applied sciences

MDPI

Review

Artificial Intelligence in the Construction Industry: Main Development Trajectories and Future Outlook

Hsiu-Ping Chen [1,2] and Kuo-Ching Ying [1,*]

1 Department of Industrial Engineering and Management, National Taipei University of Technology, Taipei 10608, Taiwan; t109379006@ntut.edu.tw
2 H&K Consulting Engineers, Taipei 10060, Taiwan
* Correspondence: kcying@ntut.edu.tw; Tel.: +886-2-2771-2171

Abstract: Recent developments in artificial intelligence (AI) have greatly influenced progress in various industries. While the complexity of the construction industry makes it an essential and potential area for AI applications, there has been no analysis conducted on the main development paths for the applications of AI technologies in the construction industry. To fill this gap, this study applied the main path analysis method to investigate the evolution of AI technologies in the construction industry. This study analyzed 587 articles published between 1989 and 2021 to identify the main development trajectories of AI technologies in the construction industry and to suggest possible directions in which AI technologies can be further applied to promote progress in architectural design, engineering design, and construction services.

Keywords: artificial intelligence; construction industry; main path analysis; systematic literature review

check for updates

Citation: Chen, H.-P.; Ying, K.-C. Artificial Intelligence in the Construction Industry: Main Development Trajectories and Future Outlook. *Appl. Sci.* **2022**, *12*, 5832. https://doi.org/10.3390/app12125832

Academic Editors: Andrea Prati and Arcangelo Castiglione

Received: 15 April 2022
Accepted: 6 June 2022
Published: 8 June 2022

1. Introduction

Artificial intelligence (AI) can be defined as the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. When the computer was invented in the 1950s, it was expected that machines would be more powerful and intelligent than humans. The term "artificial intelligence" was coined by John McCarthy at a workshop at Dartmouth College in 1956 to distinguish the field from cybernetics [1]. Among the famous scientists who attended this workshop, Newell and Simon presented the world's first AI program, Logic Theorist, which could automatically prove some well-known mathematical theorems [2]. Since then, there have been three main phases of technological revolutions in AI, in which many different approaches have been tried and discarded. In the 1950s, the development of AI technology was mainly based on mathematical logic. Then, AI entered an inglorious phase called the "AI winter", during which it was difficult to obtain funding for research projects. In the 1980s, machine learning (ML), e.g., Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Artificial Neural Network (ANN), took off and became the main stream of AI research. However, the collapse of the Lisp machine market, as well as various other issues, led to a second, longer-lasting AI winter in 1987. In 2007, Hinton [3] successfully proposed a Restricted Boltzmann Machine (RBM) model that could successfully train a multilayer neural network and called it Deep Learning (DL). The RBM is a variant of the Boltzmann machine, with the restriction that its neurons must form a bipartite graph: A pair of nodes from each of the two groups of "visible" and "hidden" units may have a symmetric connection between them, and there are no connections between nodes within a group. This technological revolution can be applied to develop an efficient learning procedure for deep, directed, and generative models, but it received little attention from academics and practitioners until it won the famous ImageNet competition in 2012. Since then, DL has dominated the field and proven highly successful in solving various challenging problems in industry and academia. In recent years, faster computers, improved algorithms, and access to large amounts of data have enabled rapid advances in DL. From advanced web search engines to chat robots, image recognition, and self-driving cars, AI solutions are widely used behind the scenes and are changing our daily lives in many ways. With the rapid progress of relevant technologies, more and more companies in various industries are trying to incorporate AI technologies into some offerings or processes to improve their competitiveness. Figure 1 shows the word cloud resulting from various applications of AI created by Word Art. The frequency of each term was brought from bing.com (accessed on 31 January 2022) using the search result text descriptions of 150 websites and displayed in font size.

Figure 1. Word cloud generated from the applications of AI.

Recent research shows that applications of AI technologies are increasingly permeating the construction industry in all areas of architectural design, engineering design, and construction services [4]; thus, human professionals, such as architects, are gradually being replaced by Artificial Neural Networks (ANN). While some early pioneers conducted relevant studies in the construction industry as early as the 1960s, e.g., Architecture Machine [5], this cycle of AI research in the construction industry ended with the second AI winter in the 1980s; however, studies and interest in this topic never stopped. The early connotation of the Architecture Machine was simply referred to as a computer-aided design facility, and the use of AI technologies was still at its infancy in the 1960s. Over the past five decades, an increasing number of publications have been proposed to address construction-specific challenges using various AI technologies. For example, machine learning [6] has overtaken knowledge-based systems as a new area of interest in the construction industry; optimization [7] is also one of the most interesting topics in this research area; robotics [8], such as 3D printing, has become an important application of AI in the construction sector. In the last decade, a variety of digital technologies have been integrated with AI to solve problems in the construction industry, including the Internet of Things (IoT), Quantum Computing, Augmented Reality (AR), and Blockchain [9,10]. Currently, AI research in the construction industry is focused on the development and implementation of various mathematical optimization techniques, formal logic, Artificial Neural Networks, statistical methods, probabilistic methods, and economic methods, which are collectively referred to as Architectural Artificial Intelligence (AAI). The sophistication of the various technologies has had a significant impact on the advancement of the construction industry. To obtain an overview of the applications of AI technologies in the construction industry, the first step is usually a review of the main academic literature in this field; however, an overview of the historical development of the applications of AI technologies in architectural design, engineering design, and construction services is still lacking. This study aims to fill this gap by using the main path analysis (MPA) method to provide a comprehensive literature review and identify future prospects for the applications of AI technologies in the construction industry. Unlike traditional literature reviews, this study has two major advantages; first, it can eliminate bias and render the analysis more objectively and fairly; second, this study focuses on the static analysis of statistical indicators and presents the dynamic process of the development paths for applications of AI technologies in the construction industry.

2. Data and Methodology

2.1. Data Collection

In order to conduct a high-quality study, we used a set of query keywords to search related literature data on the Web of Science (WoS) for further analysis by MPA. The WoS, which provides world-class publication and citation data to researchers, is one of the most reliable and powerful global citation databases in the world. It offers subscription-based access to multiple databases covering more than 10,000 significant journals and provides comprehensive citation data for a wide range of academic disciplines.

The database selected for this study is the Web of Science Core Collection, which contains books, proceedings in the sciences, social sciences, arts and humanities, and the world's leading scholarly journals, including the Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI), Arts & Humanities Citation Index (AHCI), and Emerging Sources Citation Index (ESCI). Unlike other WoS databases, this database contains CR fields, from which citation information can be exported for further analysis by MPA. The entire citation network is searched to ensure that all citations for all publications are fully indexed and searchable. The time span is from 1989 to 2021 and the dataset was last updated on 31 December 2021. In order to conduct an accurate search of related literature data in WoS, the following search queries were used in this study.

(((TS = ("architectural design")) AND TS = ("artificial intelligence" OR "machine learning" OR "computer vision" OR "automated planning" OR "robotics" OR "knowledge-based system" OR "natural language processing" OR "optimisation" OR "optimization")) OR (TS = ("construction industry") AND TS = ("artificial intelligence" OR "machine learning" OR "computer vision" OR "automated planning" OR "robotics" OR "knowledge-based system" OR "natural language processing" OR "optimisation" OR "optimization"))) OR (TS = ("engineering design" and "architectural") AND (TS = ("artificial intelligence" OR "machine learning" OR "computer vision" OR "automated planning" OR "robotics" OR "knowledge-based system" OR "natural language processing" OR "optimisation" OR "optimization"))) OR (TS = ("engineering design" and "construction") AND (TS = ("artificial intelligence" OR "machine learning" OR "computer vision" OR "automated planning" OR "robotics" OR "knowledge-based system" OR "natural language processing" OR "optimisation" OR "optimization"))).

The above query strings are combinations of the keywords (architectural design, construction industry, engineering design) with artificial intelligence and its seven emerging, ripe, and mature subfields, i.e., machine learning, computer vision, automated planning, robotics, knowledge-based system, natural language processing, and optimisation/optimization.

This study collected a total of 1335 articles and 21,528 indexed records in the raw dataset collected from the Web of Science Core Collection using these query strings. Then, this study performed citation checking on all articles in the raw dataset and eliminated all noise data, including unrelated and isolated articles, i.e., articles that do not cite other articles and are not cited by other articles. Finally, the remaining dataset contains 587 articles, called the Final Dataset A, which was created to perform MPA. In addition, as some meaningful knowledge diffusion paths might be overshadowed by review articles, the dataset without review articles, called the Final Dataset B, was also created to perform MPA. Figure 2 shows the collected datasets for MPA.

