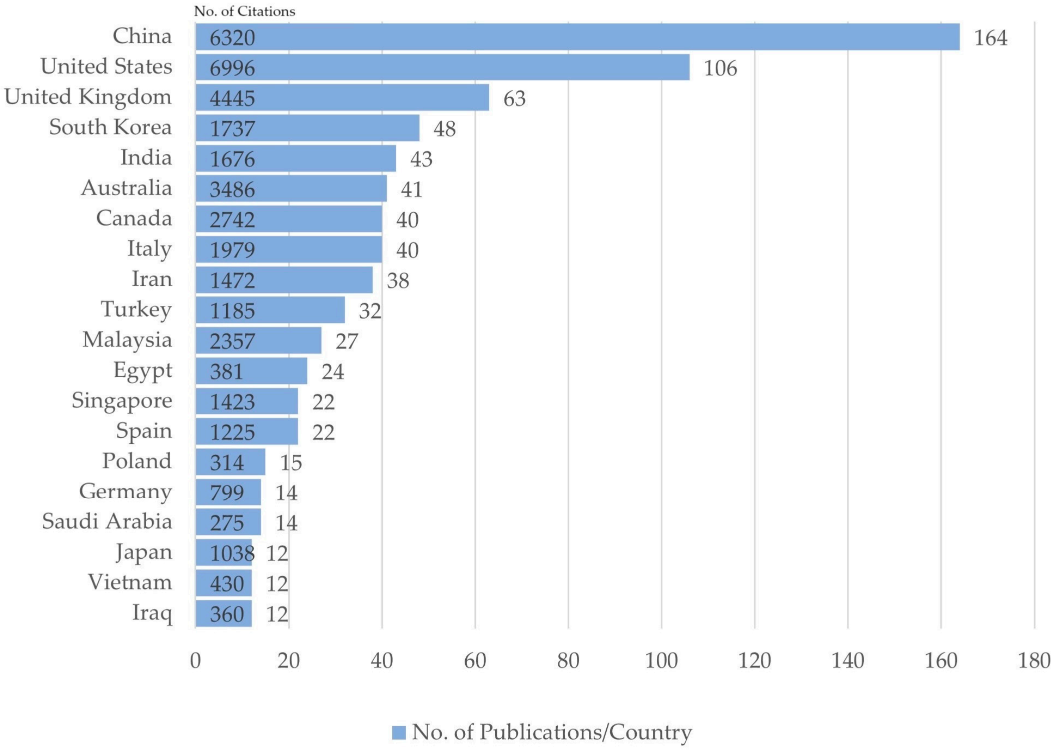

Figure 5. Number of publications and citations for the top-ranked countries.

3.1.2. Co-Authors Analysis

The co-authors analysis shows the most productive authors in the AEC sector who utilized ANNs in their applications. This table was generated through the "co-authorship analysis" in VOSviewer (Visualization for Similarities). For this analysis, the minimum number of documents per author was set to three, with a minimum citation of 100. Thirty-three authors met the thresholds. Figure 6 lists the authors with the highest citations aligned with the number of publications by each author. Yacine Rezgui tops the list with six publications spanned between 2014 and 2018 in building energy optimization and modelling [28,29]. Fariborz Haghighat is second in place with five articles but leads the race with a citation number that exceeds 1000 citations. Haghighat publications between 2009 and 2020 show a high interest in the relationship between occupant behavior, building design, and energy modelling using genetic algorithms [30,31]. In the construction management section, Mehrdad Arashpour has significant publications on predictive models for labour productivity and construction safety, costs, and automation in construction [32–34]. However, studies and reviews on the relationship between occupant behavior and energy consumption are led by Mengjie Han [35,36].

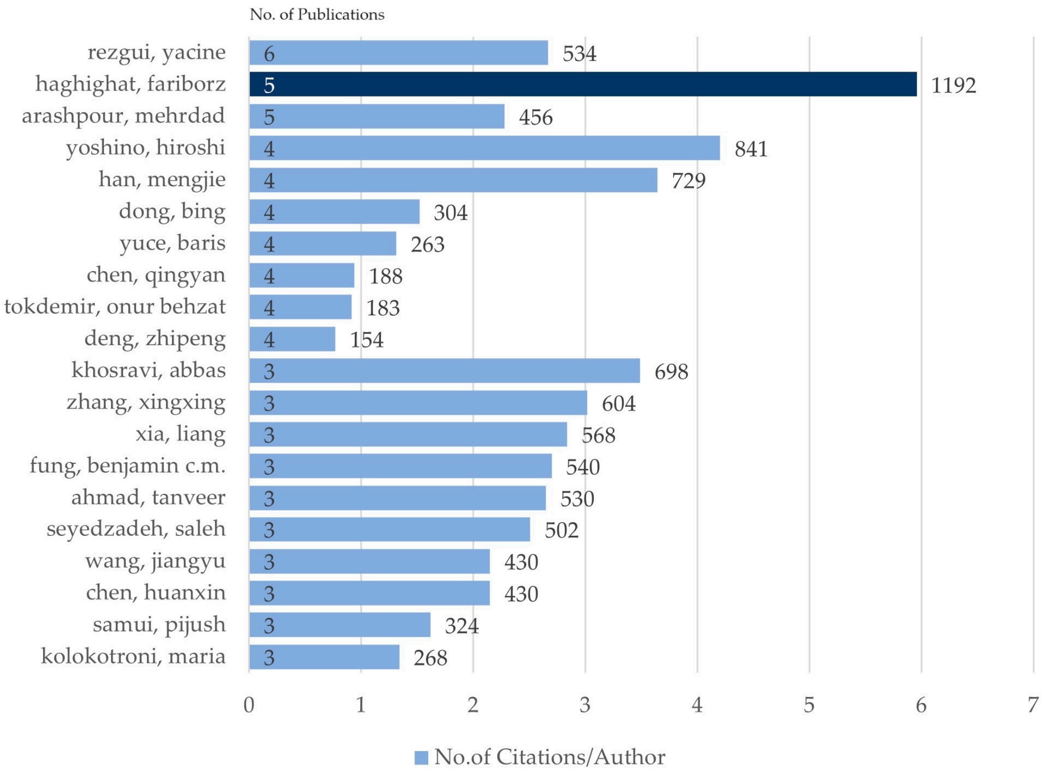

Figure 6. Highly productive and cited authors.

3.2. Citation Analysis

3.2.1. Journals Citation Analysis

The following analysis revealed the influence of the sources publishing research documents in applying ANNs in construction and the built environment. The type of analysis conducted was "citation" analysis for "sources" in VOSviewer, and the limit was set to five publications within the research topic, by which 31 journals meet the threshold. The rank of the journals according to the number of publications indicates the weight of the different applications for ANNs in the construction sector. Four out of the top six journals were energy-themed journals. The *Energy and Buildings* journal had the highest number, with an above-average 60 publications and around 5900 citations. The *Applied Energy* journal followed the lead with 27 publications. The *Building and Environment* journal represents environmental-based research, which came in third place with 26 publications and over 1790 citations. This category may not represent the largest publication number, but it has been a topic of interest since 2020. The third theme is applications within the construction and civil disciplines with two journals: the *Journal of Construction and Management* and *Automation in Construction*. The latter showed the highest impact among the list, with more than 2000 citations for only 20 publications. Figure 7 shows the list of journals ranked according to the number of publications and aligned with the number of citations for each journal.

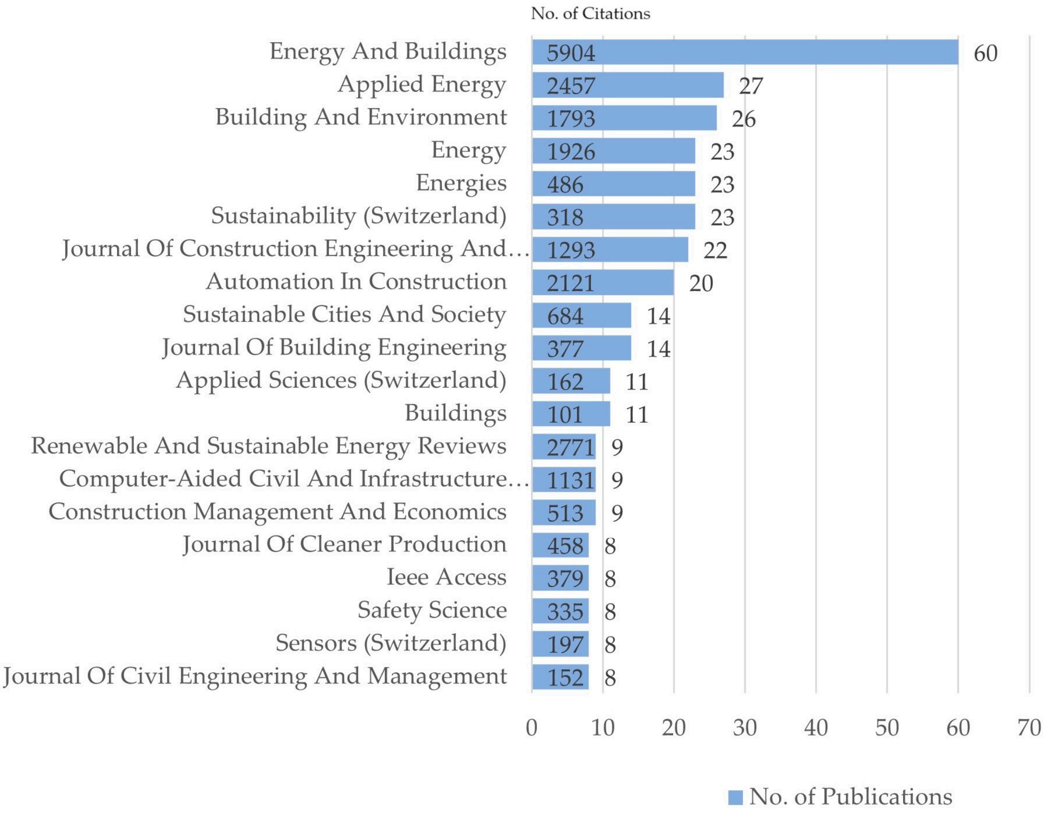

Figure 7. Analysis of the top 20 journal publications and citations for research work of ANNs in construction.

