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Review

Architectural 3D-Printed Structures Created Using Artificial Intelligence: A Review of Techniques and Applications

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Featured Application: A review of Artificial Intelligence-driven approaches to 3D printing of large-scale architectural structures can provide practitioners and academic researchers with a comprehensive understanding of the current state of the field, reinforce innovative design, inform material and fabrication method choices, support sustainability goals, and provide practical insights through the review of different cases.

Abstract: Artificial Intelligence (AI) and 3D printing (3DP) play considerable roles in what is known as the Fourth Industrial Revolution, by developing data- and machine-intelligence-based integrated production technologies. In architecture, this shift was induced by increasingly complex design requirements, posing important challenges for real-world design implementation, large-scale structure fabrication, and production quality standardization. The study systematically reviews the application of AI techniques in all stages of creating 3D-printed architectural structures and provides a comprehensive image of the development in the field. The research goals are to (1) offer a comprehensive critical analysis of the body of literature; (2) identify and categorize approaches to integrating AI in the production of 3D-printed structures; (3) identify and discuss challenges and opportunities of AI integration in architectural production of 3D-printed structures; and (4) identify research gaps and provide recommendations for future research. The findings indicate that AI is an emerging addition to the 3DP process, mainly transforming it through the real-time adjustment of the design or printing parameters, enhanced printing quality control, or prediction and optimization of key design features. However, the potential of the application of AI in large-scale architectural 3D printing still needs to be explored. Lastly, the study emphasizes the necessity of redefining traditional field boundaries, opening new opportunities for intelligent architectural production.

Keywords: architectural design; digital design; digital fabrication; additive manufacturing; 3D printing; artificial intelligence; machine learning; deep learning; artificial neural networks; computer vision

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1. Introduction

Similar to other engineering domains, automation is increasingly playing a significant role in architecture as advancements in Artificial Intelligence (AI) streamline various processes and enhance design capabilities [1–5]. AI-based automation is researched in diverse aspects of architecture design, including Building Information modeling (BIM), generative design, parametric design, performance analysis and simulation, project management, documentation generation and evaluation, as well as digital fabrication. As for the latter, automation is transforming the way various architectural forms and elements are designed and manufactured. Advanced additive manufacturing (AM) technologies, including 3D printing (3DP), allow designers to implement rapid prototyping design methodologies and fabricate complex and customized components directly, reducing material waste and construction time. Moreover, automation using AI and 3DP is widely explored across different fields using different materials and production scales [6,7], including metal 3DP technology for aerospace and mechanical industries [8,9], parts manufactured in composite materials using photopolymer 3DP [10], as well as biomedical materials advancement through AI-assisted 3D and 4D printing technology explorations [11]. In all the mentioned fields, robotic fabrication systems can automate tasks that are traditionally time- and effort-consuming, enabling efficient and precise construction processes [12–18]. It is important to note that, while automation can enhance production speed and creativity in architectural design, human expertise remains indispensable in the decision-making process.

Exploring the synergetic potential of AI and AM in architecture could advance both technologies and push the boundaries of what is possible in architectural design and construction. Studies on this topic are important because they aid technological improvements that support advances in design, optimization, customization and personalization, performance-driven explorations, and resource allocation towards increased efficiency and sustainability and facilitate industry applications. The integration of AI in the 3DP process promises to overcome specific challenges posed by AM technology. For example, reinforced concrete AM faces challenges regarding the accuracy of material placement during printing, phase transition control and measurements, cold joint formation during the layering process, reinforcement implementation, and surface finish [19]. Given that production usually begins after the design process is mostly or fully completed, 3DP might be viewed as inefficient because multiple iterations of the printing process are needed to produce the desired structure. Therefore, AI systems have been explored to overcome these challenges through real-time control of the printing parameters or autonomous adjustment of the printing process. In line with the previous, the main aim of this research is to overview previously published studies on AI-driven approaches for 3DP in architecture. The study focuses on the design and fabrication of large-scale architectural structures.

Such 3DP technologies have been actively researched and used in the construction industry in recent years because of the geometric complexity and material efficiency they can facilitate compared to traditional building methods [20]. However, there are still many challenges and opportunities for improvement regarding this technology [21,22], such as low print accuracy or unreliable mechanical properties of printed parts. AI tools were recognized as a prospective method for overcoming these challenges [23]. Previous state-of-the-art studies have been found in the fields of 3DP for large-scale architectural structures [22,24] and the adoption of AI technologies in the construction industry [25,26], yet no review study has been found to explore the application and correlation of the combined technologies in architectural design and fabrication, apart from several reviews on Machine Learning (ML) in 3DP [27,28].

ML, specifically, has successfully been used to optimize 3DP processes in engineering industries, as presented in the study by Goh [29], offering a comprehensive review of ML in 3DP across several engineering disciplines. Other AM challenges have also been addressed using different AI tools. For example, real-time defect detection is achieved using deep learning tools [30–32], while several ML methods are used for porosity predictions for 3D-printed structures [33,34]. The implementation of these tools in the construction industry is still in the early stages of research; however, several studies have recognized both 3DP and AI as technologies with a high potential for development and increased use in the next decade [25,35].

To the best of the authors' knowledge, no study has provided a comprehensive overview of the application of several AI techniques used for the design and production planning of large-scale 3D-printed structures in architecture up to this point. Regarding the above, the objective of this study is to identify, evaluate, and provide a summary of the relevant studies. The specific tasks include the systematization of the available knowledge, including research papers, journal articles, conference proceedings, and other relevant sources, to establish the scope of the current state of the field. The purpose of the study is to provide an in-depth understanding of the field, identify research gaps, and assess technological advancements. This knowledge can contribute to further research, inform decision making, and promote the effective integration of AI and 3DP in architectural practice.

Furthermore, the study seeks to understand how AI techniques have enhanced the design, fabrication, and performance of large-scale 3D-printed architectural structures. This purpose helps researchers and practitioners stay informed about the latest technological developments and potential applications. Finally, the study intends to explore the practical implications of AI in the 3DP of architectural elements.

The systematic literature review (SLR) method was used to identify, categorize, evaluate, and report relevant literature on the topic, extract and interpret data, and derive conclusions about the questions under consideration. Conducting the research included the following activities: forming a literature sample as the result of a database search and selection of relevant publications; analyzing the literature sample using quantitative and qualitative methods; summarizing the evidence; interpreting the findings; and discussing recognized opportunities and challenges for future research and application of these structures in the industry.

This study promotes innovative design, informs ways of affecting material- and fabrication-related decisions through intelligent tools and techniques, supports sustainability goals, and provides an insightful review of the cases. By exploring the intersection of AI and AM, researchers can shape the future of architecture and construction toward creating a more sustainable environment.

2. Methodology

The SLR methodology was applied in the study to investigate the existing knowledge scope of the 3D-printed large-scale architectural structures using AI. This methodology was chosen since it provides a systematic approach that ensures objectivity, meticulousness, and transparency while providing insight into theoretical knowledge and current trends and developments related to the research problem [36,37]. The review was carried out in accordance with the PRISMA statement for systematic reviews and meta-analysis [38,39]. Based on these guidelines, a three-step systematic protocol was implemented to generate and evaluate a relevant body of research consisting of literature (1) search, (2) selection, and (3) analysis.

Following the established protocol, the sample was collected and refined [40]. In the first step, the Web of Science (WoS) database was searched using defined keywords. Initial search results were then refined to exclude all research fields unrelated to the architecture and building industry. The remaining papers were then assessed against predefined exclusion criteria through several iterations to select the most relevant literature sample for the research topic. In addition to database searches, manual and reference list searches were undertaken to identify additional papers. After the selection process, the identified literature sample was then further analyzed using quantitative and qualitative methods to help answer the main research questions, as presented in Figure 1.

2.1. Forming Literature Sample

The application of AI tools for 3DP structures is wide, encompassing several engineering disciplines that often overlap; this poses a challenge in searching for the relevant body of literature on architectural applications. The first exclusion criterion that was implemented had the goal of limiting the database search results to research categories relevant to this study. The three main categories were chosen to be (1) Architecture, (2) Engineering, Civil, and (3) Construction and Building Technology, as they all refer to the built environment; therefore, relevant topics were expected to be included in them. The second limitation was the publishing period set to 2013–present, aiming to collect the most current research. The final literature search was performed on 11 July 2023, following the set search criteria presented in Table 1.