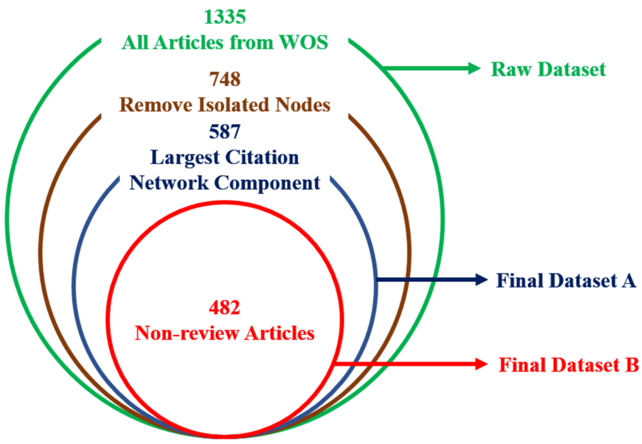


Figure 2. Collected datasets for MPA.

2.2. Methodology

This study used MPA to conduct an unbiased and systematic literature review on the applications of AI technologies in the construction industry. MPA is an effective citation-based mathematical method of bibliometrics, which is primarily used to identify technological trajectories, explore scientific knowledge flows, and conduct literature reviews on a selected research field by mapping the citation network to a few significant citation chains. This method was first presented by Hummon and Doreian [11] in 1989. As the computational algorithm is very complex and there is no software and hardware to perform sophisticated network computations, MPA was not widely used until Batagelj [12] proposed efficient algorithms in 2003, which made it applicable to large datasets. In recent years, due to the improvement and extension of the MPA method by various researchers [13–15], the interest in MPA has increased among researchers from a variety of disciplines.

MPA works with the article citation network, as formed from the created dataset, to provide the basis for further review of the literature and investigate the knowledge diffusion paths of various fields [16]. By representing the articles in the created dataset as nodes, and considering the citation relationships of the articles as links between adjacent nodes, the citation links between all articles are created using the citation data from the reference section. Then, the paths leading from cited articles to other further cited articles can be plotted in a citation network. As can be seen in Figure 3, by following the direction of the links, the created citation network is an acyclic directed network (ADN), where the nodes within an ADN are acyclic, directed, and cannot be encountered twice in an exhaustive search.

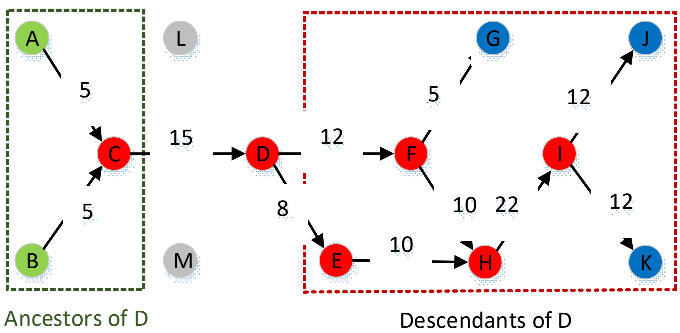


Figure 3. Example of a citation network.

In a citation network, a "citation link" is the link between two adjacent nodes; the "direction of citation links" denotes the path along which cited nodes lead to citing nodes; the "sources" are the nodes that are only cited by other nodes, but do not cite any nodes (i.e., green nodes in Figure 3); the "sinks" are the nodes that cite other nodes, but are not cited by any nodes (i.e., blue nodes in Figure 3); the "intermediates" are the nodes that cite other nodes and are cited by other nodes (i.e., red nodes in Figure 3); the "isolates" are the nodes that have no citation links to the others (i.e., grey nodes in Figure 3); a "citation chain" is the chain consisting of the nodes that move from a source to a sink via citation links, as well as all the intermediates they pass through; the "head" and the "tail" are the nodes in a citation link that the arrow points to and the nodes at the other end of the arrow, respectively; the "descendants" and the "ancestors" of a node are the nodes it can visit and the nodes that can be visited by citation chains, respectively.

After the citation network is formed, the main paths can be extracted using various algorithms to investigate the streams of knowledge diffusion and conduct a systematic literature review in this research field. This study applies the two-stage MPA approach [11,12] to analyze the citation network and identify the main paths. The details of the two-stage MPA are described using a simple citation network, as follows.

2.2.1. Stage 1: Converting the Citation Network into a Weighted Network

The first stage of MPA is to calculate the traversal weights for all citation links to convert the citation network into a weighted network. In order to efficiently calculate the traversal weights for all citation links, this study used the Search Path Link Count (SPLC), which is recommended by Liu et al. [15] as the better method to fit the knowledge diffusion model among the available approaches. The SPLC value of a link is defined as the number of possible citation chains emanating from all ancestors of the tail node (including itself) to all sinks via that link in the network.

As shown in Figure 3, the SPLC value of link D-F is 12 because there are 12 citation chains emanating from the tail (D) and three ancestors (A, B, C) to three sinks (G, J, K) via link D–F, namely A–C–D–F–G, A–C–D–F–H–I–J, A–C–D–F–H–I–K, B–C–D–F–G, B–C–D–F–H–I–J, B–C–D–F–H–I–K, C–D–F–G, C–D–F–H–I–J, C–D–F–H–I–K, D–F–G, D–F–H–I–J, D–F–H–I–K. After calculating the SPLC values for all citation links, the citation network can be fully transformed into a weighted network, where the larger the SPLC value of a link, the greater its influence.

2.2.2. Stage 2: Extracting Main Paths

The second stage of MPA consists of extracting the main paths in the weighted network, as obtained in the first stage, using a selected method from different search algorithms. The nodes in the extracted main paths are the most significant articles in the most influential citation network. There are three main types of path search algorithms: local search, global search, and key route. Local searches always select the nearest neighboring link(s) with the largest traversal weight(s) as the outgoing link(s) to obtain the main path(s) among all citation chains, while global searches simply choose the citation chain(s) with the largest total traversal weight(s) to identify the most influential main path(s) in the weighted network. Key-route searches identify the main paths based on the links with the largest traversal weights (i.e., key routes) in the network to avoid the problem of missing significant links in both local and global searches [15]. The number of key routes, i.e., links with the largest traversal weights, is determined by the user, thus, the more key routes are used, the more main paths from the key routes are displayed [13], and the problem of missing significant main paths can be avoided. This study used the global key-routes search because it considers both the overall importance of a knowledge flow and the individual significant links in the network [15].

In the following, we set the number of key routes to two to illustrate the details of the global key-routes search method. As shown in Figure 3, the global key-routes search with two key routes starts by exploring the main path(s) by selecting the link H–I which has the largest SPLC value of 22 among all links. Then, the main paths A–C–D–F–H–I–J, A–C–D–F–H–I–K, B–C–D–F–H–I–J, and B–C–D–F–H–I–K, meaning those that have the largest total traversal weight (5 + 15 + 12 + 10 + 22 + 12=) of 76, are identified from link H–I. Subsequently, link C–D, with the second largest SPLC value of 15, was selected, which resulted in the main paths of the second key route: A–C–D–F–H–I–J, A–C–D–F–H–I–K, B–C–D–F–H–I–J, and B–C–D–F–H–I–K. After combining all the main paths found through links H–I and C–D, the four main paths of the two key routes were obtained. These main paths reveal the main flows of knowledge diffusion by mapping the most significant flows in the citation network [13].

This study used the MainPath456 program provided by the Da Vincier Lab at the National Taiwan University of Science and Technology to perform MPA. After inputting the final dataset into the MainPath456 program, it automatically compiled the citation data, created a citation network, and then found the main paths from the citation network according to the options specified by the user. In order to determine the most appropriate number of key routes for the Final Dataset A and B, we performed a preliminary experiment with 10, 20, and 30 key routes, and the experimental result showed that the most appropriate number of key routes for analysis of the Final Dataset A and B was 10 and 20, respectively. Moreover, one of the most widely used social network analysis software, Pajek64 version 5.14, that created by Batagelj and Mrvar [17] was used to analyze the MPA-related features. The tool suite of Pajek64 can visualize the analysis results of MainPath456; thus, we can clearly understand the direction of knowledge flow and the relationships between literature citations.

3. Results

The citation network of the 587 articles from the Final Dataset A is shown in Figure 4. As can be seen, such a complex network diagram is quite chaotic, and no valuable information can be found directly; therefore, this study applied MPA to extract valuable information from the citation network. In order to provide a systematic literature review on AI technologies in the construction industry, the content of articles on the key-route main paths is detailed according to different development phases. Cluster analysis and descriptive statistics, including the number of articles by geographic data, journal publication, and year of publication, are also provided in the following subsections.