3.2.2. Articles Citation Analysis

In this section of the scientometric analysis, the top-cited articles were extracted through a "citation" analysis in VOSviewer, choosing the type as "documents" and the documents with a minimum citation of 100 as a threshold. Out of the 730 articles, 84 documents met the threshold.

Table 1 lists the top 20 cited articles. The top of the list is reviewing articles in the different fields of ANN application. Energy modelling for forecasting, prediction modelling, and demand estimations [13,36–39]. Among the list is a top-cited article [40] addressing thermal comfort and energy consumption optimization in residential buildings using ANN training for less time and significantly enhancing thermal comfort and energy consumption. Further articles worked on thermal comfort modelling and its relation to energy savings [41,42], while other studies modelled heating/cooling loads addressing the environmental parameters [43,44]. Over the years, other scholars have used ANNs in civil engineering studies with top-cited review articles by [20], leading to very advanced studies that deal with highly processed construction materials, especially concrete, as the main structural element [11].

Table 1. Top-cited articles.

References	Title	Year	Citations
[13]	A review of applications of ANN and SVM for building electrical energy consumption forecasting	2014	686
[20]	Neural networks in civil engineering: 1989–2000	2002	677
[37]	A review on artificial intelligence-based load demand forecasting techniques for smart grid and buildings	2015	653

Table 1. *Cont.*

References	Title	Year	Citations
[40]	Multi-objective optimization of building design using TRNSYS simulations, genetic algorithm, and artificial neural network	2010	532
[36]	A review of data-driven approaches for prediction and classification of building energy consumption	2018	470
[38]	A decision tree method for building energy demand modelling	2010	458
[39]	Deep learning for estimating building energy consumption	2016	432
[16]	A review of artificial intelligence-based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models	2017	407
[45]	Artificial neural networks for the prediction of the energy consumption of a passive solar building	2000	403
[41]	Neural networks based predictive control for thermal comfort and energy savings in public buildings	2012	356
[46]	Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application	2014	346
[42]	Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design	2015	314
[47]	Prediction of hourly energy consumption in buildings based on a feedback artificial neural network	2005	310
[48]	Modelling heating and cooling loads by artificial intelligence for energy-efficient building design	2014	306
[49]	Prediction of building energy consumption by using artificial neural networks	2009	301
[44]	Predicting hourly cooling load in the building: A comparison of support vector machine and different artificial neural networks	2009	301
[50]	Review on home energy management system considering demand responses, smart technologies, and intelligent controllers	2018	289
[51]	Artificial neural network model for forecasting sub-hourly electricity usage in commercial buildings	2016	286
[11]	Predicting the compressive strength of normal and high-performance concretes using ANN and ANFIS hybridized with Grey Wolf Optimizer	2020	283
[52]	Artificial neural networks for energy analysis of office buildings with daylighting	2010	249

3.3. Authors' Keywords Analysis

The final section of the scientometric analysis is the co-occurrence of author keywords to visualization essential contents of the publications [53,54]. There are two perspectives to analyze the keyword diagrams. First, there is the study of the relation between ANN as the main keyword and its different applications in the AEC sectors we are studying. This also includes studying the weight of each cluster. Another way to perceive this analysis is by studying the development of the research focus over the years using these co-occurrences.

3.3.1. Co-Occurrence Analysis

Figure 8 represents the output of the VOSviewer program for the "co-occurrence" analysis of author keywords. The following measures were taken for the inclusion and exclusion criteria of the keywords: (1) the threshold value was set at a minimum of three (hence including keywords occurring three or more times); (2) other keywords with a semantically consistent meaning were combined, for example, ANN and "Artificial Neural Network" or BIM and "Building Information Modelling". Finally, 162 keywords were shortlisted and visualized.

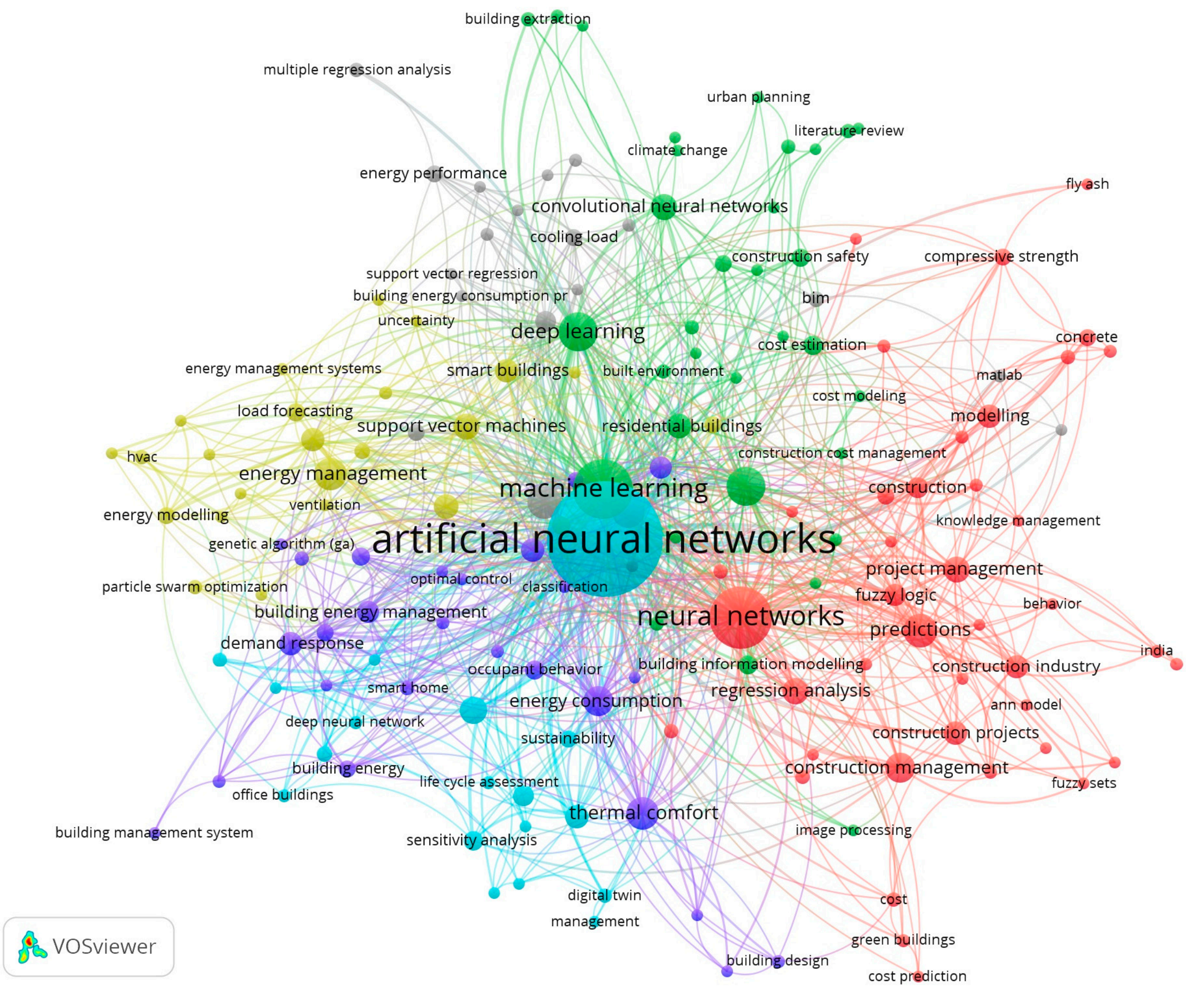

Figure 8. Co-occurrence analysis of authors' keywords.