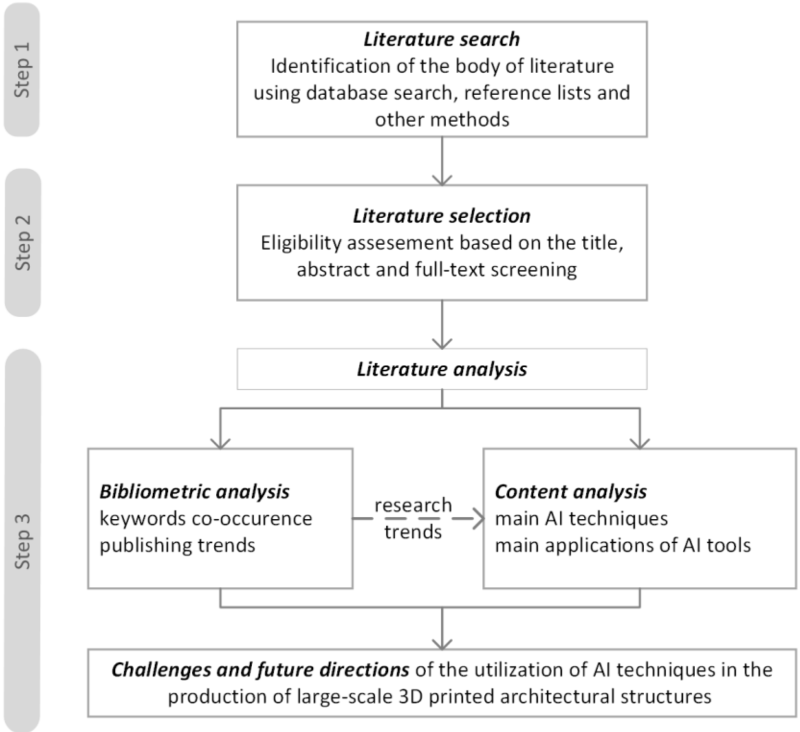

Figure 1. Layout of the research process.

Table 1. Search criteria.

Source	Search Method	Search Criteria
Web of Science	Keyword method	(a) Research category: Engineering, Civil, Construction and Building Technology, or Architecture
Online repositories Google Scholar	Reference list search Internet search	(b) Paper type: Journal article, proceeding papers (c) Years published: 2013–present (d) Language: English

2.1.1. Literature Search

The initial search and paper collection were carried out in the WoS database, which includes leading peer-reviewed publications with bibliometric data. Other databases, such as Scopus, were also considered for this research, since they also offer a comprehensive sample pool. However, this review required screening a topic that is growing across multiple research disciplines and needed to be narrowed down to the ones relevant to the construction industry. Further, WoS was chosen as the primary literature source for its built-in categorization of papers by research categories. Meanwhile, the Scopus search engine is more keyword-oriented with fewer in-depth categorization filters, with Engineering being the closest category, which proved to be too wide a literature pool for efficient retrieval of results for this study.

The search was conducted using topic-relevant keywords. As this paper focuses on the application of AI tools in AM, keywords were divided into two sets, one addressing the most used AI tools and the other referring to the terms commonly used for AM in architecture. The AM and design sets mostly consist of synonyms often used to describe 3DP technologies and several architectural design terms to cover the whole design and fabrication process. On the other hand, the topic of AI tools covers a wide range of different technologies that need to be included, as they are not used synonymously.

The keyword search string "artificial intelligence" OR "AI" OR "augmented intelligence" OR "machine learning" OR "ML" OR "simulated annealing" OR "computer vision"

OR “pattern recognition” OR “genetic algorithm*” OR “evolutionary algorithm*” OR “neural network*” OR “deep learning” OR “reinforced learning” OR “fuzzy logic” OR “adversarial network*” OR “convolutional network*” OR “supervised learning” OR “unsupervised learning” AND “material extrusion” OR “large-scale 3d print*” OR “additive manufacturing*” OR “concrete 3D print*” OR “3D print*” OR “generative design” OR “structural design” OR “computational design” was used to search paper titles, abstracts, and keywords. Based on the established search criteria, the search was limited to the relevant categories and publication date range, as shown in Figure 2. The asterisk sign at the end of several phrases in Figure 2 is written to include wildcard search results and can represent any group of characters.

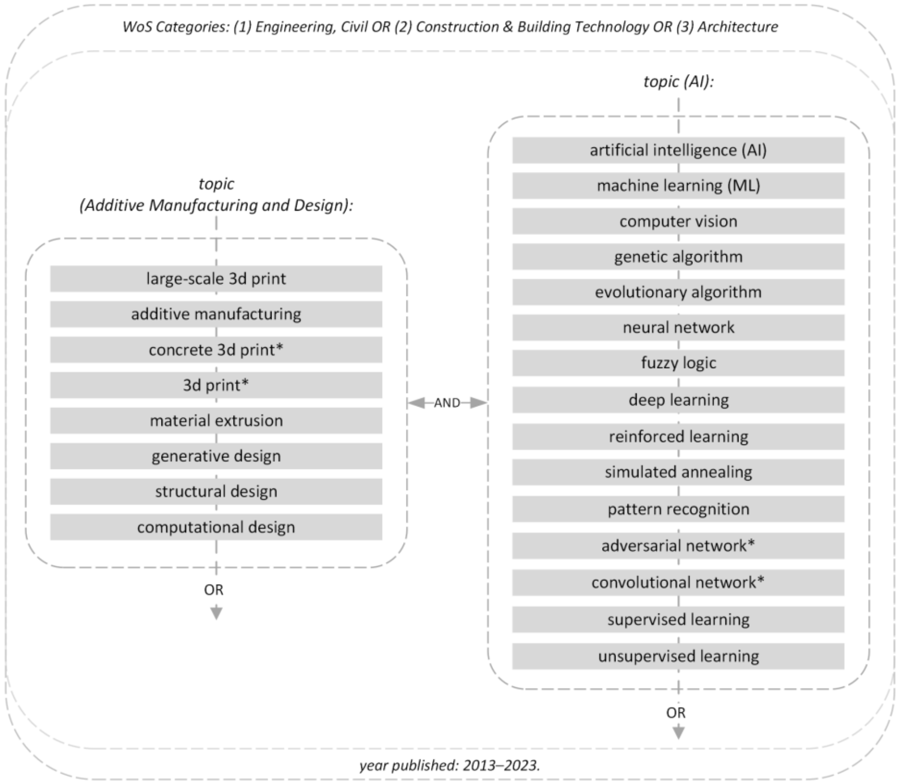

Figure 2. Illustration of the literature search domain and topics.

The initial search yielded 394 results matching the search criteria, which were then subjected to the literature selection process. Simultaneously, an unstructured search using the same keywords was performed in the Scopus and Google Scholar databases and multiple online repositories to uncover additional potentially relevant papers. This method contributed to an additional 44 papers.

2.1.2. Literature Selection

The identified literature sample was screened following the defined inclusion criteria, as shown in Table 2. Firstly, as many papers still belonged to multiple research categories, all categories unrelated to the building industry were excluded. Secondly, only papers written in English were preserved, resulting in 287 items eligible for screening from the database search. These documents were then screened based on their titles and abstracts to include those that belong to the research topic. Following this step, 64 papers remained that needed to be screened in their entirety. Finally, the full-text assessment took place to verify the papers’ relevance to this review. In this step, another 37 papers were eliminated, as they would not directly contribute to research questions, since the focus of the studies was more centered on other disciplines, such as computer science or material science, exploring in detail technological processes relating to AI or 3DP that would not directly contribute to the topic at hand.

Table 2. Papers inclusion criteria.