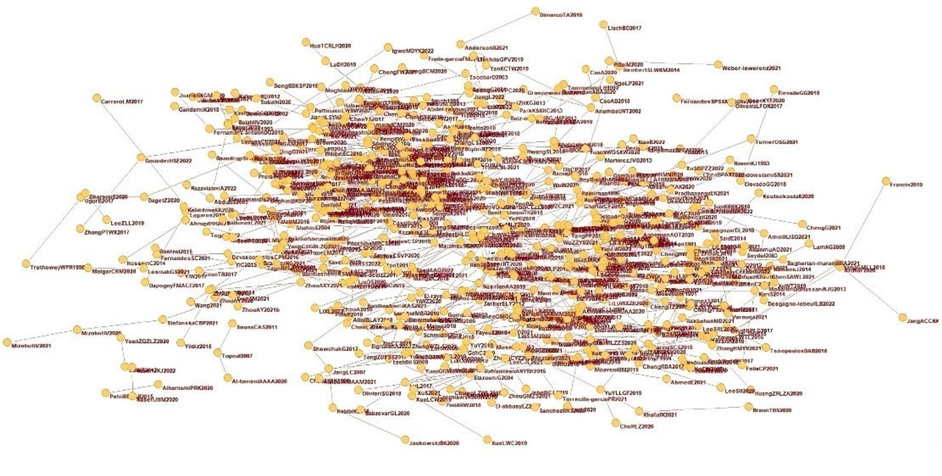


Figure 4. Citation network for the 587 articles in the Final Dataset A.

3.1. Main Path Analysis

In this subsection, the main paths of the Final Dataset A were first analyzed to investigate the overall research progress of AI technologies in the construction industry. Then, the MPA was applied to the Final Dataset B to investigate the main technological development trajectories without review articles.

3.1.1. Key-Route Main Paths with Review Articles

This subsection first analyzes the main paths of the Final Dataset A to examine the overall research progress of AI technologies in the construction industry. Figure 5 shows the top 10 global key-route main paths of the Final Dataset A, hereafter referred to as the "Main Paths A". In Figure 5, each node represents an article and is labeled with the first author's last name and the initials of the other authors' last names (if any), followed by the year of publication. The links represent the citation relationships between articles, while the arrows indicate the direction of knowledge dissemination, and the thickness of an arrow indicates the magnitude of knowledge flow through the link. As shown in Figure 5, 20 representative articles were published between 2002 and 2021, of which 6 articles marked with ® are review papers. The nine articles marked with an underline also appear in the global top 20 key routes of the Final Dataset B presented in the next subsection. Based on the structure of the network and the topics of the articles, the network can be divided into three phases. The articles in each phase are listed in Table 1, and the various research topics covered in each phase are explained below.

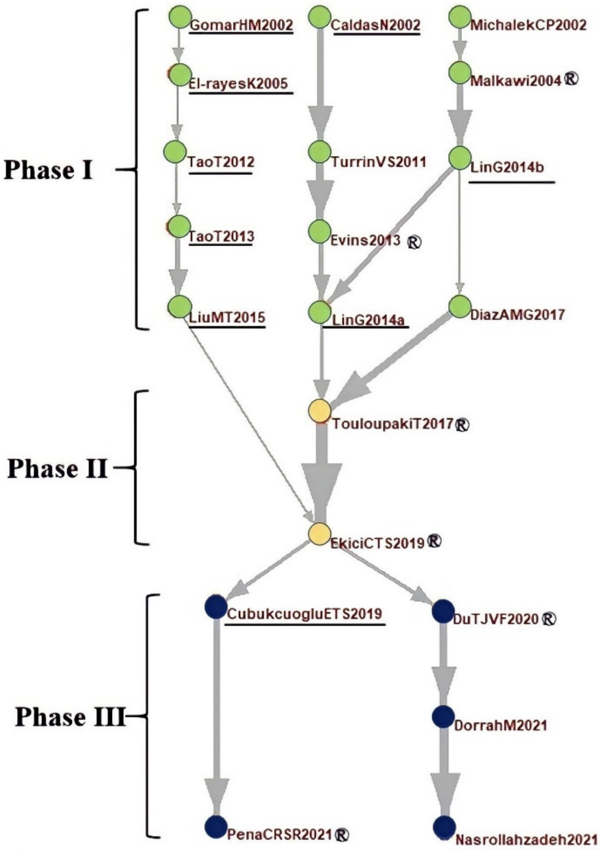


Figure 5. Main Paths A.

Table 1. Articles in Main Paths A.

Phase	Main Path	Label	Title	Citations
I	**1**	GomarHM2002	Assignment and allocation optimization of partially multiskilled workforce	77
		El-RayesK2005	Time-cost-quality trade-off analysis for highway construction	185
		TaoT2012	System reliability optimization model for construction projects via system reliability theory	14
		TaoT2013	System reliability theory based multiple-objective optimization model for construction projects	12
		LiuMT2015	Building information modeling based building design optimization for sustainability	71

Table 1. *Cont.*

Phase	Main Path	Label	Title	Citations
	2	CaldasN2002	A design optimization tool based on a genetic algorithm	188
		TurrinV2011	Design explorations of performance driven geometry in architectural design using parametric modeling and genetic algorithms	163
		Evins2013®	A review of computational optimisation methods applied to sustainable building design	366
		LinG2014a	Designing-in performance: A framework for evolutionary energy performance feedback in early stage design	59
	3	MichalekCP2002	Architectural layout design optimization	122
		Malkawi2004®	Developments in environmental performance simulation	28
		LinG2014b	Evolutionary energy performance feedback for design: Multidisciplinary design optimization and performance boundaries for design decision support	34
		DíazAMG2017	Multidisciplinary Design Optimization through process integration in the AEC industry: Strategies and challenges	17
II	**1**	TouloupakiT2017®	Performance Simulation Integrated in Parametric 3D Modeling as a Method for Early Stage Design Optimization-A Review	27
		EkiciCTS2019®	Performative computational architecture using swarm and evolutionary optimisation: A review	25
III	**1**	CubukcuogluETS2019	OPTIMUS: Self-Adaptive Differential Evolution with Ensemble of Mutation Strategies for Grasshopper Algorithmic Modeling	11
		PenaCRSR2021®	Artificial intelligence applied to conceptual design. A review of its use in architecture	5
	2	DuTJVF2020®	Gaps and requirements for automatic generation of space layouts with optimised energy performance	2
		DorrahM2021	Integrated multi-objective optimization and agent-based building occupancy modeling for space layout planning	9
		Nasrollahzadeh2021	Comprehensive building envelope optimization: Improving energy, daylight, and thermal comfort performance of the dwelling unit	0

Phase I (2002–2017): Development and Application of AI-Based Optimization Technologies

As can be seen in Figure 5, there are 3 knowledge diffusion paths in Phase I, which include the 13 most important and significant articles published between 2002 and 2017. In this phase, applications of AI-based optimization technologies in architectural design have been steadily developed, which has had a measurable impact on the way architecture is designed, analyzed, and constructed. The articles in the left stream of the key-route main paths are GomarHM2002 [18], El-RayesK2005 [19], TaoT2012 [20], TaoT2013 [21], and LiuMT2015 [22]. This stream is mainly concerned with the application of innovative optimization models that are coupled with AI techniques to improve the productivity of various operations in the construction industry. Gomar et al. [18] proposed a linear programming model to optimize the allocation and assignment of multi-skilled workers in a construction project or between projects in a company. This optimization approach is suitable for short-term assignment decisions and can be extended to the assignment of multi-functional construction equipment, such as skid steers, excavators, and hoists. El-Rayes et al. [19] presented a multi-objective optimization model to determine an optimal plan for resource utilization in highway construction that minimizes construction costs and time while maximizing quality, and this model is useful for decision makers involved in novel contracts that require high-quality performance. Tao and Tam [20] proposed a system reliability optimization model to improve the quality of construction projects. In the following year, Tao and Tam [21] developed a multi-objective optimization model based on the system reliability theory to select Pareto-optimal solutions for construction projects, which represents a trade-off between cost and quality. These two studies successfully brought the concept of reliability and the theory of system reliability to the quality optimization of construction projects. Liu et al. [22] presented a building design optimization method based on Building Information Modeling (BIM) to facilitate designers' ability to optimize their designs and improve building sustainability. This model can effectively and efficiently search for optimal design solutions for the trade-off between life cycle cost and life cycle carbon emissions of an office building.

In Phase I, the middle stream of the key-route main paths consists of four representative articles, namely CaldasN2002 [23], TurrinVS2011 [24], Evins2013 [25], and LinG2014a [26]. This path was dedicated to the application of AI-based optimization algorithms, in particular the genetic algorithm (GA), in order to optimize architectural design problems. Caldas and Norford [23] proposed a GA-based optimization metaheuristic as a tool for generative and goal-directed design to evaluate the thermal and lighting performance of an office building. The simulation results can be visualized with an AutoLisp routine for window placement and size, and guide the search of the GA-based algorithm to find an optimal configuration under different climate conditions. The same approach can be applied to a variety of other architectural design problems, such as selecting construction materials, designing shading elements, or sizing a building's lighting and mechanical systems. Turrin et al. [24] presented a design method that combines parametric modeling and genetic algorithms to solve performance-based architectural design problems. This approach can automatically generate a wide range of alternative design solutions to explore architectural geometry, based on the performance evaluations in the early design phase. The two case studies have shown that this method also supports retrospective design investigations, improves vertical transformations within the conceptual design, and decomposes complex aspects into multiple levels of abstraction by achieving multi-level design solutions.