3.3.2. Thematic Clusters

The co-occurrences mapping highlighted six clusters of keywords networked with the main keyword "Artificial Neural Networks". It gives a comprehensive overview of the research field indulged with ANNs within the AEC sector as follows:

1. Cluster one—"Red": the largest cluster has 42 keywords. It is more related to the basics of the artificial neural networks within the early years of ANN integration in the AEC section, as it refers to research themes between 2007 and 2016 [13,15]. It includes keywords related to themes such as the construction industry and numerical models for data analysis. The construction theme focuses on construction management, concrete strength analysis, demolition waste estimates, labor productivity, and personnel issues on site. The second theme includes studies that use ANN algorithms for the prediction analysis for cost, behavior, and risk assessment. It includes keywords for fuzzy logic/sets, regression analysis, decision support systems, ensemble algorithms, genetic algorithms, and the Adaptive Neuro-Fuzzy Inference System (ANFIS).
2. Cluster two—"Green": this cluster (34 keywords) has one major theme that includes the typical hierarchy of artificial intelligence, including machine learning, deep learning, and convolutional neural networks (CNNs). On the other hand, it includes a construction safety theme [55,56]. The CNN theme is connected to all computer vision, remote sensing, and semantic analysis [57–59]. CNNs are also for building/urban extraction studies, the newest study fields in urban and built environments [60,61]. The second theme is an extension of the construction industry that shifted more towards

construction safety [62,63] and cost estimations [64,65] within different project phases, not only the initial or conceptual phases.

3. Cluster three—"Blue": the cluster has three main themes: energy consumption, thermal comfort, and occupant behavior [66,67]. They are interconnected with keywords such as BMS, IoT, smart/intelligent, and homes/grid [37,68–70]. The interrelation between the three themes aligns with the significance of a holistic approach to serve each other towards adequate, sustainable, and energy-considered "building design" [71–74].
4. Cluster four—"Yellow": this cluster shows a greater focus on energy management and modelling systems based on HVAC controls. This cluster focuses on a group of algorithms such as long short-term memory (LSTM) [75], pattern recognition [76], recurrent neural networks [77], and random forest [78,79].
5. Cluster five—"Grey": the highest co-occurrence and length strength in this cluster is "energy efficiency" and then "data-driven" models. It refers to the set of publications that were published between 2018 and 2020. It ensures the track of development within this area using ML and ANN through models such as multiple regression analysis, support vector regression, and transfer learning. Thus, it helped to improve the energy models' simulation efficiency and prediction accuracy.
6. Cluster six—"Cyan": this seems to be the smallest cluster with only 18 keywords; however, it was considered the core cluster in this analysis. It includes the primary keyword ANN together with major concepts of deep neural networks, genetic algorithms, digital twins, life cycle assessment, and sustainability [80–84].

This analysis highlights the presence of energy modelling, which appears in nearly all the clusters with various weights and link strengths. Energy models are studied for estimation, optimization, efficiency, prediction, forecasting, and control, with the different controlling parameters of HVAC, heating/cooling loads, thermal comfort, occupant behavior, etc. Also, the construction and project management sector used data-driven models extensively for cost estimation and risk assessment. Finally, ANN was used in a segregated mode to study thermal comfort, life-cycle assessment, indoor air quality, building design, urban planning, and more design-based approaches.

As for the timeline study and the results of VOSviewer yearly overlay analysis, there are three main phases that represent the shift from one research focus to another, which can be presented as follows:

- (2007–2014); represents the start of the integration of the ANN models into the AEC sector depending on the numerical models for data management, analysis, and forecasting over very considered phases of the construction project feasibility study or energy consumption analysis.
- (2014–2018); the intermediate phase, which followed the evolution of the concept of the IoT and publications, appears to integrate ANN, ML, and deep learning with three main themes: demand response within smart buildings, energy models, and the integration with BMS as a complementary approach for the IoT.
- (2018–Present)In recent years, the rate of trial experiments on the various core themes mentioned has been increasing in alignment with digital transformation. There is a paradigm shift that makes use of the development of remote-sensing technologies, which impose CNN and its related applications, such as computer vision, image processing, and semantic analysis.

In conclusion, data-driven models are the core concept for many studies, whether it is mentioned or not. The change occurs within the application field or the type of data used. Construction management and project cost models are highly prevalent in early studies. In 2019, indoor air quality and life cycle assessments led the scientific platform. Then, the data-driven model was shifted again for the data acquired from real-time monitoring through different types of remote sensing into BIM and construction management.

4. Results

The data collection results and the scientometric analysis phases are the core bases for this qualitative analysis. A qualitative analysis typically requires a smaller sample than quantitative research [85,86]. A proposed approach to define the sample size for the qualitative analysis is the "rule of thumb", based on the methodological considerations and experience with similar studies [87]. Consequently, this study adopts approaches from previous research articles, setting the inclusion criteria for the qualitative analysis [88–90]. The research team performed the process manually. The selection procedure took into consideration the results of the scientometric analysis: (1) The authorship analysis for the active countries and productive authors; (2) The journals and articles citation analysis; and (3) The research clusters resulting from the co-occurrence of authors keywords.

The quantitative analysis provides an overview of the articles' quality. However, studies from different themes and different study domains have different quantitative thresholds that reflect the citation rates. Therefore, some studies with a relatively lower citation impact are manually added because they are novel ideas or trials that no one has taken the lead to construct. These studies will be presented within each cluster, defining new research gaps or proposed fields for future scientific discoveries. Another inclusion criterion was an intentional tracking of the author's research findings within the same theme. Some were added to cover the application within different typologies or the change in research methodology at different years.

As a result, among the 730 publications resulting from Phase 1, 165 articles were selected (Appendix A). The resulting articles were categorized into six themes (Figure 9): energy management in buildings, occupant comfort in buildings, health and safety in construction, cost prediction, design optimization, and soil mechanics. The categorization was developed through a unanimous agreement among the research team. Two factors were considered while determining the research themes: (1) phases of a construction project; and (2) co-occurrence mapping of the authors' keywords.

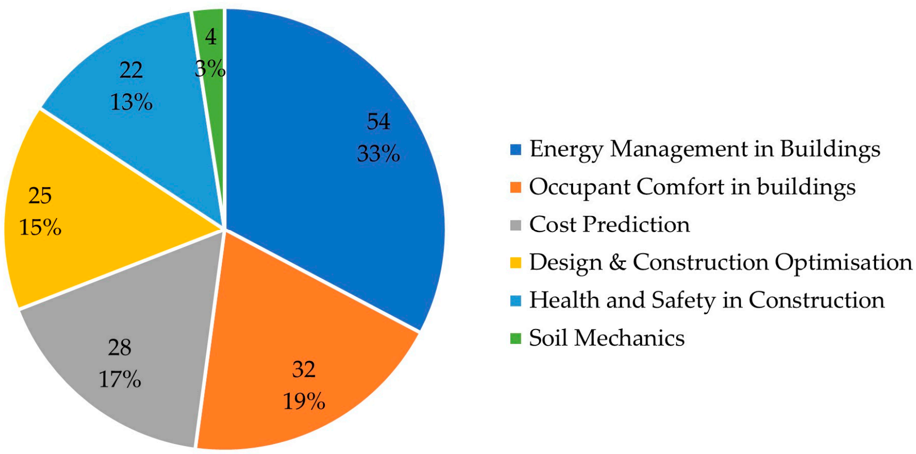

Figure 9. Number of articles included in each research category.

4.1. Energy Management in Buildings

Improving the energy performance of buildings has been a significant area of interest within the construction industry due to its importance in decreasing resource depletion and global warming [91]. Artificial intelligence in energy management in buildings was a key research area, with 33% of the chosen publications discussing this topic. The application of ANNs in energy management within buildings focuses on two areas: predicting the energy consumption of buildings during the design phase and using ANNs to model, optimize, and improve the energy performance in buildings.

4.1.1. Predicting Energy Consumption

Designing energy-efficient buildings has become essential to conserve energy, reduce emissions, and enhance occupants' quality of life [92]. Forecasting energy use in buildings is crucial in digitizing the built environment and assessing the energy-saving prospects [93]. Artificial neural networks can predict buildings' energy performance in the early design phases. They can assist architects and engineers in creating sustainable built assets [13,49]. Several studies have used ANNs to predict the energy consumption of buildings [45,94]. Studies such as [45,94,95] used energy consumption data from an office building located in Shanghai as inputs to set up three different hourly consumption prediction models (artificial neural network, support vector regression, and autoregressive integrated moving average models). The study concluded that the prediction capabilities of the ANN model were better than those of the two other models. Moreover, hourly forecasted and measured temperatures are another methodology used for energy prediction using ANNs [44,47,51]. These studies provide a high precision of prediction among the data-driven approaches.

Wei et al. [96] proposed using a blind system identification method to predict the energy consumption in office buildings based on an ANN and the number of occupants as the input. With a different approach, Bui et al. [97] examined the use of datasets obtained by monitoring the effect of a façade system and the dimensions of a building to validate a hybrid artificial neural network model. The proposed approach exhibited capabilities in forecasting the energy consumption in buildings. Refs. [98,99] developed recurrent neural network models for predicting tlectricity consumption in commercial and residential buildings. The developed neural network models performed well in medium- to long-term predictions. Dong et al. [100] specified their study for cross-laminated timber office buildings in severely cold regions. The results showed that when the number of hidden layers in an ANN exceeds five, the ANN has multiple outputs that enhance the accuracy of the energy prediction and cost consumption. The studies by [101,102] identified vital building variables that can be used for clustering to impact tnergy consumption. Deb and Lee [101] considered energy audit reports pre- and post-retrofit approaches in air-conditioned office buildings to understand their energy-saving prospects.

Further studies were conducted on office and commercial buildings [51,95,103–105], while some studies were conducted for prediction within educational settings [106,107]. Residential and hospitality buildings are considered one of the highest energy-consuming building sectors. Therefore, the energy prediction analysis is covered during the different building phases of planning [108], designing [109], construction [9,110], and post-occupation [111].