Inclusion Criteria	Value
Papers belonging to the research categories unrelated to the construction industry	Exclude
Papers written in the English language	Include
The title includes at least one searched keyword	Include
The abstract includes at least one searched keyword from each topic	Include
An abstract is relevant to the research question	Include
Papers that are not accessible in full text	Exclude
Full text is relevant to the research question	Include

Another 22 papers were discovered through a reference list search during the full paper screening. The same full-text screening process was applied to the papers collected from other sources. After the screening, 17 papers from the database search and 4 papers collected through other sources were determined to fit the inclusion criteria. Finally, 21 papers were included in this review (Figure 3).

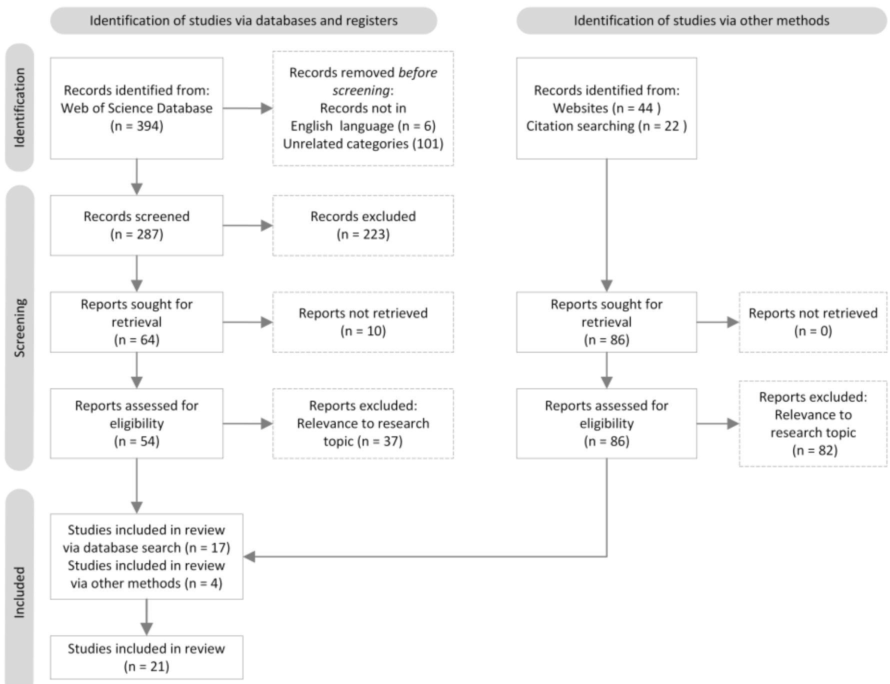

Figure 3. PRISMA flow diagram of literature review.

2.2. Analyzing Literature Sample

The selected literature sample, which included 21 papers, was analyzed using quantitative and qualitative methods. Quantitative analysis was performed to gain insight into the characteristics of the collected sample related to the publication trends and main research topics. The former was achieved using the bibliometric analysis method, which is an applied mathematical analysis of bibliographical units [41]. By analyzing the publication data, citations, and keywords, this method systematically represents citation patterns and publication trends within a specific field or across several disciplines [42].

Authors of this study performed the described three-step research process. Two researchers were involved in the literature search and collection steps, while the third author was engaged in overseeing and reviewing the collected sample to ensure the quality of the research. The search was performed independently by two researchers to avoid bias.

Later, combining search parameters and the screening process was performed in two steps, with one of the researchers performing the title and abstract screening phase and the other author performing full-text screening. Similarly, the data analysis phase was performed by two authors, with the third author independently verifying the results.

2.2.1. Bibliometric Analysis

The network analysis technique was used for this research. This method relies on the analysis of bibliographic data to visualize the connections between different articles based on citations, publications, or keyword co-occurrences. By forming these connections, the data are systematized, and research trends are uncovered. The analysis was performed using the VOSviewer software version 1.6.18, which is designed to construct and visualize bibliographic networks [43], which application proved to be highly efficient and beneficial in the previously conducted studies [44,45]. The literature data were imported to create the network based on the discovered keyword co-occurrences, enabling researchers to gain insight into trends in the field.

2.2.2. Content Analysis

The collected sample was qualitatively analyzed to systematize and assess the findings based on the bibliometric analysis results. This step provided a deeper understanding of the principal themes uncovered during the quantitative analysis. Furthermore, content analysis was used to identify and research the principal applications of AI tools for 3D-printed structures and the main AI tools used in the industry. These tools and applications are systematized and classified along with the most important findings in the literature review to assess the state of the art in the field and the main challenges.

3. Results

The key results of the bibliometric and content analyses are reported in this section under the topics listed below.

3.1. Bibliometric Analysis

3.1.1. Publishing Trends

The development of the researched field is better understood through the observation of the publishing trends in the collected literature sample. Firstly, it was noted that the publication period for this study was limited to the last ten years. However, the literature screening process showed that no topic-relevant papers were found before 2018, as shown in Figure 4. All the papers collected in the sample were published in the last six years, showing a growth in the number of relevant articles in the last two years, with 14 (67%) published papers. This observation confirms the novelty of this research field and shows the contemporaneity of the research problem. This trend underlines the need for this kind of study, as all available literature is contemporary and comprehensive reviews in the field have not been conducted.

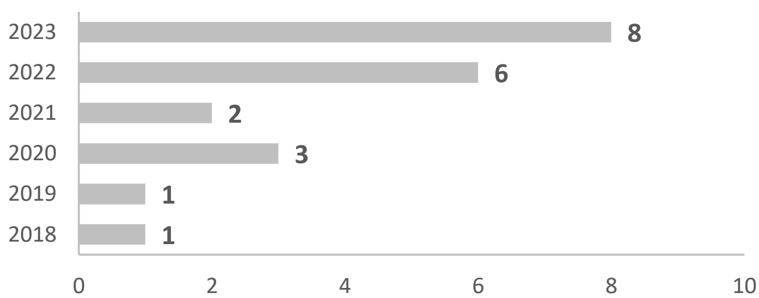

Figure 4. Number of articles published per year.

The relevance of the research problem is also shown by analyzing the source journals for the retrieved sample. In the final sample, only two were conference proceeding papers [46,47]; the rest were journal articles. This study includes 19 articles published in 13 different journals. Table 3 summarizes the source journals by the number of reviewed papers and the journals' impact factors. One journal, *Construction and Building Materials*, had a considerably higher occurrence rate than the rest, with four published papers on the topic [48–51]. The previous shows the existing focus on using AI tools to analyze materials' structural properties in construction. Another three journals had more than one published article, including *Cement and Concrete Research*, *Buildings*, and *Automation in Construction*. The previous study [52] showed that these journals actively publish research on the 3DP technology's application in architecture. However, it can be noted that these journals showcase the interest in research conducted on using AI tools in 3DP.

Table 3. Source journals for the analyzed literature sample.

Journal	No. of Articles	IF (2022)
Construction and Building Materials	4	7.4
Cement and Concrete Research	2	11.4
Buildings	2	3.8
Automation in Construction	2	10.3
Additive Manufacturing	1	11.63
Virtual and Physical Prototyping	1	10.96
Journal of Intelligent Manufacturing	1	8.3
Case Studies in Construction Materials	1	6.2
Structures	1	4.1
Materials and Structures	1	3.8
Applied Sciences	1	2.7
International Journal of Architectural Computing	1	1.7
Construction Innovation	1	-

The support trend for research in this field is also sustained by the fact that almost all reviewed articles were published in leading journals in the field of digital fabrication and construction with high impact factors. Four of the identified journals, publishing six (28.5%) of the reviewed papers, had significantly high impact factor values above 10.

3.1.2. Keywords Analysis

A network analysis was performed based on the keyword co-occurrence rates, visualizing keyword relations and co-occurrence rates in the analyzed data sample. There are two possible methods of obtaining data for network visualization: automatically extracting the most common words by scanning article titles or abstracts or generating a data map based on the bibliographic metadata keywords [43]. For this study, the second method was used, since it provides a clear picture of the principal themes discussed in the studies, as predefined keywords often correspond with the main themes presented in the research. As the literature sample was collected from multiple sources, bibliographic metadata for this analysis were obtained from the reference manager software and subsequently imported into VOSviewer for the analysis.