Among the Phase I articles, Evins [25] had the highest citation count of 366, making it the most notable in the network. The author reviewed and summarized 74 papers dealing with the application and improvement of computational optimization technologies, including direct search, evolutionary methods, and other bio-inspired algorithms, for sustainable building design problems, and pointed out that the application and evaluation of computational optimization technologies to architectural design problems is steadily increasing due to the ever-growing computational power, and many designers have realized its great potential, such as optimization technologies for all aspects of architectural design. Lin and Gerber [26] proposed a design framework called Evolutionary Energy Performance Feedback for Design (EEPFD) for early-stage architectural designs, which enables rapid iterations with performance feedback through parameterization, automation, and multi-criteria optimization to support decision making in the early stage of architectural design. The four representative articles in the middle path reveal that the application of AI-based optimization algorithms deserves further exploration and quantification.

In the remaining representative publications of Phase I, four articles appeared on the right stream of the key-route main paths, namely MichalekCP2002 [27], Malkawi2004 [28], LinG2014b [29], and DíazAMG2017 [30]. The right path highlights the application of different AI-based optimization models in architectural design from different perspectives. In the first article on the right path, Michalek et al. [27] proposed an optimization model for the quantifiable aspects of architectural floorplan layout design. In this article, Michalek et al. combined gradient-based algorithms with evolutionary algorithms to present a new approach for optimizing floorplan layouts. The next representative article on the right path is Malkawi [28], which reviewed the developments in the field of environmental performance simulation in the context of architectural design. In this article, the author described several new optimization techniques for developing environmental performance simulation tools, as well as some of the challenges that exist in this research area. Malkawi [28] stated that simulation is far from being fully integrated into the architectural design process and further research is needed. The two remaining representative articles on the right path explored the application of Multidisciplinary Design Optimization (MDO) with software tools in architectural design. Lin and Gerber [29] presented an MDO framework to consider energy performance in the early stage of the architectural design process. This approach, which uses energy performance as a feedback mechanism, enables designers to make more efficient decisions than other available approaches. After reviewing the relevant literature, Díaz et al. [30] tested five software tools for MDO to identify the technical requirements, tool behaviors, interoperability challenges, and viable strategies for developing MDO through Process Integration and Design Optimization (PIDO) platforms. After exploring three technical requirements for tools, including component interoperability, tool automation, and model parameterization capability, the authors highlighted the challenges and strategies for developing MDO through PIDO.

Phase II (2017–2019): Systematic Review and Outlook of Architectural Design Optimization

As shown in Figure 5, Phase II contains two representative review articles published in 2017 and 2019, respectively, which form the single stream of the key-route main paths. In this phase, the two significant review articles, TouloupakiT2017 [31] and EkiciCTS2019 [32], provide a systematic review of the available core literature on the methodology and performative computational architecture of architectural design optimization. In the first article, Touloupaki and Theodosiou [31] provided an overview of the performance-driven design optimization methodologies, identified the current state, approaches, challenges, and directions for future research, and surveyed the existing core literature on computational/parametric design and optimization topics. Touloupaki and Theodosiou [31] confirmed that there is tremendous potential for the application of various computational performance-driven design optimization tools for designing buildings with high energy and thermal efficiency; however, there are still many challenges to be overcome.

In Phase II, Ekici et al. [32] surveyed and summarized the performative computational architecture using swarm and evolutionary optimization in the last decades. Based on the results, future perspectives on the aspects of various performative computational architectures were presented. Given the tremendous research efforts on this topic, there is no doubt that the methodology and performative computational architecture of architectural design optimization can effectively improve the sustainability performance of buildings. Due to the diversity of objectives, constraints, domains, and environments, there is no optimization algorithm that provides the best results for all architectural designs; thus, in order to make appropriate decisions, robust algorithms for solving architectural design problems need to be developed in the future.

Phase III (2019–2021): Development of Innovative AI-Based Optimization Technologies

Phase III ranges from 2019 to 2021 and focuses primarily on the development of innovative AI-based optimization technologies. In this phase, the number of articles regarding innovative AI-based optimization technologies increased significantly. As shown in Figure 5, the main articles of this phase include two streams of the key-route main paths. The left stream of the key-route main path includes two representative articles, CubukcuogluETS2019 [33] and PenaCRSR2021 [34]. Considering that most architectural design problems are basically optimization problems, Cubukcuoglu et al. [33] introduced a new optimization tool called Optimus, which adds the self-adaptive differential evolution algorithm to the computer-aided design (CAD) programs, and the experimental results showed that Optimus significantly outperformed state-of-the-art optimization tools and could achieve better results than other tools for architectural design problems; thus, this study proved that the best solutions for architectural design optimization problems can be improved by using innovative algorithms. Pena et al. [34] investigated the application of AI in the process of conceptual designs in architecture. Since 2015, the number of articles applying AI methods to solve conceptual architectural design problems has increased by 85%. They pointed out that most studies are no longer focused on generating complex and unexpected architecture shapes, but on improving existing designs and finding solutions to optimize shapes. After conducting an overview of the application of state-of-the-art

AI techniques to conceptual architectural design problems, they proposed a tour of major research projects that used AI-based technologies to explore client requirements and find potential solutions for conceptual architectural design problems.

In Phase III, the right stream of the key-route main paths consists of three representative papers, DuTJVF2020 [35], DorrahM2021 [36], and Nasrollahzadeh2021 [37]. Since space layouts have a profound impact on energy performance, a number of automatic generation of space layouts (AGSL) approaches have been proposed to meet the demand for energy-efficient architectural design. Du et al. [35] analyzed ten related studies to identify the gaps and requirements for combining AGSL with energy performance optimization (EPO), and the analytical results showed that combining AGSL with EPO is a promising approach for energy-efficient space layout planning. Dorrah and Marzouk [36] integrated multi-objective optimization and agent-based building occupancy modeling to solve the space layout problem (SLP), which can effectively distribute activities among multi-purpose service buildings to meet functional and proximity requirements. They presented a two-component framework for solving SLPs and illustrated the practical application of the framework through a case study of an administrative building. The analytical results showed that this framework effectively enabled the modeling, analysis, and optimization of large-scale SLPs through a holistic detailed assessment of building performance. Nasrollahzadeh [37] presented a comprehensive building envelope optimization model that considers a variety of building envelope parameters to improve the performance of the dwelling unit in terms of energy, daylighting, and thermal comfort, and the proposed model can be used in the early stages of architectural design, renovation, and refurbishment cases. According to the results of optimizing a real-world duplex house, the optimal solution model was significantly better than those obtained with the original model.

The above 20 representative articles published between 2002 and 2021 represent the main development trajectories for the application of AI technologies in the construction industry. Analysis of the key-route main paths revealed three findings. First, most representative articles focused on the applications of AI-based optimization technologies in architectural design, while the applications of AI-based optimization technologies in engineering design and construction services required further investigation. Second, in the past two decades, great progress has been made in applying AI-based technologies to conceptual architectural design problems and sustainable building design problems. Third, based on the knowledge development paths of the previous studies, it is expected that more innovative AI-based optimization techniques will be proposed in the near future, which will greatly support progress in architectural design, engineering design, and construction services.

3.1.2. Key-Route Main Paths without Review Articles

In this subsection, the main paths of the Final Dataset B are analyzed to investigate the research progress without review articles. Figure 6 shows the top 20 global key-route main paths of the Final Dataset B, hereafter referred to as "Main Paths B". By examining the technological development paths without review articles, 39 representative articles were published between 2002 and 2021. Based on the structure of the network and the topics of the articles, the network can be divided into three main steams. The various research topics covered in each stream are explained below.

The first main stream begins with the left source node GomarHM2002 [18]. As shown in Figure 6, the first main stream contains 15 representative articles published between 2002 and 2021. The research topics in the first main stream include:

(1) The consideration of quality in multi-objective optimization models for architectural design, such as the research presented by GomarHM2002 [18], El-RayesK2005 [19], TaoT2012 [20], and TaoT2013 [21].
(2) The application of BIM-based optimization methods in architectural design, such as the research presented by LiuMT2015 [22], LuWCL 2017 [38], HeSK2019 [39], SantosCSV2019 [40], SantosCSV2020 [41], SantosCSV2020 [42], and HeLW2021 [43].

(3) The application of innovative technologies, models, and strategies to optimize construction operations, such as the research presented by ZhouAKY2021 [44], ZhouAY2021a [45], HongKACHPL2021 [46], and HeeLXWA2021 [47].