4.1.2. Improving Energy Performance

Improving the energy performance of buildings has become a critical issue, as buildings are responsible for 40% of the energy consumption. Several studies have explored the use of ANNusing ANNs to enhancemance in different types of buildings [112,113]. ANNs can include different variables and weigh them, as well as assess and provide decision-making algorithms for optimization. Studies include different variables, such as greenhouse gas emissions, indoor climate control [78], retrofitting strategies [52], and building thermal properties [114], for enhancing building energy performance. Therefore, multi-objective frameworks have been used to adapt energy modelling to the varying and interconnected variables in the building energy optimization process [115–117].

Li et al. [115] presented an optimization energy framework for residential buildings. A simple backpropagation neural network has been compared in a study by Turhan et al. [118] with a building energy simulation tool called KEP-IYTE-ESS to predict the buildings' heating load. It has been observed that ANNs have advantages over the simulation tool in terms of their simplicity, the speed of the calculations, and the ability to learn from limited numbers of datasets. Along the same lines, Rahman and Smith [98] developed a deep recurrent neural network for heating demand prediction over a medium- to longer-term horizon. Chou and Bui's [48] study addressed the same issue by constructing prediction models using 768 experimental datasets to forecast heating and cooling loads in buildings in the design stage. Ngo [92] compared cooling load predictions made through machine learning with models from physics-based energy simulations. The study demonstrated how the machine-learning model agreed with the physics-based model, thus offering a substitute for the conventional design process. Adopting a different approach, Ashouri et al. [119] focused on the impact of occupants' behavior on the energy performance of buildings. They developed a framework using multiple data-mining methods (including clustering, association rules mining, and neural networks) to unveil the possibilities of energy savings in buildings when occupants are more cautious. Some scholars directed their studies to minimize energy consumption in buildings without disturbing occupants' comfort using several optimization models (including a genetic algorithm, a neural network algorithm, and an artificial bee colony) [29,57,120,121]. Others have utilized artificial neural networks to develop decision-support systems for improving building energy efficiency [122].

Energy modelling for optimization is a common application on different typologies, which include commercial and office buildings [52,123,124]. Moreover, Refs. [121,125] performed their studies on educational buildings, while other studies were conducted in domestic settings [110,126]. Energy consumption is not constrained to single-building end uses. However, the investigation into integrated urban systems is the key to reducing consumption and coping with rapid resource depletion. Urban scale modelling is a unique study field that deals with big data and considers the efficient integration with smart grids [39,127].

Energy optimization using data-driven approaches is the most reliable solution for effective energy modelling and optimization. However, the increase in the existing frameworks adoptinghine-learning methods can provide a base for further investigation into unrecognized errors and unseen data bias for generalization [128]. Another perspective investigated generalization as a comprehensive framework in the existing literature [104,129].

The studies presented show the new possibilities of applying artificial intelligence tools in energy modelling and forecasting. Conventional methods are falling behind in their ability to process large datasets. Consequently, ANN models are answering this demand, although the comfort of occupants is also an important factor, sometimes raising a potential conflict with the energy efficiency demands. This issue of occupant comfort in buildings will be discussed in the next section.

4.2. Occupant Comfort in Buildings

Occupant comfort in buildings is essential when designing a building and plays a key role in occupants' health and productivity. Two integrated research topics emerged within this field in the overall sample of the articles. These will be discussed in the following subsections.

4.2.1. Thermal Comfort of Occupants

The first research topic that gained attention from numerous scholars was the use of ANN models to predict occupants' thermal comfort in indoor environments. This study area is essential in determining occupants' satisfaction and evaluating the building's energy consumption. However, it is challenging because it depends on tangible and intangible factors. Researchers have used ANN models to predict thermal comfort in indoor environments. They have incorporated input data on air temperature, relative humidity, and several factors concerning occupants, such as their clothing and behavior [130]. Some researchers have considered the behavioral adaptions of occupants, applying a Bayesian neural network (BNN) algorithm to predict the thermal occupant preferences using the ASHRAE Global Thermal Comfort Database II [131]. Studies have demonstrated that thermal comfort and other indoor environmental quality factors influence the performance of occupants in various settings. Alzahrani et al. [132] investigated these effects on teachers' performance in a technical college in Saudi Arabia using ANN. The study concluded that the optimum temperature for the best performance of teachers ranges between 23 and 25 °C, with a relative humidity range of 65% and a ventilation rate of 0.4 m/s.

A considerable amount of literature has addressed the issue of achieving the desired thermal comfort levels for occupants by controlling heating, ventilation, and air conditioning (HVAC) systems through deploying different neural network methods [41,42,133–139]. Building information modelling (BIM) has also been incorporated alongside ANNs in thermal comfort studies. Ma et al. [140] proposed a BIM and ANN-based system to estimate the individual thermal comfort of the occupants. The proposed system integrated thermal information into the BIM model, an approach that aims to assist designers in creating a comfortable and green indoor environment. On the other hand, Orosa et al. [141] addressed internal covering materials in buildings. A neural network procedure was trained and employed to predict indoor ambiences, thermal comfort, and energy consumption based on the permeability levels of the internal coverings. The study found that the permeable coverings required a lower energy consumption in HVAC systems during the summer to reach acceptable comfort levels. Other indoor environmental quality factors have been the focus of some studies, such as indoor air quality [142–144] and daylight illuminance [145].

The latest developments in thermography technology have allowed for further non-invasive methods to measure occupants' thermal sensations using CNNs and computer vision [146,147]. However, this novel strand of science is still way ahead of generalization and real-life application due to the complexity of the variables that undergo the ANN algorithms.

In conclusion, prediction models incorporating input variables relating to the individual thermal comfort of occupants are more likely to be implemented in new buildings as they give better predictions of the thermal comfort levels of the occupants.

4.2.2. Modelling Occupant Behavior

Several methods have been used to model occupants' presence and behavior in buildings in the past four decades [148,149]. A considerable number of these methods utilized neural networks and deep learning. Neural networks demonstrate a learning capability to identify the relationship between input signals while capturing crucial information during training [150]. Moreover, they have fault tolerance capabilities as well as pattern detection. Acharya et al. [151] integrated a BIM system with a CNN for the indoor positioning of occupants in large spaces in real-time, which would previously be time-consuming. Predicting occupant behavior is essential for design energy optimization and modelling.

Within the detection pattern of occupants in space, predicting workers' productivity in construction is of great concern for construction management efficiency and timeline alignment. The development of this sector has evolved since 2005, using AI to analyze the survey data [152] until the development of using image-based data for evaluating workers' productivity [33,153–156].

Occupant control of the heating, ventilation, and air conditioning (HVAC) systems of the indoor environment is crucial to determining the occupancy information of the building in the design stages [157]. Several studies have addressed the impact of occupant behavior on building energy consumption. Ref. [158] pointed out that occupant behavior influences the energy consumption in buildings up to over seven times. Occupancy information is vital and highly complex. Studies have proposed a generative adversarial network (GAN) framework to model building occupancy and validated the framework through real-life experiments [157]. Ref. [66] argued that occupant behavior should be accounted for when conserving energy in buildings. They used a machine-learning model to determine the heating and cooling loads in a building, using occupant behavior as a predictive variable in the model. However, some scholars observed that it is vital to consider other factors influencing occupant behavior, such as interior design, mechanical systems, and occupancy. Deng and Chen [149] considered these factors when they developed a reinforcement learning model of occupant behavior by adjusting the thermostats and clothing levels. This transfer-learning model successfully predicted occupant behavior in office and residential buildings. In an earlier study, Deng and Chen [133] implemented a behavioral ANN model when simulating the energy consumption of office buildings using the EnergyPlus software. The study concluded that thermostat setback control could reduce energy consumption by 30%. Similarly, it can be reduced by 70% with occupancy control. Along the same lines, Ashouri et al. [30] suggested that savings of up to 20% could be attained by adjusting occupants' behavior through feedback that helps them to take the proper steps to reduce energy consumption in buildings.

A broader perspective has been adopted by Dong et al. [35]. They argued that occupant behavior studies have mostly been limited to the building level and indicated that big data allow the modelling of occupant behavior at the urban scale. Based on the results of the mentioned studies, it is evident that occupant behavior in buildings considerably impacts the energy consumption of the built environment. Nevertheless, as discussed by Dong et al. [35], more precise and thorough modelling of occupant behavior can be achieved by considering other factors, such as geographical information and changes in occupant behavior.

4.3. Design & Construction Optimization

Artificial neural networks to accelerate and optimize the design process have received considerable attention from researchers in recent years. Some scholars have highlighted the aspects of optimizing the design of buildings, while others have focused on studies concerning the optimization of construction and structural materials.

4.3.1. Building Design Optimization

The optimization of buildings, in general, is concerned with pinpointing the best design for optimizing the building energy consumption from a set of alternatives. A research study examined using ANNs combined with a multi-objective genetic algorithm to optimize thermal comfort and energy consumption in a residential building [40]. This approach resulted in tens of potential building designs that have the prospect of significantly reducing energy consumption whilst improving thermal comfort. Meanwhile, Li et al. [159] addressed the uncertainties in design inputs that considerably impact building performance, specifically in subtropical regions. The study utilized an ANN model for building performance evaluation, thus reducing the computational time. In a more recent study, Hu et al. [160] investigated the aspects of optimizing the design of built and yet-to-be-built environments for human occupancy and behavior.