The two options for counting keyword occurrence rates are full counting and fractional counting [53]. For this study, the network was generated by the full counting method, where each link for one co-occurrence has the same strength. Since the collected literature sample is relatively small, the minimal number of co-occurrences in the network was set to 2, resulting in 25 keywords repeating more than twice. These words were then used to generate a visualization network based on the number of occurrences and their link strength. Table 4 systematizes the top 15 included keywords based on the number of occurrences and total link strength.

Table 4. The identified keywords, their co-occurrence rate, and link strength.

Keyword	Research Areas	No. of Occurrences	Link Strength
compressive strength	Civil Engineering	6	28
concrete	Materials Science	5	22
machine learning	Computer Science	6	21
3D printing	Manufacturing Engineering	5	18
artificial neural networks	Computer Science	4	17
performance	Civil Engineering	4	15
construction	Civil Engineering	4	14
additive manufacturing	Manufacturing Engineering	3	12
cementitious materials	Materials Science	3	11
artificial intelligence	Computer Science	2	11
design	Architecture	4	10
mix design	Manufacturing Engineering	2	10
prediction	Computer Science	2	10

The identified keywords are strongly related to the main topic, with most of them referring to AI tools, such as "machine learning" or "artificial neural networks". In contrast, others refer to additive manufacturing processes like "3D printing", "concrete", or "mix design". Two terms with the highest link strength and number of incidences are "compressive strength" and "concrete", which indicate a research focus on the material and structural design optimization for 3DP, with multiple papers focusing on the application of AI tools in this field [51,54,55]. Another highly present term was "machine learning", indicating increased use of ML tools in the field. The previous can be better observed in Figure 5, which visually presents a keyword network grouping related keywords into four clusters.

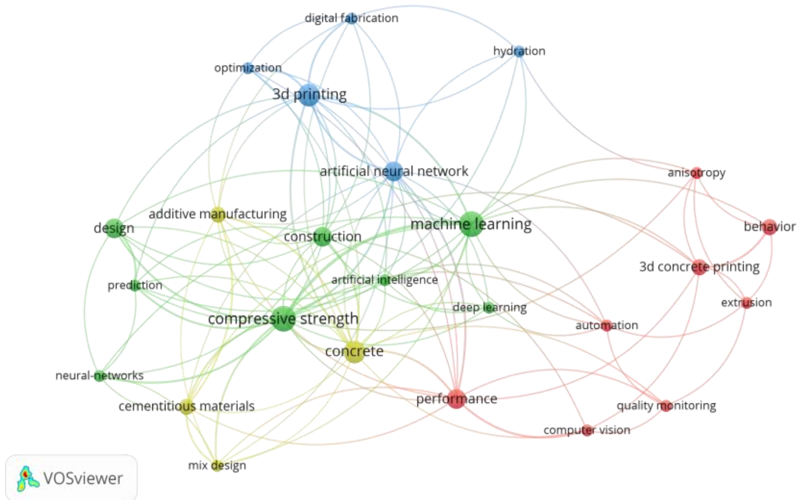

Figure 5. Visualization of the keyword network.

The keywords are divided into clusters based on their interconnections. These agglomerations can help better understand the principal themes in the existing research. The largest green cluster includes the most reoccurring words and focuses on the design and predictions in construction using ML tools. The red cluster is more focused on 3D concrete printing through performance and behavior analysis. The main AI tool in this cluster is computer vision, which is closely related to the rest of the terms. The blue cluster is formed around 3DP optimization and digital fabrication processes. This cluster includes artificial neural networks (ANNs) as a representative AI tool. The smallest yellow cluster is centered around material design for AM without including the specific AI tools.

The keyword cluster analysis identified three principal categories representing the central research topics (Table 5). These topics differentiate the domains of AI tool application in the production process of 3D-printed large-scale structures in architecture. Representative keywords identified in the map and given for each category in Table 5 indicate the AI methods used most, including ML, ANN, and computer vision.

Table 5. Principal research themes.

No.	Topic	Representative Keywords
1	AI-driven design of 3D-printed architectural structures	Design Construction Machine learning Neural networks Deep learning
2	AI-driven optimization of 3D-printed architectural structures	Optimization Digital fabrication 3D printing Artificial neural networks Concrete Performance
3	AI-driven diagnostics of 3D-printed architectural structures	Computer vision Quality monitoring Automation Prediction Behavior

3.2. Content Analysis

The scientometric analysis provided insight into the topics most often researched: AI tools and techniques, their applications, and their correlations. To fully grasp the relationship between AI and 3DP in the architectural domain, a more in-depth analysis of the discovered data is given in the following subsections.

3.2.1. Techniques

ML is a computer science field that relates to the algorithms that learn how to solve complex real-world problems from given datasets. The most common problems met by ML include classification, clustering, and prediction [56]. The generally accepted types of ML, distinguished by significant functional differences, include (1) Supervised Learning (SL), which uses input data for identification and fulfillment of certain tasks, among which classification and regression are the most well-known; (2) Unsupervised Learning (UL), which is mostly concerned with identifying groups and organization patterns within unlabeled datasets, with the common task of clustering; (3) Semi-Supervised Learning (SSL), which learns from both labeled and unlabeled data, commonly used for classification and clustering purposes; and (4) Reinforcement Learning (RL), which functionality lies within a reward–punish system where the algorithm automatically evaluates the best behavior patterns and takes further actions to optimize the system [57]. Deep learning (DL) is a subset of ML with key features represented in numerous layers or stages of nonlinear information processing and supervised (SDL) or unsupervised (UDL) feature representation at progressively higher, more abstract layers [58]. Defining ANN in the scientific and practical domains remains challenging [59]. The architecture and functionality of artificial neurons forming ANNs are based on biological neurons. These networks function by processing information in their fundamental constituents—artificial neurons—in a non-linear, distributed, parallel, and local manner [60]. Lastly, computer vision represents a technical system whose primary goal is to mimic the functional modules of human vision, which is achieved through tasks including visualization, image formation, control of irradiance, focusing, irradiance resolution, tracking, and processing and analysis [61].

Out of the twenty-one reviewed studies, ML is found to be the main topic of six studies, with applications ranging from design, optimization, and diagnostic purposes for 3DP structures [28,47,55,62–64]. ANN as a category is found to be dominantly present in nine studies overall, with applications belonging to the diagnostic domain [46,50,51,54,65–69].

The combined appearance of ML and ANN is dominantly found in a total of four studies, where the use is focused around optimization and diagnostics [49,70–72]. Lastly, computer vision algorithms are present solely in the diagnostic domain and cover a total of four papers [47,48,54,73]. Figure 6 displays the identified AI techniques, their domains of application, and the related references.

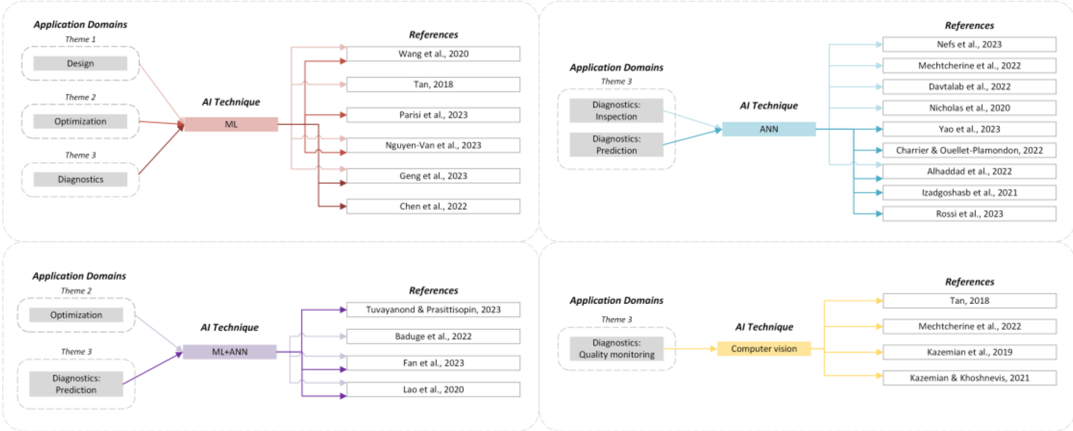

Figure 6. Overview of AI techniques and main applications in 3DP in architecture [28,46–51,54,55,62–73].