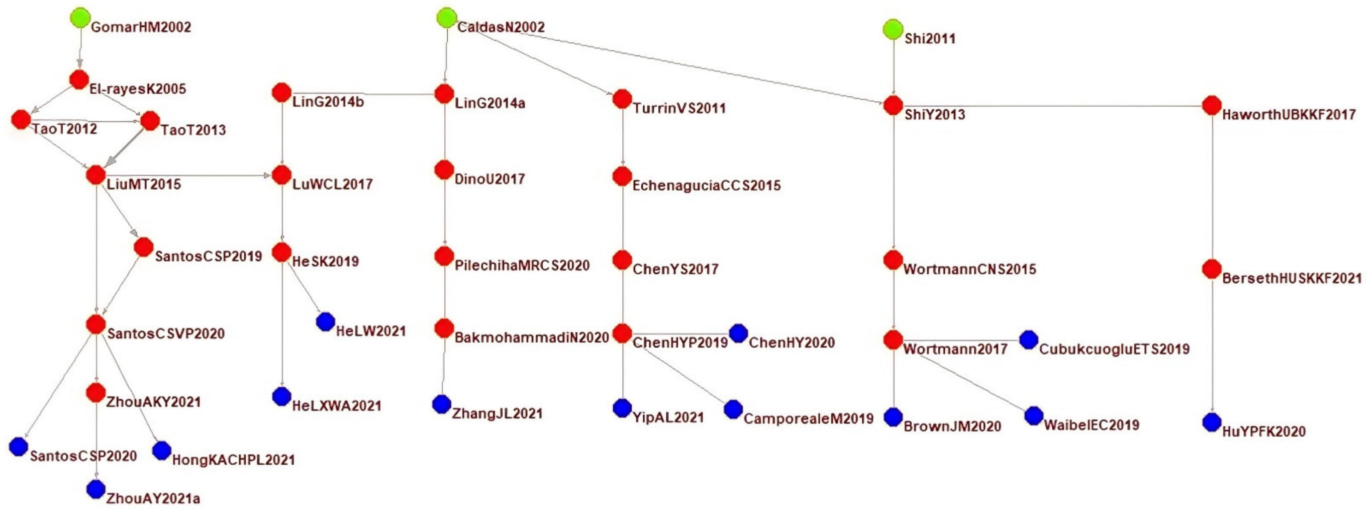


Figure 6. Main Paths B.

The second main stream begins with the middle source node CaidasN2002 [23]. As shown in Figure 6, the second main stream contains 14 representative articles published between 2002 and 2021. The research topics in the second main stream include:

(1) The application of AI-based optimization algorithms and models to optimize architectural design, such as the research presented by CaidasN2002 [23], LinG2014a [26], LinG2014b [29], and TurrinVS2011 [25].
(2) The application of innovative multi-objective optimization approaches in architectural design, such as the research presented by DinoU2017 [48], PilechihaMRCS2020 [49], BakmohammadiN2020 [50], and ZhangJL2021 [51].
(3) The application of optimization approaches and models to optimize the energy consumption of buildings, such as the research presented by EchenaguciaCCS2015 [52], ChenYS2017 [53], ChenHYP2019 [54], CamporealeM2019 [55], ChenHY2020 [56], and YipAL2021 [57].

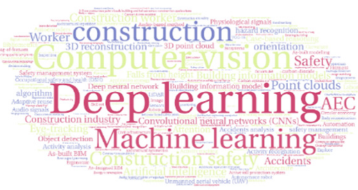
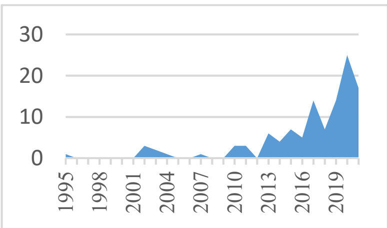
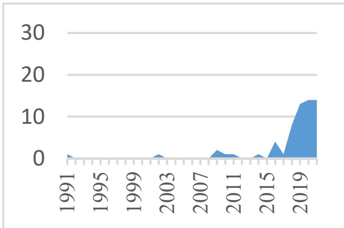
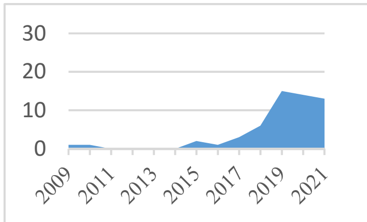
The third main stream begins with the right source node Shi2011 [58]. As shown in Figure 6, the third main stream contains 10 representative articles published between 2011 and 2021. The research topics in the third main stream focused on the application of innovative optimization technologies to solve a variety of architectural design problems. Representative articles in the third main stream include Shi2011 [58], Shi2011 [59], WortmannCNS2015 [60], HaworthUBKKF2017 [61], CubukcuogluET2019 [34], WaibelEC2019 [62], BrownJM2020 [63], HuYPFK2020 [64], and BersethHUSKKF2021 [65]. This knowledge diffusion path will be one of the main streams of future research.

3.2. Cluster Analysis

Based on the analytical results of MPA, we can trace the main pathways of knowledge diffusion for the application of AI-based technologies in the construction industry over the past decades. To further identify the meaningful subfields in the field, this study analyzed the citation network by applying the edge-betweenness clustering method to the 587 articles in the Final Dataset A. The modularity of cluster analysis was 0.74, which indicates that the clustering was very effective. Based on the keywords of the articles in the subfields, we can identify their topics. As shown in Table 2, the three subfields with the largest number of articles are as follows: Solving Architectural Design Problems with Optimization Methods, Application of Information Technologies in Construction

Industry, and Application of Artificial Intelligence Technologies in Construction Safety, which have 113, 61, and 56 articles, respectively. The most frequently mentioned keywords in the three subfields are optimization, machine learning, and Deep Learning. The word clouds of the keywords in the three subfields are also shown in Table 2. According to the growth trend graph of each subfield, the number of articles related to the three subfields has increased rapidly since 2018, and it is expected that these three subfields will continue to be the most important research topics in the near future.

Table 2. Analytical results of cluster analysis.

Subfield	Solving Architectural Design Problems with Optimization Methods	Application of Information Technologiesin Construction Industry	Application of Artificial Intelligence Technologies in Construction Safety
Number of Articles	113	61	56
Keyword/Ratio	Optimization/0.18 Genetic algorithm/0.17 Architectural design/0.16 Building design/0.14 Multi-objective optimization/0.06 Performance-based design/0.05	Machine learning/0.28 Construction industry/0.20 Building information modeling/0.18 Artificial neural networks/0.13 Artificial intelligence/0.10 Natural language processing/0.10	Deep learning/0.18 Computer vision/0.16 Machine learning/0.14 Construction/0.13 Construction safety/0.13 Building information models/0.11
Word Cloud			
Growth Trend Chart			

3.3. Descriptive Statistics

The following subsections further analyze the geographic and journal publication statistics to learn more about the distribution of published articles from the Final Dataset A. This study also applied an advanced time-sequential analysis technique, the sigmoid model, to analyze the growth trend of articles regarding the application of AI-based technologies in the construction industry, which are presented in chronological order.

3.3.1. Geographical Statistics

Figures 7 and 8 show the number of articles published on different continents and the number of articles published in the top 15 countries where the corresponding authors reside, respectively. As can be seen in Figure 6, the three continents with the most published articles are Asia, Europe, and North America, with shares of 42.93%, 26.74%, and 19.3%, respectively. The other continents gradually joined this research field after the authors originating from Asia published the first article in 1989. Since then, Asia has been the leading continent in publishing articles on the application of AI-based technologies in the construction industry. Figure 7 can help us better understand the distribution of articles published in different countries; as can be seen, the three countries that have published the most articles are China, the United States, and the United Kingdom, with shares of 19.76%, 14.48%, and 5.62%, respectively.

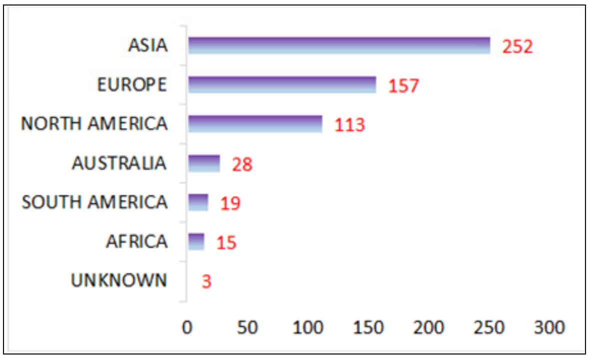


Figure 7. Number of articles published on different continents.