Building information modelling (BIM) supported the atomization of construction and building management in different aspects [161]. Demianenko and De Gaetani [162] developed a procedure for pairing BIM models to building energy models using ANNs and transfer-learning techniques to speed up the process. This method will help architects and designers predict the energy consumption in a building during the design stage. Wang et al. [163] proposed a classifying 3D model under the BIM environment using the deep belief network (DBN) to save costs. The proposed method attained good results in the 3D model classification for efficient BIM. There is potential for looking into the use of ANNs in mass construction.

4.3.2. Construction Material Optimization

With rapid urbanization, construction waste has increased considerably in several parts of the world. There is a growing body of literature that recognizes the importance of utilizing recycled aggregates in concrete production. However, it is essential to predict the properties of concrete with different components. Thus, many scholars have employed numerous methods to predict the properties of concrete. Artificial neural networks have been used to predict the compressive strength of different concrete mixtures, with a variety of additives to enhance and optimize those construction materials with older studies, such as [164–166], and more recent studies, such as [11,83,167,168]. Ref. [169] used a deep neural network with high-order neurons to predict the compressive strength of foamed concrete. The results obtained from the study can guide researchers and engineers in optimizing the design of foamed concrete. Ukrainczyk and Ukrainczyk [170] analyzed concrete durability using neural networks, and the outputs were used to aid in repairing reinforced concrete constructions.

Ferreiro-Cabello et al. [171] addressed improving the design of one-way slabs using deep-learning neural networks to reduce their environmental impact. Other scholars experimented with convolutional neural networks to predict the compressive strength of recycled aggregate concrete [172]. The results indicated the advantages of using this model, such as being more precise and efficient and having higher generalization abilities than traditional ANN models. Some studies also considered the environmental impact by reducing the concrete test's destructive impact or by testing the strengthening properties of the green concrete [173,174].

Anysz and Narloch [175] proposed a technique using ANNs to establish the precise proportions of the components that make a cement-stabilized rammed earth (CRSE) mixture. This technology utilized inorganic soil taken from construction sites and ranked the components' influence on its compressive strength with explainable artificial intelligence tools [176].

Naser [177] studied, using artificial neural networks (ANNs) and genetic programming, the effects of elevated temperatures on the properties of several construction materials, including concrete, brickwork, and different types of steel and wood.

Considerable research has been conducted to investigate different design optimization measures to improve the overall performance of buildings by minimizing energy consumption and maximizing thermal comfort. This category investigated 28 journal articles on the topic. In future studies, occupant behavior should be considered as one of the optimization factors, as this factor significantly impacts energy consumption.

4.4. Cost Prediction

Cost estimating is one of the essential steps in managing a construction project. Scholars have identified the uncertainties surrounding construction cost estimates and recognized the necessity of enhancing data-based cost-prediction models [10,178,179]. Construction costs rely on various factors, such as materials, labor, equipment, construction duration, and scheduling. Furthermore, economic fluctuations cause cost variations. These changes are usually overlooked in traditional cost estimations. Rafiei and Adeli's [180] study addressed the issue by proposing a machine-learning model for estimating construction costs, incorporating economic variables and indexes into their model. Similarly, Cheng et al. [181] proposed using an artificial intelligence model to estimate the conceptual construction costs more precisely in a study focused on estimating project costs during the planning and design stage. Accentuating the importance of decision-making in the early phases of construction projects, Koo et al. [182] proposed a CBR-based hybrid model for estimating the construction duration and cost for multifamily housing projects.

Several other scholars have proposed cost-estimate solutions for more specific types of buildings, such as high-rise buildings [183], commercial buildings [184], and residential buildings [185]. On the other hand, Tatari and Kucukvar [186] implemented a neural network model to evaluate and predict the cost premium of LEED-certified green buildings. The study unveiled relationships between the LEED's different categories, revealing that the LEED categories with the highest sensitivity in cost-premium prediction were sustainable sites and energy and atmosphere.

Several scholars have utilized these ANN model capabilities in construction cost estimation for studies specific to their countries, such as Jordan [187], Egypt [188], and Nigeria [189]. Chen and Huang [190] developed neural network models to predict the cost and duration of school reconstruction projects in Taiwan.

Much of the available literature has adopted approaches for forecasting and estimating construction costs at the conceptual design phase [74,181,182,191–195]. Few studies have been performed on building retrofitting or reconstruction [179,190,196]. However, limited research has investigated cost-management techniques in the post-contract phase of the construction process. One is a study by Omotayo et al. [8], who implemented an ANN approach to predict project managers' most applicable post-contract cost-controlling techniques. ANN application is sensitive to the input data. It has better estimation capabilities when trained with large datasets. However, when the input cost factors increase, the complexity of the ANN models increases, and the construction cost estimate accuracy decreases [65].

Hence, there is scope for improvement in ANN models regarding the number of input factors. So far, there has been little discussion on using machine learning and ANN, particularly in developing a life cycle cost assessment (LCCA). Gao and Pishdad-Bozorgi [197] proposed an applicable framework to forecast facilities' LCCA using machine-learning methods. Adopting a similar position, Alshamrani and Alshibani [198] developed a decision-support system to forecast the LCCA for educational facilities. Recently, studies have approached LCCA using an environmental impact assessment as a significant parameter for the analysis [74,185,199]. Finally, building information modelling (BIM) was also used with machine-learning algorithms to predict the construction costs [183], the net costs associated with BIM adoption [34,200], and the green building costs [201].

4.5. Health and Safety in Construction

Safety in the construction industry is an essential part of the structure's safety and durability and the well-being of the construction workers. This was the focus topic for 13% of the chosen studies in the qualitative analysis sample.

4.5.1. Safety of Workers

Yang et al. [139] used a deep learning-based classification system to measure workers' exposure to physical loads, such as pulling, pushing, and carrying materials and tools, whilst performing different construction tasks. In a similar study, Zhang et al. [202] developed a system to recognize the poor posture of workers performing manual construction tasks. The proposed system used 3D view-invariant features from a 2D camera. The data extracted from the images were then fed into a multi-stage convolutional neural network. This enables a postural ergonomic assessment and, in turn, improves workers' health and safety. For instance, the development of remote sensing and image processing accuracy allowed the precise detection of safety elements, such as checking on safety garments [55,203]. A futuristic approach that is yet to be developed is the use of unmanned aerial vehicles. This idea was adopted by Gard et al. [204] to monitor and track workers on construction sites. The paper proposed deep learning and an anthropometric plane-based workflow, which have been experimented with in a nuclear plant, showing promising tracking results.

Convolutional neural network algorithms have been used to detect workers' activities and the safety risks that may occur on-site [62,205,206]. The evolution of vision-based studies in this sector provides an opportunity for faster emergency intervention or accident prevention in construction sites [32].

4.5.2. Safety of Structures

Butcher et al. [207] focused on detecting the defects in reinforced concrete. The study relied on the data collected from actual concrete structures to train the neural networks. It aided in providing information on the electromagnetic properties of the reinforcing steel. In a similar study, Chatterjee et al. [208] experimented using a multi-objective genetic algorithm to train a neural network-based model on 150 reinforced concrete buildings to classify the structural failures in reinforced concrete. Concha and Oreta [209] investigated the effects of the corrosion of steel reinforcement on the bond strength of rebar in concrete to avoid the adverse effect that hostile environments cause on the structural health of concrete structures. The study used neural networks to model the effects of corrosion on bond strength. The model results can be used as a guide during the design stage, maintaining procedures that will prolong the service life of concrete structures. Steel structures are the least studied for damage and failure assessments since the pre-execution assessments are getting more accurate during the early design phases with advanced simulation programs. However, image-driven assessments for steel damage assessments [12].

A different study utilized ANNs to investigate structural failures due to seismic actions, such as earthquakes and floods, as they increase the vulnerability of the structures [210–212]. Abdollahzadeh et al. [213] proposed a method of simulating artificial aftershock motions based on the data obtained from trained neural networks, while Alvanitopoulos et al. [210] used neuro-fuzzy systems to train and test neural networks on the assessment of three reinforced concrete structures.

Apart from simulation models, remote sensing is also used for post-earthquake assessment, saving time and effort for direct emergency interventions [58,214]. Moreover, Zhao et al. [215] used CNNs to process images of three different urban scenes in China, Italy, and Germany to enhance image classification. The implication of such a study is the interpretation of such macro-scale urban areas for planning and disaster rescue.

A study on safety in the built environment was established to predict smoke motion via transposed convolutional neural networks [216]. The AI method proposed in the study was proven to deliver more reliable results in a shorter time, thus producing more feasible solutions for establishing fire safety in built environments. Incorporating ANNs and machine-learning methods into construction safety has received critical attention. However, most of those studies remain in the theoretical stage. Future studies should test and validate these proposed safety measures [217].