3.2.2. Applications

Topics identified through the bibliometric analysis, including AI-driven (1) design, (2) optimization, and (3) diagnostics of architectural 3D-printed structures, are analyzed in depth in this subsection (Figure 7). Within each topic, the following aspects were reviewed:

1. general uses of different AI algorithms in a specific application domain;
2. challenges of large-scale structures 3DP overcomes by integration of AI;
3. modifications of AI algorithms made to suit a specific application domain.

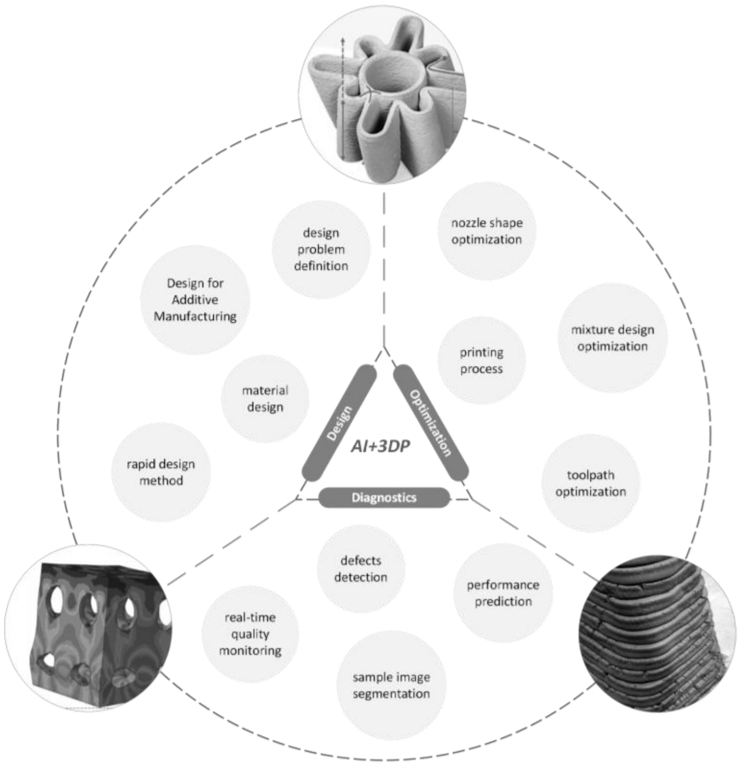

Figure 7. Overview of the main identified uses for AI in large-scale 3DP.

Topic 1. AI-Driven Design of 3D-Printed Architectural Structures

In the reviewed articles, AI integration in the 3DP design process is mainly focused on the issues of material design and design optimization of the 3DP mixes. The previous is confirmed by the fact that 75% of the represented papers deal with these specific topics. Wang et al. [64] deliver a systematic review of the emerging digital technologies used for off-site construction leading towards Industry 4.0, where among the fifteen reviewed technologies, AI and 3DP are elaborated on separately, each representing an important factor for the future development of the construction sector. On the other hand, Nguyen-Van et al. [55] review the development of predictive modeling and design optimization and the current state of the art specifically for concrete 3DP, where four characteristic steps for the implementation of ML into the 3DP are given, including the problem definition, development of the model, collection of data, and process settings. Moreover, Geng et al. [28] deliver a review of the latest research on integrating ML into construction 3DP, with an extensive discussion of current problems and future trends in the field. In another study, Tan [47] proposes a framework for AI and 3DP combinations in five specific aspects, including 3DP materials, automation design, digital construction, 3DP robots, and a 3DP BIM platform. The overview of the main findings of AI models in 3DP for designing large-scale structures is given in Table 6.

Table 6. Overview of the specific techniques, applications, and research conclusions of AI-driven design of 3D-printed architectural structures.

Applications	Techniques	Main Conclusions	Author(s) References
Design for Additive Manufacturing (DfAM) of prefabricated architectural components.	ML	• Benefits: reduced effort and cost in the design process; components' segmentation speed is increased. • Issues: time-consuming topology analysis preparation process; limitations in the components' configuration design.	Wang et al. [64]
Rapid design method development for product modeling and its structure selection.	ML	• Future research: exploring combinations of novel technologies such as BIM and AI.	Tan [47]
Design problem definition aimed at AM.	ML	• Challenge: handling large amounts of data with high computational costs. • Digital twins of AM structures could support the ML techniques in attaining better outcomes. • ML included in tasks such as topology optimization, bio-inspired concept creation, and geometry creation using Computer-Aided Design.	Nguyen-Van et al. [55]
AM material design with the real-time observation and automatic mixture alterations during the printing process.	ML	• ML application in the matching ratios' selection can improve production efficiency and reduce construction costs. • Future studies: the integration of different research areas presenting specific challenges in the construction 3DP.	Geng et al. [28]

The main challenges found in the studies include the time-consuming process and handling of large amounts of data in ML models [55,64]. Regarding the ML application in

3D concrete printing (3DCP), the challenge that may arise relates to data interpretability (specifically related to correlation-based ML models) and validation, since supervised regression models are one of the most commonly used in these types of cases. Having that in mind, for the valid application of ML, it is of utmost importance for the dataset to be correct, complete, and representative of a large data population, which is, apart from being time-consuming, also a costly process [55]. In the large-scale 3DP process, the challenges that could be met by AI include predicting and controlling material anisotropy, avoiding uneven pore distribution caused by the lack of fusion inside the material, and improving the warping behavior of the structure due to residual stresses caused by the rapid cooling characteristics of the 3DP process. In these cases, AI can be trained to learn certain principles and methods of structural design through ML models, allowing it to handle complex scenarios in the 3DP process in an efficient, intelligent, and environmentally conscious way [28].

The functional characteristics of AI models used for 3DP, specifically ML, remain true to their core logic, as explained in the introductory part of the Content Analysis section. The difference that arises is seen in the datasets that the ML models are trained on and the roles they are designed to embody. Specifically, ML is utilized for material design and property formulation to achieve optimal and desired targets [55]. Further, in the four registered stages of modeling for digital concrete fabrication, ML is introduced in the last stage, after the analytical modeling, experiments for the input data creation, and numerical simulations, contributing to the process with the ability to create a virtual 3DP simulation that could inform the design process [55]. Concerning different tasks set out for the AI algorithms, the models may vary, and researchers could select the optimal ML type regarding its future application in the 3DP process. This relatively subjective course of action could lead to an increased chance of poor ML training performance. The smoothness of the ML model training could be enhanced through the existence of a shared platform that contains the previously gathered experience from different ML models, since it can learn how to avoid making the same mistakes [28].

Topic 2. AI-Driven Optimization of 3D-Printed Architectural Structures

Among the papers that explore ML applications for the optimization of 3DP, the study by Parisi et al. [63] delivers an approach towards intelligent AI-controlled tower crane 3DP with optimization of the extruder toolpath. On the other hand, Wang et al. [64] explore ML-based optimization targeted at specific construction tasks in off-site construction applications. Moreover, Nguyen-Van et al. [55] present an overview of the current state-of-the-art development of modeling and design optimization tools for 3DCP, highlighting the possibility of reducing printing time, improving structural performance, or allowing for the adaptation to printing structures with complicated geometries by using an intelligent toolpath-generating algorithm. Additionally, this study highlights the intricate relationships between ML and ANN models, as shown in the analyzed papers. As a result, both AI categories have been included in multiple articles, particularly in the realm of optimization problems. The study by Baduge et al. [70] highlights the use of ANN, ML, and DL algorithms and their applications in various domains of the construction process, pointing out the advantages of their integration into 3DP, which leads to optimized solutions through the increased level of automation, more advanced robots, and geometrical flexibility of the structures. Lao et al. [71] explored optimized nozzle shapes for delivering high-quality surface finishes in varying types of 3DP structures' geometry. A combination of ML and ANN is found in material design, specifically in forming the optimal mixture for the 3DP process depending on the desired outcome, as presented by Fan et al. [49]. Table 7 summarizes the key features of the optimization-related studies.

Table 7. Overview of specific techniques, applications, and research conclusions of AI-driven optimization of 3D-printed architectural structures.