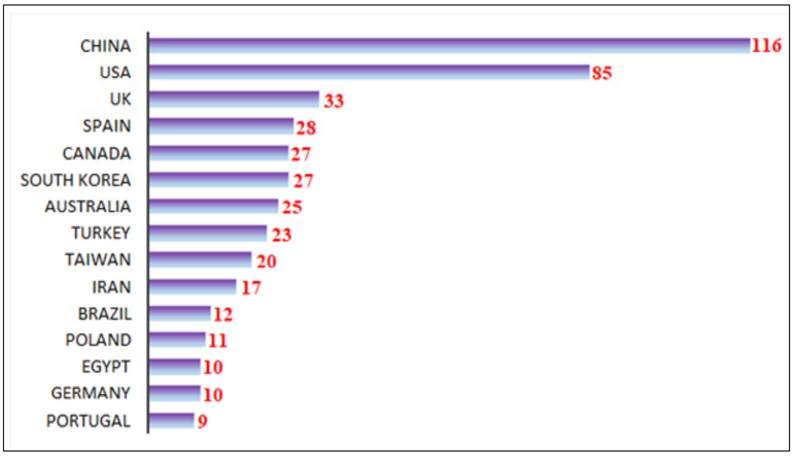


Figure 8. Number of articles published in the top 15 countries.

3.3.2. Journal Publication Statistics

The 587 articles from the Final Dataset A were published in a total of 180 journals. Figure 9 lists the top 15 journals with the most articles published; as can be seen, the 6 journals with the most published articles are Automation in Construction, Sustainability, Journal of Cleaner Production, Journal of Construction Engineering and Management, Journal of Building Engineering, and Engineering Construction and Architectural Management, comprising a total of 34.24% of the articles in all journals.

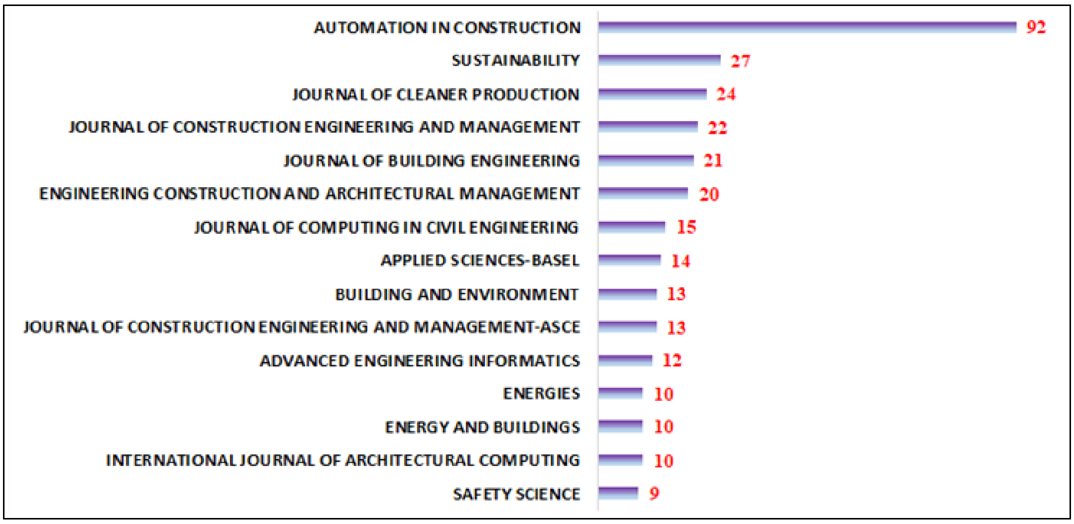


Figure 9. Number of articles published in the top 15 journals.

3.3.3. Chronological Analysis

The number of articles published each year from 1989 to 2021 is shown in Figure 10. Although the number of published articles tends to increase, the cumulative number of articles from 1989 to 2016 was only 28.62%. Therefore, the research field regarding the application of AI-based technologies in the construction industry was still in its early stages and did not receive too much attention in the first 27 years. Since 2017, the number of published articles has increased significantly every year and is higher than the previous year.

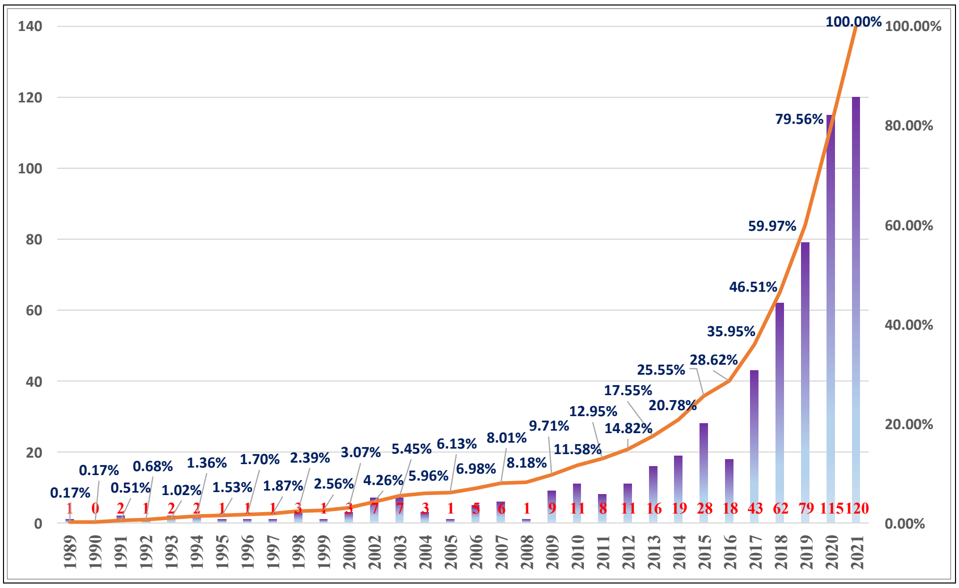


Figure 10. Annual number of articles published.

In order to understand the growing trend of articles published over the years, this study used Loglet Lab 4.0 software to perform a time-sequential analysis. As shown in Figure 11, the growth pattern of the number of articles from the Final Dataset A follows a sigmoid function as the most common pattern of innovation diffusion. Using the logistic S-curve of the basic sigmoid model, we can predict the growth trend and saturation time of the number of articles. As the S-curve of the basic sigmoid model in Figure 11 shows, the growth trend of studies regarding the application of AI-based technologies in the construction industry has increased significantly from 2017. It is predicted that research in this field will enter a mature stage around 2030 and reach saturation around 2035, when the S-curve of the basic sigmoid model is extended, meaning if no new developments are achieved in this research field, the maximum number of published articles will reach 2250 articles by 2035.

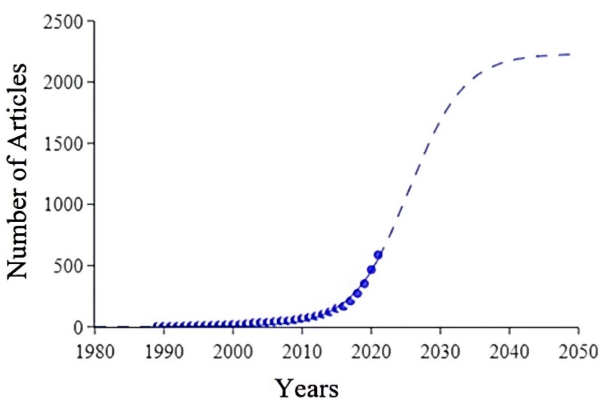


Figure 11. The growth trend of accumulated articles published over the years.

4. Discussion

There are six interesting observations that have emerged from the MPA results, which are discussed as follows.

First, as shown in Figure 5 and Table 1, more than a quarter (27.27%) of the articles in the Main Paths A are review papers, indicating that review papers play an important role in promoting research on the application of AI-based technologies in the construction industry. In the future, review papers will continue to make important contributions to this research area.

Second, some meaningful knowledge diffusion paths for the application of AI-based technologies in the construction industry might be suppressed by these review articles. By examining the dataset without review articles, three meaningful knowledge diffusion paths were discovered, including the consideration of quality in multi-objective optimization models for architectural design, the application of BIM-based optimization methods in architectural design, and the application of AI-based technologies to promote environmental sustainability in the construction industry.

Third, the research topics of the three phases of the Main Paths A are closely related. Phase I focuses on the development of various AI-based optimization technologies that have had a measurable impact on progress in the application of AI-based technologies in the construction industry. According to a systematic review and outlook of this research field in Phase II, the research topics in Phase III shift to the development of innovative AI-based optimization technologies for the construction industry, with a significant increase in the number of articles during this period.

Fourth, existing studies on the application of AI-based technologies in the construction industry only address independent tasks without linking them to an Architectural Artificial Intelligence (AIA) system, which would be a valuable research topic for future studies. Similarly, although many AI technologies have already been applied in the construction industry, there are some newer and more powerful information technologies, such as the Internet of Things, Quantum Computing, Augmented Reality, Cybersecurity, and Blockchain, which are worth further exploitation.

Fifth, the growth trend of articles published over the years shows that most articles were published after 2017 due to the rapid development of innovative AI-based technologies. Although the number of articles has increased significantly in recent years, these studies have mainly focused on the application of AI-based technologies in architectural design, construction safety, and sustainable building design problems. Thus, studies on the application of AI-based technologies in engineering design and construction services are still rare, which is a direction that should be explored in future studies.