4.6. Soil Mechanics

ANNs are also used to study soil mechanics and vibrations, which affect the settlement of structures. Refs. [218,219] used the ANN method to examine the settlement rate of structures near urban tunnels. This study reported the ability to optimize the construction and operation of underground structures using neural networks. Further exploration of soil foundation interactions using methods based on ANNs was explored in the literature, particularly in structures established in cohesionless soil [220]. A recent study highlighted a new approach to predicting soil settlement underneath a housing construction project. The main advantage of the study was the proposition of a low-cost, more reliable, and faster alternative method for estimating this soil parameter through a hybrid metaheuristic-optimized neural network [221]. Then, they were used to determine structural, architectural or any other building damage. Even though ANNs have proven capabilities in tackling soil mechanics problems, as well as exhibiting very effective estimating competencies in predicting rock mass deformation [219], this was the smallest sample area, representing only 3% of the overall themes demonstrating the use of ANNs in the construction industry.

5. Discussion

In recent years, researchers have shown an increased interest in applying ANNs in various areas of the AEC industry. ANNs exhibit high capabilities in pattern detection, numeric processing, the analysis of large datasets, and decision-making. The main application categories that emerged in this study represent the areas of construction and the built environment in which these ANN capabilities have been most helpful. This research also identified the critical articles, countries, sources, and co-authors in the existing body of literature. The co-occurrence of author keywords analysis conducted in Section 3 revealed that energy management in buildings, cost estimates, occupant comfort in buildings, and building design optimization are themes that have witnessed a growing academic interest in recent years. At the same time, topics such as ANN applications within the safety in construction and soil mechanics are less common.

Based on the thematic review and the findings derived from the scientometric analyses, it is recommended that future research be targeted in the following directions:

5.1. Broadening the Application Ranges of ANN into the Current Construction 4.0 Technologies

The co-occurrence of author keywords analysis (Figure 8) indicates that the existing literature has investigated the application of ANNs in Construction 4.0 technologies, such as building information modelling, GIS, and IoT. It is suggested that future researchers explore the other technological aspects of Construction 4.0, particularly in the following fields:

- Robotics: To date, limited research has addressed artificial intelligence applications in robotics and automated systems in construction. It is a fertile area for future study as ANNs exhibit capabilities such as adaptive learning, pattern recognition, and real-time operation [26]. These ANN capabilities can help to develop advanced robotic systems to perform several tasks in the construction industry. The findings derived from the scientometric analysis suggest a lack of studies addressing and assessing the risks faced by construction workers. Section 4.5 in the qualitative analysis shows how the safety of workers in construction sites is monitored using ANN applications, with a need for studies on using these applications in robotic systems that can replace workers in performing arduous and dangerous tasks.
- 3D Printing: Another possible area of future research would be to investigate applying ANN in 3D printing due to its capability to process large datasets and its powerful computational ability. 3D printing technology has more potential for application with BIM development [222]. Although this technology is still in its infancy in the construction industry, it would be interesting to investigate the association between ANNs and BIM technology to produce 3D-printed buildings from a BIM model in future studies.
- Digital Twins: Digital twins are identified as a "digital copy of a physical asset, collecting real-time data from the asset and deriving information not being measured directly in the hardware" [223]. This is a potentially abundant research area as the models of existing structures can be enriched dynamically by incorporating the capabilities of ANNs into training existing building data linked with real-time IoT data. Also, the current shift from building-centered to human-centered approaches adds more complexity to the application capabilities of this technology [224].
- VR Applications: Future studies can explore the combined advantages of machine learning and VR applications to develop an intelligent system that assists in various tasks in the construction industry to improve design and safety.

5.2. Constructing ANN Applications Research in Developing Countries

Based on the active countries analysis in the scientometric analysis (Figure 5), 13 of the top 30 active countries are developed or high-income countries (i.e., the United States, United Kingdom, South Korea, and Australia). Therefore, researchers may need to extend their applications to developing countries, enhance the existing body of knowledge, and define the limitations of the application in these contexts.

5.3. Potential Areas for Improvement in the Application of Neural Networks

The findings of the qualitative analysis in Section 4 also point to the need to address potential improvements in the development and application of neural networks in future studies in the following aspects:

- Prevention of overestimation in ANNs: a limitation of developing ANN models is that ANNs build the models automatically after being fed raw data. This leads to the potential risk of overestimation due to the pseudorandom nature of trained datasets [225]. Further research areas can delve into the avoidance of overestimation.
- Selection of datasets: an additional weakness is the selection of adequate training datasets. Future studies, including dataset inclusion criteria, would be worthwhile.

6. Future Perspectives

This study adopted a science-mapping approach to comprehensively review the literature that focused on applying artificial neural networks in construction and the built environment. Over 700 journal articles were extracted from the Scopus database and further analyzed quantitatively. A qualitative analysis was conducted on 165 of the 730 articles, identifying six main themes and areas of research. Furthermore, this research outlined the future directions of ANNs in construction and built environment research, as displayed in Figure 10. The fundamental points of the analysis on the future directions were as follows:

1. Broadening the application ranges of ANN into the current Construction 4.0 technologies, such as robotics, 3D printing, digital twins, and VR applications.
2. Constructing ANN applications research in developing countries.
3. Potential for improving Neural Networks through the prevention of overestimation in ANNs. The selection criteria of datasets and further research into the "white box model".

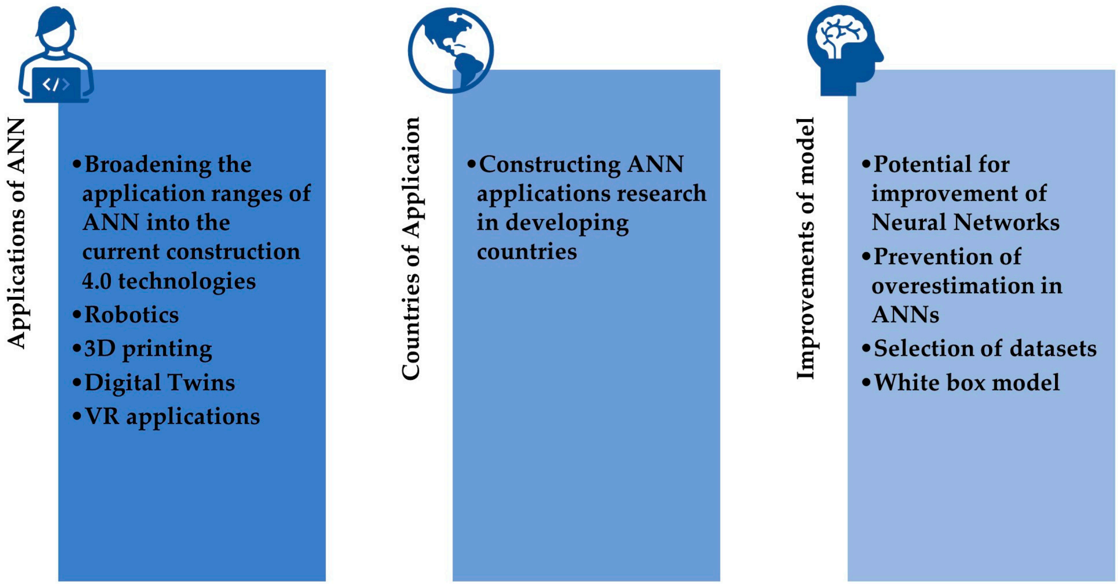

Figure 10. Summary of future directions.

6.1. Theoretical Implications

This thorough bibliometric analysis on the applications of ANN in construction and the built environment identified evolving themes to help future researchers. First, the study examined the general features of the literature, showing the key contributors in terms of countries, sources, and top-cited articles. Second, the clustering of the key thematic areas in Section 3.3 provided insight into the structure of the ANN research by dividing the field into six clusters (Figure 8). It indicated connections between subfields, such as a strong connection between the building energy performance, the energy efficiency with occupant behaviors, and thermal comfort. It also presented clusters with detailed research on the building design and energy efficiency and clusters with an emerging scope, such as decision-support systems and indoor air quality. Furthermore, Section 4 presented a detailed qualitative thematic analysis highlighting the main areas of study and their respective subareas. Thus, future researchers can understand the current state of applying ANN in studies relating to the construction industry.

6.2. Practical Implications

This analysis offers a viewpoint on the various emerging themes and topics published in the past two decades on ANN applications in the construction industry and the built environment. ANN applications have proven to be helpful within the construction industry, from offering more sustainable design options for buildings and predicting and preventing cost overruns to incorporating ANNs and machine learning into construction safety. With the current move towards the digital age, industry leaders and practitioners are embracing Construction 4.0 and the accompanying technologies. This study motivates firms to invest in implementing innovative construction technologies supported by ANN applications to attain a competitive advantage through time and money savings, increasing sustainability and improving site safety. Architectural firms are encouraged to implement design optimization techniques to plan and design buildings and infrastructure efficiently. The adoption of accurate cost estimating will prevent cost overruns. ANNs can improve construction site safety and the durability of the structures. The methodology adopted in this study for conducting the bibliometric analysis can be customized to the needs of researchers and development teams in construction companies to attain relevant documents to be used as checkpoints when conducting industry research.

7. Conclusions

This comprehensive bibliometric analysis highlights the significant advancements and emerging trends in applying artificial neural networks (ANNs) within the construction and built environment sectors. Through a meticulous review of over 700 journal articles, our study has identified key research themes, influential authors, and the geographical distribution of contributions, providing a detailed landscape of the current state of ANN research in these fields. One of the limitations of this review is that it only focused on articles in the English language.