Applications	Techniques	Main Conclusions	Author(s) References
Formation of the cloud-based 3DP system that optimizes and enhances the printing process and identifies collision-free tool path; optimum geometry partitioning and material distribution optimization.	ML, DL, ANN	• Advantages: the generation of more optimized AM solutions. • Future trends: 4D printing. • AI-enabled collaborative robots will gain market in the 3DP industry, allowing the 3DP process to be configured during the printing with the material alterations.	Baduge et al. [70]
Formation of a tower crane (TC) 3DP AI agent which dynamically activates the TC freedom degrees to minimize the swing effect, simultaneously maximizing the printing speed.	DRL TD3 architecture	• Deep Reinforcement Learning (DRL) provides optimal 3DP control solutions, without strictly needing any formal and mathematical systems model. • DRL is effective in the case of complex and non-linear systems, including real-time image processing-led control.	Parisi et al. [63]
Printing toolpath optimization for avoiding under and overfilling issue; printing mixture optimization.	ML	• Printing time is reduced, enhanced structural performance, and optimized complex shapes-adapted printing. • ML fixes the issue of the time-consuming process of the Finite Element Method (FEM) approach in the 3DCP, it aids the printing mix design, as well as assists in the modeling and optimization for the 3DCP process.	Nguyen-Van et al. [55]
Improvement of the efficiency and accuracy of other technologies, one of them being AM.	ML	• Issues: time-consuming dataset preparation and the lack of real practice validation.	Wang et al. [64]
Optimizing the mixture design of Ultra-High-Performance Concrete (UHPC).	ML, back-propagation (BP) ANN, genetic algorithm BPNN (GA-BPNN)	• Intelligent optimization has not been researched in domains such as UHPC micro-characteristics. • Future trends: more research should be done on the design theory of 3DP-UHPC to build a relation among material composition, performance, and applications.	Fan et al. [49]
Finding a proper nozzle shape for production of designated extrudate geometries.	ML, ANN	• The proposed methodology improves the surface quality of the structures with different curvatures. • The proposed approach has the potential to improve the surface quality for other types of 3DP structures.	Lao et al. [71]

Defined as one of the tasks of intelligent systems, optimization is a process executed using various AI algorithms. Specific challenges presented by the optimization tasks in

3DP include their application in the practical domain, where AI is still mostly limited to checking printability and modularization for prefabrication techniques [70]. Challenges posed include those related to the possibilities of the ML algorithms, such as one described by Lao et al. [71], which includes the non-invertible relationship between the targeted extrudate cross-sectional shape in the experiments and the nozzle shape in the ML model. The authors conclude that this challenge is still not overpowered by the benefits that the ML integration into the 3DP process creates, such as the enhanced overall efficiency for achieving extrudate control in practice [71]. The main challenge faced by the DRL method in the study by Parisi et al. [63] includes the creation of the control system, which produces an effective extruding toolpath for the 3D printer. Another common challenge in practice involves the higher geometric complexity that is derived from the optimized topologies. This issue has the potential to be resolved by generating an innovative toolpath, which would ensure the optimized concrete structures' continuous printing [55]. Challenges faced in the UHPC domain include the inability to utilize common models of AI for the purpose of mixture design, since they produce low-accuracy results [49].

The algorithms that are used for the optimization tasks vary in their basic functionality and computational cost. For example, a novel AI framework was given by Parisi et al. [63], which is the core of the proposed extrusion-based 3DP system. The basic logic of the approach is an intelligent DRL agent that dynamically activates the tower crane's degrees of freedom to minimize the extruder swing effect while maintaining maximum printing speed. The main inputs for the AI-controlled system contain the dynamic environment characteristics, the possible actions for the agent to take, the reward function, and the agent modeling with its learning algorithm. The specific type of algorithm is the twin-delayed deep deterministic policy gradient (TD3), which is suitable for models characterized by continuous action spaces [63]. The algorithms used for the optimized AM mixture design include the ones described by Fan et al. [49], where the back-propagation ANN was used to model the mixtures (ANN input), as well as the compressive strength and workability (ANN output) parameters. The algorithm was trained and tested on 53 different concrete mixtures. Another type of algorithm that was used for the AM-optimized mixture design is the Genetic Algorithm back-propagation neural network (GA-BPNN). The procedure involving this AI technique included creating a GA-BPNN prediction model based on obtained training datasets, determining the initial mixture of the UHPC in accordance with the ingredients' boundaries, inputting the initial mixture for property prediction by the developed network, identifying the predicted results, and redesigning the initial mixture until the desired requirements are met [49]. The ML model workflow introduced by Lao et al. [71] included four steps: (1) pre-testing, with the setting up of the experiment with different nozzle shapes and conducting the experiment; (2) ANN training, which involved the optimization of the ANN topology, training the model with pre-testing results, and experimentally validating the ANN model; (3) building up the database, with the generation of enough volume of random nozzles and predicting the corresponding extrudate shapes with the ANN; and (4) target printing, which involved analyzing the target extrudate shape, finding the nozzle shape in the database, and conducting the printing with the nozzle [71].

Topic 3. AI-Driven Diagnostics of 3D-Printed Architectural Structures

The reviewed articles include several approaches towards the diagnostic tasks for 3DP, based on (1) ML-driven prediction, simulation, and inspection; (2) ANN-based inspection and prediction; (3) combined use of ML and ANN for prediction; and (4) computer vision technology used for inspection and quality-monitoring purposes.

A variety of ML technologies are utilized for predictive and inspection purposes, ranging from SL, UL, SSL, and RL, with applications explored in the domains of material design optimization, control printing accuracy, printing defect detection and classification, state differentiation of the printing process, anisotropic behavior analysis, printing product classification in relation to the deformations, printing cost estimation, compensation of printing material deformation, printing process planning correction, large-scale printing product customization, and others, as presented by Geng et al. [28]. Additionally, Chen et al. [62] introduce a deep-learning module of the Dragonfly 3.6 software to extract the axes of the steel fibers in the X-ray micro-computed tomography (X-CT) images of 3DP concrete samples and evaluate their 3D orientational distribution statistics.

ANN models used for the inspective tasks in 3DP rely on several algorithm types, which differ in functionality and purpose. Yao et al. [51] explore the effect of steam curing conditions on the performance properties of 3DP materials at various ages of curing, using a specific set of algorithms to predict the performance of the material. Other types of applications are found, mostly related to the prediction of the tensile and compressive strengths of the researched materials [65,66,68]. Additionally, Rossi et al. [46] deal with modeling the curing conditions of cellulose-based 3DP components using a defined set of ANN models. The relationship between ANN and ML is intertwined, leading many researchers to employ both terms. Among the papers presented in this subgroup, two papers represent reviews of the current research status [49,72], whereas one paper presents an original methodology for finding the proper nozzle shape in the 3DP process [71].

Computer vision algorithms are seen as a promising method for assessing real-time 3DP process tracking, where the data collection usually consists of a camera being installed on the extruder to capture videos and images during the printing process. Among the four included papers, two represent frameworks for integrating computer vision technologies in the 3DP process [47,54], whereas the other two papers develop novel methods for this purpose. Kazemian et al. [73] develop a vision-based real-time extrusion quality-monitoring system for robotic construction. In another paper, four techniques for inline real-time extrusion quality monitoring during construction are given [48].

An overview of the key research aspects is given in Table 8.

Table 8. Overview of the specific techniques, applications, and research conclusions of AI-driven diagnosis of 3D-printed architectural structures.