Finally, given the current growth trend in the number of articles published in this research field, it is expected that more than 1000 new articles will be presented in the next five years. Therefore, MPA can be conducted every five years to review the new developments with a sufficient number of articles and to capture the changing trends in this research field.

5. Conclusions

Many innovative AI-based technologies already have a great impact on the construction industry; thus, further understanding of state-of-the-art AI-based technologies and their potential applications in the construction industry can help researchers and practitioners improve productivity, refine processes, and solve challenges in the future. While there are some literature reviews on the application of AI-based technologies in the construction industry, to our knowledge there is no study that used MPA to survey the literature on this topic. This study used MPA to identify the main knowledge development paths in this research field. By examining 587 articles published between 1989 and 2021, the analytical results of MPA provide researchers and practitioners with a systematic literature review of past and current research and applications of AI-based technologies in the construction industry. Based on the results of MPA, the knowledge development trajectories in this field could be divided into three phases. Phase I (2002–2017) focused on the development of various AI-based optimization technologies for the application of AI-based technologies in the construction industry. The main stream of the knowledge development in Phase II (2017–2019) focused on systematic reviews and outlooks regarding the application of AI-based technologies in the construction industry. In Phase III (2019–2021), more innovative AI-based technologies were rapidly developed and applied in the construction industry.

This study used cluster analysis to identify the three meaningful subfields in this research area, i.e., Solving Architectural Design Problems with Optimization Methods, Application of Information Technologies in the Construction Industry, and Application of Artificial Intelligence Technologies in Construction Safety. The analytical results of the cluster analysis showed that the vast majority of articles focused on the application of optimization technologies, genetic algorithms, machine learning, Artificial Neural Networks, Deep Learning, computer vision, machine learning, and Building Information Modeling in related fields. In particular, the application of Deep Learning, especially in combination with Artificial Neural Networks, is becoming increasingly popular in the construction industry. These AI-based technologies will continue to be the main approaches for application in the construction industry in the future. In addition, the applications of AI-based technologies in the construction industry have mainly focused on architectural design, construction safety, and sustainable building design; therefore, many other problems in the construction industry should be explored in the future.

In addition, three descriptive statistics were conducted, including geographic publication statistics, journal publication statistics, and the sigmoid model, in order to understand the distribution of published articles and the growth trend of articles regarding the application of AI-based technologies in the construction industry. The analytical results of the geographic and journal publication statistics show that most of the article authors are from Asia, especially China. Although other continents and countries have gradually joined this research field, the leading continent and countries in publishing articles on the application of AI-based technologies in the construction industry have not changed in the last decade. The analytical result of the sigmoid model reveals that this research field will enter a mature stage around 2030 and reach saturation around 2035. To continue progressively applying AI-based technologies in the construction industry, new innovative technologies and research topics remain a challenge for the future.

Author Contributions: Conceptualization, formal analysis, and writing—original draft preparation, H.-P.C. Methodology, validation, and writing—review and editing, K.-C.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets were collected from the Web of Science Core Collection at https://www.webofscience.com/wos/woscc/basic-search (accessed on 31 December 2021).

Acknowledgments: The authors thank John S. Liu of the Da Vincier Lab at the National Taiwan University of Science and Technology for providing the MainPath456.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. McCarthy, J. Review of the question of artificial intelligence. *Ann. Hist. Comput.* **1988**, *10*, 224–229.
2. Crevier, D. *AI: The Tumultuous Search for Artificial Intelligence*; BasicBooks: New York, NY, USA, 1993; pp. 44–46.
3. Hinton, G.E. Learning multiple layers of representation. *Trends Cogn. Sci.* **2007**, *11*, 428–434. [CrossRef] [PubMed]
4. Mrosla, L.; Koch, V.; Both, P.V. Quo vadis AI in Architecture? Survey of the current possibilities of AI in the architectural practice. *Des.-Artif. Intell.* **2019**, *2*, 45–54.
5. Steenson, M.W. *Architectural Intelligence: How Designers, and Architects Created the Digital Landscape*; The MIT Press: Cambridge, MA, USA, 2017.

6. Poh, C.; Ubeynarayana, C.U.; Goh, Y.M. Safety leading indicators for construction sites: A machine learning approach. *Autom. Constr.* **2018**, *93*, 375–386. [CrossRef]
7. Gbadamosi, A.Q.; Mahamadu, A.M.; Oyedele, L.O.; Akinade, O.O.; Manu, P.; Mahdjoubi, L.; Aigbavboa, C. Offsite construction: Developing a BIM-Based optimizer for assembly. *J. Clean. Prod.* **2019**, *215*, 1180–1190. [CrossRef]
8. Palacios, A.T.; Cordero, J.M.E.B.; Bello, M.R.; Palacios, E.T.; Martínez González, J.L. New applications of 3D SLAM on risk management using unmanned aerial vehicles in the construction industry. In *Drones-Applications*; IntechOpen: London, UK, 2018.
9. Wei, C.; Li, Y. Design of energy consumption monitoring and energy-saving management system of intelligent building based on the Internet of things. In Proceedings of the 2011 International Conference on Electronics, Communications and Control (ICECC), Ningbo, China, 9–11 September 2011; pp. 3650–3652.
10. Lanko, A.; Vatin, N.; Kaklauskas, A. Application of RFID combined with blockchain technology in logistics of construction materials. In *MATEC Web of Conferences*; EDP Sciences: Les Ulis, France, 2018; Volume 170, p. 03032.
11. Hummon, N.P.; Dereian, P. Connectivity in a citation network: The development of DNA theory. *Soc. Netw.* **1989**, *11*, 39–63. [CrossRef]
12. Batagelj, V. *Efficient Algorithms for Citation Network Analysis*; Preprint series; University of Ljubljana, Institute of Mathematics, Physics and Mechanics, Department of Theoretical Computer Science: Ljubljana, Slovenia, 2003.
13. Liu, J.S.; Lu, L.Y. An integrated approach for main path analysis: Development of the Hirsch index as an example. *J. Assoc. Inf. Sci. Technol.* **2012**, *3*, 528–542. [CrossRef]
14. Tu, Y.N.; Hsu, S.L. Constructing conceptual trajectory maps to trace the development of research fields. *J. Assoc. Inf. Sci. Technol.* **2016**, *67*, 2016–2031. [CrossRef]
15. Liu, J.S.; Lu, L.Y.; Ho, M.H.C. A few notes on main path analysis. *Scientometrics* **2019**, *119*, 379–391. [CrossRef]
16. Batagelj, V.; Ferligoj, A.; Squazzoni, F. The emergence of a field: A network analysis of research on peer review. *Scientometrics* **2017**, *113*, 503–532. [CrossRef]
17. Batagelj, V.; Mrvar, A. Pajek-program for large network analysis. *Connections* **1998**, *21*, 47–57.
18. Gomar, J.E.; Haas, C.T.; Morton, D.P. Assignment and allocation optimization of partially multiskilled workforce. *J. Constr. Eng. Manag.* **2002**, *128*, 103–109. [CrossRef]
19. El-Rayes, K.; Kandil, A. Time-cost-quality trade-off analysis for highway construction. *J. Constr. Eng. Manag.* **2005**, *131*, 477–486. [CrossRef]
20. Tao, R.; Tam, C.M. System reliability optimization model for construction projects via system reliability theory. *Autom. Constr.* **2012**, *22*, 340–347. [CrossRef]
21. Tao, R.; Tam, C.M. System reliability theory based multiple-objective optimization model for construction projects. *Autom. Constr.* **2013**, *31*, 54–64. [CrossRef]
22. Liu, S.; Meng, X.; Tam, C. Building information modeling based building design optimization for sustainability. *Energy Build.* **2015**, *105*, 139–153. [CrossRef]
23. Caldas, L.G.; Norford, L.K. A design optimization tool based on a genetic algorithm. *Autom. Constr.* **2002**, *11*, 173–184. [CrossRef]
24. Turrin, M.; Von Buelow, P.; Stouffs, R. Design explorations of performance driven geometry in architectural design using parametric modeling and genetic algorithms. *Adv. Eng. Inform.* **2011**, *25*, 656–675. [CrossRef]
25. Evins, R. A review of computational optimisation methods applied to sustainable building design. *Renew. Sustain. Energy Rev.* **2013**, *22*, 230–245. [CrossRef]
26. Lin, S.H.E.; Gerber, D.J. Designing-in performance: A framework for evolutionary energy performance feedback in early stage design. *Autom. Constr.* **2014**, *38*, 59–73. [CrossRef]
27. Michalek, J.; Choudhary, R.; Papalambros, P. Architectural layout design optimization. *Eng. Optim.* **2002**, *34*, 461–484. [CrossRef]
28. Malkawi, A.M. Developments in environmental performance simulation. *Autom. Constr.* **2004**, *13*, 437–445. [CrossRef]
29. Lin, S.H.; Gerber, D.J. Evolutionary energy performance feedback for design: Multidisciplinary design optimization and performance boundaries for design decision support. *Energy Build.* **2014**, *84*, 426–441. [CrossRef]
30. Díaz, H.; Alarcón, L.F.; Mourgues, C.; García, S. Multidisciplinary Design Optimization through process integration in the AEC industry: Strategies and challenges. *Autom. Constr.* **2017**, *73*, 102–119. [CrossRef]
31. Touloupaki, E.; Theodosiou, T. Performance simulation integrated in parametric 3D modeling as a method for early stage design optimization—A review. *Energies* **2017**, *10*, 637. [CrossRef]
32. Ekici, B.; Cubukcuoglu, C.; Turrin, M.; Sariyildiz, I.S. Performative computational architecture using swarm and evolutionary optimisation: A review. *Build. Environ.* **2019**, *147*, 356–371. [CrossRef]
33. Cubukcuoglu, C.; Ekici, B.; Tasgetiren, M.F.; Sariyildiz, S. OPTIMUS: Self-adaptive differential evolution with ensemble of mutation strategies for grasshopper algorithmic modeling. *Algorithms* **2019**, *12*, 141. [CrossRef]
34. Pena, M.L.C.; Carballal, A.; Rodríguez-Fernández, N.; Santos, I.; Romero, J. Artificial intelligence applied to conceptual design. A review of its use in architecture. *Autom. Constr.* **2021**, *124*, 103550. [CrossRef]
35. Du, T.; Turrin, M.; Jansen, S.; van den Dobbelsteen, A.; Fang, J. Gaps and requirements for automatic generation of space layouts with optimised energy performance. *Autom. Constr.* **2020**, *116*, 103132. [CrossRef]
36. Dorrah, D.H.; Marzouk, M. Integrated multi-objective optimization and agent-based building occupancy modeling for space layout planning. *J. Build. Eng.* **2021**, *34*, 101902. [CrossRef]