The findings reveal that ANN applications predominantly focus on energy management, occupant comfort, design optimization, cost prediction, health and safety, and soil mechanics. The use of ANNs has shown promising results in enhancing building energy efficiency, predicting costs more accurately, improving thermal comfort, and optimizing construction materials and processes. These applications underscore the potential of ANNs to address complex problems in the AEC sector, offering superior prediction capabilities and robust decision-support systems.

Despite these advancements, several research gaps and challenges remain. The analysis indicates a need to expand the application of ANNs into current Construction 4.0 technologies, such as robotics, 3D printing, digital twins, and VR applications. Additionally, there is a significant opportunity to extend ANN research to developing countries, ensuring a more global and inclusive approach to technological advancements. Furthermore, addressing the issues related to preventing overestimation in ANN models, selecting adequate training datasets, and improving model generalization are critical areas for future research.

The study also identified the need for further investigation into specific themes, such as construction safety and soil mechanics, which have received less attention than other areas. Moreover, integrating ANNs with emerging technologies, such as IoT and BIM, holds considerable potential for further research and practical applications.

In conclusion, ANNs offer transformative potential in the construction and built environment sectors, driving innovation, sustainability, and efficiency. Future research can significantly contribute to the construction industry's digital transformation, enhancing project performance and safety by addressing the identified research gaps and broadening the scope of ANN applications. The insights provided by this study serve as a valuable foundation for researchers and practitioners aiming to harness the full potential of ANNs in the AEC sector. This work paves the way for future studies to build on these findings, fostering the continued evolution and integration of ANNs into the construction and built environment industries.

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Appendix A

The following table is the list of documents that were selected for the qualitative analysis (Section 3). Each theme is classified into subcategories of research areas.

Table A1. List of documents for the qualitative analysis for each theme.

Energy Management in Buildings			
No.	**Title**	**Year**	**Subcategory**
1	A Comparative Analysis of Data-Driven Based Optimization Models for Energy-Efficient Buildings	2020	Improving Energy Performance
2	A comprehensive method for optimizing the design of a regular architectural space to improve building performance	2021	
3	A decision tree method for building energy demand modelling	2010	
4	A study on energy performance of 30 commercial office buildings in Hong Kong	2017	
5	A zone-level, building energy optimization combining an artificial neural network, a genetic algorithm, and model predictive control	2018	
6	Accuracy of different machine learning algorithms and added-value of predicting aggregated-level energy performance of commercial buildings	2020	
7	An ANN-GA Semantic Rule-Based System to Reduce the Gap Between Predicted and Actual Energy Consumption in Buildings	2017	
8	An original tool for checking energy performance and certification of buildings by means of Artificial Neural Networks	2014	
9	ANN-GA smart appliance scheduling for optimized energy management in the domestic sector	2016	
10	Artificial neural network-based decision support system for development of an energy-efficient built environment	2018	
11	Artificial neural networks for energy analysis of office buildings with daylighting	2010	
12	Attention-based interpretable neural network for building cooling load prediction	2021	
13	Comparative study of a building energy performance software (KEP-IYTE-ESS) and ANN-based building heat load estimation	2014	
14	Data-Driven Building Energy Modelling—Generalization Potential of Energy Signatures Through Interpretable Machine Learning	2022	
15	Data-driven model predictive control using random forests for building energy optimization and climate control	2018	
16	Deep learning for estimating building energy consumption	2016	
17	Development of a ranking procedure for energy performance evaluation of buildings based on occupant behavior	2019	
18	Early Phases predicting cooling loads for energy-efficient design in office buildings by machine learning	2019	
19	Energy performance forecasting of residential buildings using fuzzy approaches	2020	
20	Fault detection analysis using data mining techniques for a cluster of smart office buildings	2015	
21	Machine learning modelling for predicting non-domestic buildings energy performance: A model to support deep energy retrofit decision-making	2020	
22	Modelling heating and cooling loads by artificial intelligence for energy-efficient building design	2014	

Table A1. *Cont.*

Energy Management in Buildings			
No.	**Title**	**Year**	**Subcategory**
23	Modelling the energy performance of residential buildings using advanced computational frameworks based on RVM, GMDH, ANFIS-BBO and ANFIS-IPSO	2021	Improving Energy Performance
24	More Buildings Make More Generalizable Models—Benchmarking Prediction Methods on Open Electrical Meter Data	2019	
25	Multi-Objective Optimization for Energy Performance Improvement of Residential Buildings: A Comparative Study	2017	
26	Predicting heating demand and sizing a stratified thermal storage tank using deep learning algorithms	2018	
27	Predicting hourly cooling load in the building: A comparison of support vector machine and different artificial neural networks	2009	
28	Prediction of building's temperature using neural networks models	2006	
29	Short-Term Forecasting of Heat Demand of Buildings for Efficient and Optimal Energy Management Based on Integrated Machine Learning Models	2020	
30	Systematic approach to provide building occupants with feedback to reduce energy consumption	2020	
31	The London Heat Island and building cooling design	2007	
32	Usability evaluation of a web-based tool for supporting holistic building energy management	2017	
33	A data-driven interval forecasting model for building energy prediction using attention-based LSTM and fuzzy information granulation	2022	Predicting Energy Consumption
34	A hybrid model for building energy consumption forecasting using long short-term memory networks	2020	
35	A long short-term memory artificial neural network to predict daily HVAC consumption in buildings	2020	
36	An artificial neural network (ANN) expert system enhanced with the electromagnetism-based firefly algorithm (EFA) for predicting the energy consumption in buildings	2020	
37	Artificial neural network for assessment of energy consumption and cost for cross laminated timber office building in severe cold regions	2018	
38	Artificial neural network model for forecasting sub-hourly electricity usage in commercial buildings	2016	
39	Artificial neural networks for the prediction of the energy consumption of a passive solar building	2000	
40	Determining key variables influencing energy consumption in office buildings through cluster analysis of pre- and post-retrofit building data	2018	
41	Energy consumption predicting model of VRV (Variable refrigerant volume) system in office buildings based on data mining	2016	
42	Estimating building energy consumption using extreme learning machine method	2016	
43	Forecast electricity demand in commercial building with machine learning models to enable demand response programs	2022	
44	Forecasting energy demand of PCM integrated residential buildings: A machine learning approach	2023	
45	Forecasting peak energy demand for smart buildings	2021	
46	Hourly energy consumption prediction of an office building based on ensemble learning and energy consumption pattern classification	2021	
47	Improving consumption estimation of electrical materials in residential building construction	2016	
48	Measuring energy consumption efficiency of the construction industry: The case of China	2015	

Table A1. *Cont.*

Energy Management in Buildings			
No.	**Title**	**Year**	**Subcategory**
49	Modelling energy consumption in residential buildings: A bottom-up analysis based on occupant behavior pattern clustering and stochastic simulation	2017	Predicting Energy Consumption
50	Prediction of building energy consumption by using artificial neural networks	2009	
51	Prediction of hourly energy consumption in buildings based on a feedback artificial neural network	2005	
52	Prediction of occupancy level and energy consumption in office building using blind system identification and neural networks	2019	
53	Vector field-based support vector regression for building energy consumption prediction	2019	
54	Visualized strategy for predicting buildings energy consumption during Early Phases design stage using parametric analysis	2017	
Occupant Comfort in buildings			
No.	**Title**	**Year**	**Subcategory**
55	A machine-learning-based approach to predict residential annual space heating and cooling loads considering occupant behavior	2020	Modelling Occupant Behavior
56	BIM-PoseNet: Indoor camera localization using a 3D indoor model and deep learning from synthetic images	2019	
57	Building occupancy modelling using generative adversarial network	2018	
58	Development and comparative analysis of the fuzzy inference system-based construction labor productivity models	2023	
59	Engineering Approach Using ANN to Improve and Predict Construction Labor Productivity under Different Influences	2017	
60	Machine learning for occupant-behavior-sensitive cooling energy consumption prediction in office buildings	2021	
61	Modelling occupant behavior in buildings	2020	
62	Occupant behavior modelling methods for resilient building design, operation, and policy at urban scale: A review	2021	
63	Opportunistic occupancy-count estimation using sensor fusion: A case study	2019	
64	Predicting the construction labor productivity using artificial neural network and grasshopper optimization algorithm	2023	
65	Reinforcement learning of occupant behavior model for cross-building transfer learning to various HVAC control systems	2021	
66	Simulating the impact of occupant behavior on energy use of HVAC systems by implementing a behavioral artificial neural network model	2019	
67	Applying Artificial Neural Networks for Measuring and Predicting Construction-Labor Productivity	2015	
68	A building information model (BIM) and artificial neural network (ANN) based system for personal thermal comfort evaluation and energy efficient design of interior space	2019	Thermal Comfort of Occupants
69	A novel method based on neural networks for designing internal coverings in buildings: Energy saving and thermal comfort	2019	
70	Adaptive behavior and different thermal experiences of real people: A Bayesian neural network approach to thermal preference prediction and classification	2021	
71	Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design	2015	
72	Artificial neural network analysis of teachers' performance against thermal comfort	2021	
73	Artificial neural network for the thermal comfort index prediction: Development of a new simplified algorithm	2020	