Applications	Techniques	Main Conclusions	Author(s) References
Automatic robotic detection of the printing defects; printing parameters reconfiguration in real-time.	ML Computer vision	• AI and BIM provide useful methods for the issues which arise in the large-scale 3DP.	Tan [47]
Extraction and 3D analysis of the centerlines of steel fibers in the X-ray micro-computed tomography image sequence.	DL U-Net module	• U-Net is a newly approved neural network in the ML field where the computer is allowed to segment according to the semantics of the images.	Chen et al. [62]
The automatic image segmentation of the 3DP fiber-reinforced materials.	DCNN U-Net module	• Data augmentation procedure eliminates the time-consuming task of the manual annotation. • The automated image segmentation method is suitable for the efficient identification of complex micro-structures.	Nefs et al. [50]
Real-time layer extrusion monitoring during 3DCP.	Computer vision DCNN	• The quality control methods should include easy-to-perform tests at a high frequency.	Mechtcherine et al. [54]

Table 8. *Cont.*

Applications	Techniques	Main Conclusions	Author(s) References
Detection of bending deformations in the 3DP layers, during or after the printing process.	DCNN	• The developed model only defects bending of the layers. Other concerns are not addressed. • The performance of the system under an actual construction site environment should be verified. • The potential of computer vision and DL for automated inspection, quality control, and progress monitoring during 3DP is seen.	Davtalab et al. [67]
Detection of the extruded layer and measurement of the layer width in real-time. Automatic adjustment of the material deposition rate.	Computer vision	• The proposed method does not need sample preparation. • The method is limited to laboratory environment, without known outcomes if it were tested on a real construction site. • High precision and responsiveness of the developed extrusion monitoring system under the experimental conditions.	Kazemian et al. [73]
Real-time quality-monitoring system which detects variations in the material properties before the deposition.	Computer vision	• The vision-based techniques have the highest precision and responsiveness to material variations, compared to other methods.	Kazemian & Khoshnevis [48]
Panel performance prediction and the printing toolpath predictive generation.	cGAN	• The encoding and result parsing within Grasshopper makes the NN work as an immediate design tool for the user. • NN trained on digitally compiled datasets have potential to integrate analytic and predictive information into the real-time design and fabrication processes.	Nicholas et al. [69]
Performance prediction for 3DP concrete. BAS method is used for the ANN hyperparameter adjustment, along with the cross validation which solves the ANN overfitting problem.	ANN, ML Beetle antennae search (BAS) Cross validation	• The construction of a suitable ML model with high precision and dependability is laborious and time-consuming. • The hardening performance of the material under the same printing parameters is maximized.	Yao et al. [51]
Prediction of the fresh properties of cementitious materials, such as yield stress and mini-slump.	ANN	• ANN was successfully trained to be able to predict the yield stress as a function of the percentage in weight of cement of each admixture. • Future research: involving the time factor in the ANN to describe the evolution of the yield stress during printing.	Charrier & Ouellet-Plamondon [66]

Table 8. *Cont.*

Applications	Techniques	Main Conclusions	Author(s) References
Quality control of the fused deposition modeling (FDM) printing technology, predicting the ultimate tensile strength, and optimizing the printing and material parameters.	ANN	• The model is a credible guideline for designers and researchers to manufacture FDM of optimal mechanical properties. • The developed ANN model accurately predicts the UTS of FRP. • Future activities: creation of an open-source tool for users of FDM 3D printers.	Alhaddad et al. [65]
Prediction of the 3DP concrete compressive strength.	ANN	• Difficulties: the accuracy of the model depends on the number of patterns. • Limited amount of research on patterns concerning 3DP concrete's compressive strength. • For accurate ANN model creation, one hidden layer in its structure is enough.	Izadgoshasb et al. [68]
Properties prediction of the Ultra-High Performance Concrete (UHPC) such as mechanical strength, flowability, filling capacity and segregation.	ML, ANN	• The complexity of the UHPC system results in insufficient predicting accuracy when using common models of AI. • There are not enough studies on the topic of the micro-structures of the UHPC.	Fan et al. [49]
Statistical modeling of the curing of cellulose-based 3DP components.	ANN	• The dataset size is a constant constraint for getting good predictions out of physically generated datasets.	Rossi et al. [46]
CNN is utilized for optimal proportions of 3DP products prediction; SL is utilized for printing products' geometric deviations prediction; UL is utilized for 3DP material porosity prediction; RL is utilized for print trajectory geometry prediction and planning.	ML	• ML techniques are used for printing concrete filament geometrical shapes prediction, and automatic detection of layer deformations. • ML is used for the automatic detection of surface defects; ANN is used for predicting crack patterns and stress-crack width curves of pore structures in 3DP. • Future research: interlayer bond performance, real-time status monitoring, anisotropic behavior control.	Geng et al. [28]
DfAM, including geometry deviation prediction, material analytics, prediction of defect and others.	ML, ANN	• Although many ML methods for DfAM have been researched in various applications, only several research programs have been conducted in the construction industry.	Tuvayanond & Prasittisopin [72]
Development of a predictive model for extrudate geometry in 3DCP.	ML, ANN	• A predictive model was developed to correlate the nozzle shape and the extrudate shape counterpart using ANN.	Lao et al. [71]

The main issue in which DCNN was utilized as an effective solution, as presented by Nefs et al. [50], is the manual annotation of micro-structural objects in 3DP strain-hardening cementitious composite (SHCC) materials, which would be an extremely time- and effort-consuming task because the fibers may be oriented in arbitrary directions and never positioned in the same plane. This issue would arise if the typical ML algorithm was used instead of the DCNN. Instead, a new methodology is presented in which the image segmentation of fiber-reinforced materials is performed with automated annotations of physical sample data [50]. One of the common large-scale 3DP issues that has been addressed is the fact that in the robotic construction process, which could take as little as one day to complete, there is not enough time for manual inspections to resolve problems. The reason for the high-speed construction is seen in the structural benefits that arise from it, such as enhanced interlayer bonding. Therefore, to monitor the printing process, these systems should ideally be equipped with an automated process inspection system that documents all relevant printing parameters [67]. Another set of 3DP-related issues is the assessment of material characteristics that impact the 3DP process, such as pumpability, yield stress, viscosity, and cement hydration, for which various scholars have focused their research on ML and ANN [66]. Specifically regarding UHPC, one of the main issues involves the integration of fibers, which could impact structures in a positive or negative manner, depending on their amount and distribution. Therefore, to maximize the positive role of fibers, a multi-disciplinary approach is necessary, including material science, mechanics, and intelligent manufacturing [49]. Another common issue in large-scale 3DP production relates to surface quality problems, such as the jagged surface or staircase effect on the 3DP object. This issue has been acknowledged and introduced to specific ANN models to affect the nozzle shape during 3DP [71].

Among the studies in the diagnostic domain, the Deep Convolutional Neural Network (DCNN) has been explored in three out of six papers [50,54,67], representing the algorithms that excel in processing organized arrays of data, such as images, as their primary functional characteristic [74]. Another explored type of ANN is the Conditional Generative Adversarial Network (cGAN) [69], whose main characteristic is the fact that it constitutes a pair of networks, known as the forger/generator and expert/discriminator, which compete in the parallel training process [75]. Further, the ANN combined with the Backpropagation Learning model was used together with the Artificial Bee Colony optimization algorithm, which creates an effective feed-forward model for the inspection and prediction of the 3DP printing and material parameters [65]. Similarly, specific types of ANNs are employed to predict the characteristics of 3DP structures. In the case presented by Nefs et al. [50], the dataset for the DCNN training was created by scanning a basic specimen composed of a single, prestressed yarn of fiber surrounded by a cementitious matrix with air voids. Later, the scan was divided into smaller windows, whose dimensions corresponded to those at which fibers in real fiber-reinforced materials appear straight. To generalize the algorithm, a data augmentation procedure was employed, where the windows of the obtained scan were rotated along the three axes at arbitrary angles, which allowed the DSCNN to train for the segmentation of arbitrarily oriented fiber samples. The DCNN network was constructed using Python, with the utilization of the Tensorflow and Keras packages [50].

4. Discussion and Conclusions

The interpretation of the results is presented in a wide context, along with the research's limitations and suggested directions for future study.

4.1. Results Interpretation and Implications

The review on large-scale 3DP architectural structures produced using AI was performed on a representative literature sample, which included 21 relevant papers examined using bibliometric and content analyses. The bibliometric analysis shows that the reviewed papers have been published over the past five years, with a growing trend in the number of publications in the past two years. Additionally, the bibliometric analysis revealed that the journals covering engineering, fields, architecture, and construction are most frequently published. Moreover, co-occurrence network analysis discovered keywords that were strongly interrelated within the literature sample. This analysis enabled the identification of three principal research thematic frames that coincide with AI tools' application domains in the production of large-scale 3DP architectural structures: AI-driven design, optimization, and diagnostics. Keywords included co-occurrence analysis and isolated AI techniques (including ML, ANN, and computer vision) commonly applied in the production of architectural structures by 3DP. Further, full-text content analysis of the literature sample deeply reviewed specific AI techniques and their applications. Lastly, the systematic review on using AI technologies in creating 3D-printed architectural structures enabled knowledge synthesis, technology assessment, and knowledge gap identification.