37. Nasrollahzadeh, N. Comprehensive building envelope optimization: Improving energy, daylight, and thermal comfort performance of the dwelling unit. *J. Build. Eng.* **2021**, *44*, 103418. [CrossRef]
38. Lu, Y.; Wu, Z.; Chang, R.; Li, Y. Building Information Modeling (BIM) for green buildings: A critical review and future directions. *Autom. Constr.* **2017**, *83*, 134–148. [CrossRef]
39. He, W.; Shi, Y.; Kong, D. Construction of a 5D duration and cost optimisation model based on genetic algorithm and BIM. *J. Eng. Des. Technol.* **2019**, *17*, 929–942. [CrossRef]
40. Santos, R.; Costa, A.A.; Silvestre, J.D.; Pyl, L. Integration of LCA and LCC analysis within a BIM-based environment. *Autom. Constr.* **2019**, *103*, 127–149. [CrossRef]
41. Santos, R.; Costa, A.A.; Silvestre, J.D.; Vandenbergh, T.; Pyl, L. BIM-based life cycle assessment and life cycle costing of an office building in Western Europe. *Build. Environ.* **2020**, *169*, 106568. [CrossRef]
42. Santos, R.; Costa, A.A.; Silvestre, J.D.; Pyl, L. Development of a BIM-based environmental and economic life cycle assessment tool. *J. Clean. Prod.* **2020**, *265*, 121705. [CrossRef]
43. He, W.; Li, W.; Wang, W. Developing a resource allocation approach for resource-constrained construction operation under multi-objective operation. *Sustainability* **2021**, *13*, 7318. [CrossRef]
44. Zhou, Z.W.; Alcalá, J.; Kripka, M.; Yepes, V. Life cycle assessment of bridges using Bayesian networks and fuzzy mathematics. *Appl. Sci.* **2021**, *11*, 4916. [CrossRef]
45. Zhou, Z.; Alcalá, J.; Yepes, V. Optimized Application of Sustainable Development Strategy in International Engineering Project Management. *Mathematics* **2021**, *9*, 1633. [CrossRef]
46. Hong, J.; Kang, H.; An, J.; Choi, J.; Hong, T.; Park, H.S.; Lee, D.E. Towards environmental sustainability in the local community: Future insights for managing the hazardous pollutants at construction sites. *J. Hazard. Mater.* **2021**, *403*, 123804. [CrossRef]
47. He, W.; Li, W.; Xu, S.; Wang, W.; An, X. Time, cost, and energy consumption analysis on construction optimization in high-rise buildings. *J. Constr. Eng. Manag.* **2021**, *147*, 04021128. [CrossRef]
48. Dino, I.G.; Üçoluk, G. Multiobjective design optimization of building space layout, energy, and daylighting performance. *Am. Soc. Civ. Eng.* **2017**, *31*, 04017025. [CrossRef]
49. Pilechiha, P.; Mahdavinejad, M.; Rahimian, F.P.; Carnemolla, P.; Seyedzadeh, S. Multi-objective optimisation framework for designing office windows: Quality of view, daylight and energy efficiency. *Appl. Energy* **2020**, *261*, 114356. [CrossRef]
50. Bakmohammadi, P.; Noorzai, E. Optimization of the design of the primary school classrooms in terms of energy and daylight performance considering occupants' thermal and visual comfort. *Energy Rep.* **2020**, *6*, 1590–1607. [CrossRef]
51. Zhang, J.; Ji, L. Optimization of daylighting, ventilation, and cooling load performance of apartment in tropical ocean area based on parametric design. *Adv. Civ. Eng.* **2021**, *2021*, 6511290. [CrossRef]
52. Echenagucia, T.M.; Capozzoli, A.; Cascone, Y.; Sassone, M. The early design stage of a building envelope: Multi-objective search through heating, cooling and lighting energy performance analysis. *Appl. Energy* **2015**, *154*, 577–591. [CrossRef]
53. Chen, X.; Yang, H.; Sun, K. Developing a meta-model for sensitivity analyses and prediction of building performance for passively designed high-rise residential buildings. *Appl. Energy* **2017**, *194*, 422–439. [CrossRef]
54. Chen, X.; Huang, J.; Yang, H.; Peng, J. Approaching low-energy high-rise building by integrating passive architectural design with photovoltaic application. *J. Clean. Prod.* **2019**, *220*, 313–330. [CrossRef]
55. Camporeale, P.E.; Mercader-Moyano, P. Towards nearly zero energy buildings: Shape optimization of typical housing typologies in ibero-american temperate climate cities from a holistic perspective. *Sol. Energy* **2019**, *193*, 738–765. [CrossRef]
56. Chen, X.; Huang, J.; Yang, H. Multi-criterion optimization of integrated photovoltaic facade with inter-building effects in diverse neighborhood densities. *J. Clean. Prod.* **2020**, *248*, 119269. [CrossRef]
57. Yip, S.; Athienitis, A.K.; Lee, B. Early stage design for an institutional net zero energy archetype building. Part 1: Methodology, form and sensitivity analysis. *Sol. Energy* **2021**, *224*, 516–530. [CrossRef]
58. Shi, X.; Yang, W. Performance-driven architectural design and optimization technique from a perspective of architects. *Autom. Constr.* **2013**, *32*, 125–135. [CrossRef]
59. Shi, X. Design optimization of insulation usage and space conditioning load using energy simulation and genetic algorithm. *Energy* **2011**, *36*, 1659–1667. [CrossRef]
60. Wortmann, T.; Costa, A.; Nannicini, G.; Schroepfer, T. Advantages of surrogate models for architectural design optimization. *Artif. Intell. Eng. Des. Anal. Manuf.* **2015**, *29*, 471–481. [CrossRef]
61. Haworth, B.; Usman, M.; Berseth, G.; Khayatkhoei, M.; Kapadia, M.; Faloutsos, P. CODE: Crowd-optimized design of environments. *Comput. Animat. Virtual Worlds* **2017**, *28*, e1749. [CrossRef]
62. Waibel, C.; Evins, R.; Carmeliet, J. Co-simulation and optimization of building geometry and multi-energy systems: Interdependencies in energy supply, energy demand and solar potentials. *Appl. Energy* **2019**, *242*, 1661–1682. [CrossRef]
63. Brown, N.C.; Jusiega, V.; Mueller, C.T. Implementing data-driven parametric building design with a flexible toolbox. *Autom. Constr.* **2020**, *118*, 103252. [CrossRef]
64. Hu, K.; Yoon, S.; Pavlovic, V.; Faloutsos, P.; Kapadia, M. Predicting crowd egress and environment relationships to support building design optimization. *Comput. Graph.* **2020**, *88*, 83–96. [CrossRef]
65. Berseth, G.; Haworth, B.; Usman, M.; Schaumann, D.; Khayatkhoei, M.; Kapadia, M.; Faloutsos, P. Interactive architectural design with diverse solution exploration. *IEEE Trans. Vis. Comput. Graph.* **2021**, *27*, 111–124. [CrossRef]