Table A1. *Cont.*

Occupant Comfort in buildings			
No.	**Title**	**Year**	**Subcategory**
74	Artificial neural network models using thermal sensations and occupants' behavior for predicting thermal comfort	2018	Thermal Comfort of Occupants
75	Automated classification of indoor environmental quality control using stacked ensembles based on electroencephalograms	2020	Thermal Comfort of Occupants
76	Comparative performance of machine learning algorithms in the prediction of indoor daylight illuminances	2020	
77	Data driven indoor air quality prediction in educational facilities based on IoT network	2021	
78	Development and application of linear ventilation and temperature models for indoor environmental prediction and HVAC systems control	2019	
79	Fast prediction for multi-parameters (concentration, temperature, and humidity) of indoor environment towards the online control of HVAC system	2021	
80	Indoor environmental quality evaluation of lecture classrooms in an institutional building in a cold climate	2019	
81	Infrared infused cicion-based	2022	
82	Model predictive control with adaptive machine-learning-based model for building energy efficiency and comfort optimization	2020	
83	Neural networks based predictive control for thermal comfort and energy savings in public buildings	2012	
84	Temperature-preference learning with neural networks for occupant-centric building indoor climate controls	2019	
85	Thermal comfort prediction in a building category: Artificial neural network generation from calibrated models for a social housing stock in southern Europe	2019	
86	Toward contactless human thermal monitoring: A framework for Machine Learning-based human thermo-physiology modelling augmented with computer vision	2023	
Occupant Comfort in buildings			
No.	**Title**	**Year**	**Subcategory**
87	A neural network approach to predicting the net costs associated with BIM adoption	2020	BIM adoption
88	Construction Cost Prediction Based on Genetic Algorithm and BIM	2020	
89	Developing an Integrative Data Intelligence Model for Construction Cost Estimation	2022	
90	Forecasting the net costs to organizations of building information modelling (BIM) implementation at different levels of development (LOD)	2019	
91	A CBR-based hybrid model for predicting a construction duration and cost based on project characteristics in multi-family housing projects	2010	Early Phases
92	A computer-based cost prediction model for institutional building projects in Nigeria an artificial neural network approach	2014	
93	A hybrid approach for a cost estimate of residential buildings in Egypt at the Early Phases stage	2020	
94	A model utilizing the artificial neural network in cost estimation of construction projects in Jordan	2021	
95	A neural network approach for Early Phases cost estimation of structural systems of buildings	2004	
96	Conceptual estimation of construction costs using the multistep ahead approach	2016	
97	Efficient estimation and optimization of building costs using machine learning	2023	
98	Improved similarity measure in case-based reasoning: a case study of construction cost estimation	2020	

Table A1. *Cont.*

Occupant Comfort in buildings			
No.	**Title**	**Year**	**Subcategory**
99	Investment decision management: Prediction of the cost and period of commercial building construction using artificial neural network	2011	Early Phases
100	Neural Network-Based Model for Predicting Preliminary Construction Cost as Part of Cost Predicting System	2020	
101	Predicting construction cost and schedule success using artificial neural networks ensemble and support vector machines classification models	2012	
102	Web-based conceptual cost estimates for construction projects using Evolutionary Fuzzy Neural Inference Model	2009	
103	Cost premium prediction of certified green buildings: A neural network approach	2011	Environmental Impact Assessment
104	Environmental impacts cost assessment model of residential building using an artificial neural network	2021	
105	A framework of developing machine learning models for facility life-cycle cost analysis	2020	LCA
106	Extreme Gradient Boosting-Based Machine Learning Approach for Green Building Cost Prediction	2022	
107	Life cycle environmental and cost assessment of prefabricated components manufacture	2023	
108	Multi-objective optimization of building design for life cycle cost and CO_2 emissions: A case study of a low-energy residential building in a severe cold climate	2022	
109	An artificial neural network approach to predicting most applicable post-contract cost controlling techniques in construction projects	2020	Post-contract
110	Application of artificial neural network methodology for predicting seismic retrofit construction costs	2014	Reconstruction
111	Approximately predicting the cost and duration of school reconstruction projects in Taiwan	2006	
112	Predicting cost deviation in reconstruction projects: Artificial neural networks versus regression	2003	
113	Construction cost prediction model for conventional and sustainable college buildings in North America	2017	
114	Novel Machine-Learning Model for Estimating Construction Costs Considering Economic Variables and Indexes	2018	

Design & Construction Optimization			
No.	**Title**	**Year**	**Subcategory**
118	Modelling the confined compressive strength of hybrid circular concrete columns using neural networks	2011	Building Design Optimization
119	Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application	2014	
120	Multi-objective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network	2010	
121	On-demand monitoring of construction projects through a game-like hybrid application of BIM and machine learning	2020	
122	Predicting Crowd Egress and Environment Relationships to Support Building Design Optimization	2020	
123	Robust optimal design of zero/low energy buildings considering uncertainties and the impacts of objective functions	2019	
124	A neural network method for analyzing concrete durability	2008	Construction material optimization
125	An artificial neural network approach for prediction of long-term strength properties of steel fiber reinforced concrete containing fly ash	2008	

Table A1. *Cont.*

Design & Construction Optimization			
No.	**Title**	**Year**	**Subcategory**
126	ANN-Python prediction model for the compressive strength of green concrete	2023	
127	Artificial neural networks in classification of steel grades based on non-destructive tests	2020	Construction material optimization
128	Compressive strength prediction of recycled concrete based on deep learning	2018	
129	Concrete compressive strength prediction using the imperialist competitive algorithm	2018	
130	Deep belief network-based 3D models classification in building information modelling	2015	
131	Deep neural network with high-order neuron for the prediction of foamed concrete strength	2019	
132	Designing the composition of cement stabilized rammed earth using artificial neural networks	2019	
133	Feature importance of stabilized rammed earth components affecting the compressive strength calculated with explainable artificial intelligence tools	2020	
134	Metamodel-based design optimization of structural one-way slabs based on deep learning neural networks to reduce environmental impact	2018	
135	Predicting concrete compressive strength using hybrid ensembling of surrogate machine learning models	2021	
136	Predicting the compressive strength of normal and High-Performance Concretes using ANN and ANFIS hybridized with Grey Wolf Optimizer	2020	
137	Predicting the core compressive strength of self-compacting concrete (SCC) mixtures with mineral additives using artificial neural network	2011	
138	Prediction of concrete compressive strength: Research on hybrid models genetic based algorithms and ANFIS	2014	
139	Properties and material models for common construction materials at elevated temperatures	2019	
Health & Safety in Construction			
No.	**Title**	**Year**	**Subcategory**
140	A machine learning-based prediction and analysis of flood affected households: A case study of floods in Bangladesh	2019	Safety of structures
141	Application of the Artificial Neural Network for Predicting Mainshock-Aftershock Sequences in Seismic Assessment of Reinforced Concrete Structures	2021	
142	Defect detection in reinforced concrete using random neural architectures	2014	
143	Evolutionary learning based sustainable strain sensing model for structural health monitoring of high-rise buildings	2017	
144	Fusing damage-sensitive features and domain adaptation towards robust damage classification in real buildings	2023	
145	Image-driven structural steel damage condition assessment method using deep learning algorithm	2019	
146	Integration of super-pixel segmentation and deep-learning methods for evaluating earthquake-damaged buildings using single-phase remote sensing imagery	2020	
147	Investigation of the effects of corrosion on bond strength of steel in concrete using neural network	2021	
148	Neuro-fuzzy techniques for the classification of earthquake damages in buildings	2010	
149	Object-Based Convolutional Neural Network for High-Resolution Imagery Classification	2017	
150	Operational earthquake-induced building damage assessment using CNN-based direct remote sensing change detection on superpixel level	2022	
151	Smart performance-based design for building fire safety: Prediction of smoke motion via AI	2021	

Table A1. *Cont.*

Health & Safety in Construction			
No.	**Title**	**Year**	**Subcategory**
152	Structural failure classification for reinforced concrete buildings using trained neural network based multi-objective genetic algorithm	2017	Safety of structures
153	Accident Analysis for Construction Safety Using Latent Class Clustering and Artificial Neural Networks	2020	Safety of workers
154	Construction Safety Risk Model with Construction Accident Network: A Graph Convolutional Network Approach	2022	
155	Convolutional neural networks: Computer vision-based workforce activity assessment in construction	2018	
156	Deep learning-based classification of work-related physical load levels in construction	2020	
157	Detecting safety helmet wearing on construction sites with bounding-box regression and deep transfer learning	2021	
158	Enhancing construction safety: Machine learning-based classification of injury types	2023	
159	Ergonomic posture recognition using 3D view-invariant features from single ordinary camera	2018	
160	Prediction of engineering performance: A neuro-fuzzy approach	2005	
161	Research on Safety Helmet Detection Algorithm Based on Improved YOLOv5s	2023	
Soil Mechanics			
No.	**Title**	**Year**	
162	A fuzzy-neural network method for modelling uncertainties in soil-structure interaction problems	2003	
163	A new approach of hybrid bee colony optimized neural computing to estimate the soil compression coefficient for a housing construction project	2019	
164	Assessment of optimum settlement of structure adjacent urban tunnel by using neural network methods	2013	
165	Prediction of Soil Deformation in Tunnelling Using Artificial Neural Networks	2016	

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