The synthesis and summary of existing published research papers related to the application of AI technologies in the production of 3D-printed architectural structures were presented in the study. Consequently, the study helps consolidate the current state of knowledge in the field and provides a comprehensive overview of the subject matter. Moreover, light was shed on the way that AI techniques, such as ML, ANN, and computer vision, have enhanced the design, optimization, and diagnostics of 3D-printed architectural structures, providing information on technological development and prospective use. By synthesizing the literature, the study offers insights into techniques and integration strategies relevant to architectural production. The capabilities, limitations, and potential of AI technologies that support the production of 3D-printed architectural structures were discovered. Reviewing literature facilitated the assessment of the state of technology, identifying its strengths and weaknesses, and providing insights into its feasibility and applicability in the architectural field. Through our examination, we identified literature, methodologies, algorithms, or frameworks utilizing AI to design or optimize designs for structural integrity, aesthetics, energy efficiency, or other criteria. The study also inquired how AI can enhance structural performance, material efficiency, and environmental sustainability. This helped perceive the benefits and limitations of AI-based approaches in achieving desired outcomes. A gap analysis and identification of areas for further research within the subject matter domain were conducted. Analysis of existing literature enabled the identification of topics or aspects that have yet to be extensively explored, paving the way for future research and development. In addition, the literature review highlights innovative approaches, novel applications, and emerging trends, generating new ideas and possibilities.

The findings of this research provide researchers and practitioners with information on existing research and applications of 3D-printed architectural structures created using AI. By investigating and developing AI-driven strategies for 3D printing of building structures, researchers can drive innovation, improve efficiency, and expand the capabilities of architectural practice. The study can also be valuable for architects and engineers looking to understand the technical aspects, benefits, and limitations of 3DP and AI technologies used in architecture. The research gives insights into aspects of design, optimization, diagnostics, as well as feasibility in real-world applications. Moreover, the review may help researchers and practitioners to understand how 3DP and AI technologies can contribute to sustainable design and construction practice. Previous knowledge can assist in making informed decisions regarding material selection, energy efficiency, and waste reduction during the design and construction stages, contributing to creating safe and efficient structures with enhanced functionality and performance. Finally, identified challenges, barriers, and opportunities for integrating AI into architectural projects could provide information to industry professionals, policymakers, and stakeholders about the potential impact of AI on industry and business models.

4.2. Research Limitations

Application of the SLR method in this research allowed the generalizability and consistency of research findings, following the goal to systematize and comprehend the scope of application of AI in the creation of 3D-printed architectural structures. To provide transparency, clarity, integration, focus, equality, accessibility, and coverage of the study, the authors strictly followed the PRISMA statement [38,39]. The previous approach aimed at minimizing bias or chance results and producing reliable findings. However, the paper has several limitations. Firstly, the analysis was performed on a data sample limited primarily to the WoS database. Additional papers were included in the sample through manual and reference list searches to provide a more thoughtful overview and overcome this limitation. Secondly, the review limitation could be induced by the study retrieval process and linguistic biases. Thirdly, the keywords applied in the search needed to be standardized, excluding authors who use distinct keyword variations. Finally, one should be mindful of the authors' bias and that no formal risk-of-bias evaluation was carried out when using the research's findings. Nevertheless, the author's expertise in the field provides context for interpreting bibliometric analyses.

4.3. Future Research Directions

Based on the results of the literature review presented in this study, three specific sets of challenges (corresponding to identified application domains) could be summarized.

1. **Challenges of AI-driven design of 3D-printed architectural structures**, including:
    - time-consuming and costly data acquiring and labeling process,
    - computational costs of handling large amounts of data,
    - data interpretability and validation, and
    - the prediction and control of the material anisotropy and other characteristics.
2. **Challenges of AI-driven optimization of 3D-printed architectural structures**, including:
    - application of AI in the practical domain, since it is mostly limited to checking printability and modularization for prefabrication techniques,
    - ML models' non-invertible relationship between the input (targeted extrudate cross-sectional shape) and output (3DP nozzle shape),
    - creation of the control systems for effective extruding toolpath,
    - higher geometric complexity of the optimized topologies, and
    - inability to utilize common AI models since they give out low accuracy results.
3. **Challenges of AI-driven diagnostics of 3D-printed architectural structures**, including:
    - effort consuming tasks of manual annotation of data,
    - short timeframe for 3DP production which allows for a limited number of diagnostic and inspective methods on-site,
    - 3DP material characteristics such as pumpability, yield stress, viscosity, and cement hydration assessment, and
    - extrudate surface quality issues such as jagged surface finish or the staircase effect.

Future research will presumably address some of listed challenges through advancing various aspects of AI and 3DP technologies and their integration with architectural practice. Some other promising research directions are specified in the following.

- **Integration of AI tools in the conceptual design stage of 3D-printed architectural structures.**

More research on the conceptual design stage of AM in architecture is needed [72]. Also, a more user-centric and inclusive design approach may result from researching human–computer interaction and investigating technologies that promote cooperation between architects and AI models. Future research could focus on developing AI tools that assist designers in the creative design process. However, it is essential to investigate the overall implications of AI-driven architectural 3DP design for large-scale structures and ensure the technology aligns with generally acceptable ethical values.

- **Advancements of AI algorithms and generative design techniques to optimize the performance and functionality of 3D-printed architectural structures.**

This involves developing AI models that could consider multiple design objectives, constraints, and user preferences to generate optimized and efficient designs. Another interesting area is the advancement of AI-based techniques for structural analysis and verification of 3DP architectural structures. Developing AI models that can efficiently analyze the structural performance of complex designs will help architects ensure safety and make informed decisions. However, further research is needed in the field of data collection, as the lack of readily available datasets in the construction industry poses challenges for the wider implementation of AI-driven tools [55,64].

- **Exploration of AI-driven algorithms for multi-scale, multi-material 3DP process.**

As 3DP often requires novel and unique material mixes, AI tools have proven to be useful tools for rheology optimization and the design of new printing mixes. To produce complex and customized architectural structures, researchers could investigate how AI can be utilized to control printing processes involving numerous materials with different qualities and scales. Also, the effectiveness and scalability of 3DP in architectural construction could be increased by studying the integration of AI with construction robotics and automation. For example, research in this area could consider developing AI-controlled robotic systems for on-site 3DP and the assembly of large-scale structures.

- **Exploration of AI systems that offer real-time feedback and adaptation during the 3DP process.**

As addressed in the literature, the effectiveness and quality of printed structures could be increased by integrating AI systems that offer real-time feedback and adaptation during the 3DP process. Further research in this area could focus on developing AI models that monitor and adjust printing parameters based on real-time sensor data, ensuring accurate fabrication and reducing errors. Also, large-scale AM quality monitoring and inspection have not been as thoroughly studied [67].

- **AI-driven approaches to circular economy concepts and sustainable design of 3D-printed architectural structures.**

This involves exploring how AI may help with material selection, waste reduction, and life cycle evaluation to create buildings that are more resource- and environmentally friendly. On the other hand, as 3DP architectural structures become more prevalent, it is important to study the legal and regulatory implications of their design, fabrication, and implementation [52]. In this respect, research could focus on understanding intellectual property rights, liability issues, building codes, and safety standards for AI-driven 3DP in architecture. Moreover, future research could examine the policy and industry implications of adopting AI and AM technologies in the architectural sector. It is necessary to discuss further regulatory challenges, standards, economic issues, and potential implementation impediments.

In conclusion, future research should emphasize interdisciplinary collaboration between architects, engineers, material scientists, computer scientists, and other experts. Such collaborations could facilitate a holistic approach to AI-driven 3DP, leading to more integrated and innovative architectural solutions. As AI and 3DP technologies continue to evolve, these research directions will play a crucial role in shaping the future of architectural design and construction practice.

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