Review

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Review

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

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Featured Application: A review of AI-driven approaches to 3D-printing architectural structures can provide architects, designers, and researchers with a comprehensive understanding of the current state of the field, inspire innovative design and research ideas, inform material and fabrication choices, guide structural analysis, support sustainability efforts, and provide practical insights through project examples.

Abstract: Artificial intelligence (AI) and 3D printing (3DP) play critical roles in what is known as the 4th Industrial Revolution by developing data- and machine-intelligence-based integrated production technologies. This shift has led to increasingly complex design requirements and fabrication methods, posing several challenges for implementing design, fabrication process, and architectural quality standardization. This paper systematically reviews AI techniques applied in diverse stages of 3DP production in architecture. 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 3DP structures; and (4) identify gap and provide recommendations for future research. The findings indicate that topics related to AI applications are current and trending, receiving increasing attention from researchers in general and particularly those working in machine and deep learning, artificial neural networks, and pattern recognition. However, the potential of the application of AI in architectural production using additive manufacturing still needs to be explored. Considering this, the paper emphasizes the necessity of redefining traditional field boundaries and opening new opportunities in the sector.

Keywords: architectural design; digital design; digital fabrication; additive manufacturing (AM); 3D printing (3DP); artificial intelligence (AI); machine learning (ML); deep learning (DL); artificial neural networks (ANN); computer vision

1. Introduction

Automation is increasingly playing a significant role in architecture, streamlining various processes, and enhancing design capabilities, due to advancements in artificial intelligence (AI) [1–5]. It is applied in diverse areas of architecture, including Building Information Modelling (BIM), generative design, parametric design, performance analysis and simulation, project management and documentation, and digital fabrication. As for the latter, automation is transforming the way architectural elements are manufactured. Advanced additive manufacturing (AM) technologies allow architects to fabricate complex and customized components directly, reducing material waste and construction time. Robotic fabrication systems can automate tasks enabling efficient and precise construction processes [6–12]. It is important to note that while automation can enhance efficiency and creativity in architecture, architects' human input and expertise remain indispensable in the design and decision-making processes. Automation tools are best utilized as aids to complement and augment human capabilities rather than replace them.

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 advancement and support design exploration and optimization, facilitate customization and personalization, support performance-driven design, promote resource efficiency and sustainability, and facilitate industry adoption. In line with the previous, the main aim of this research is to overview previously published works on AI-driven approaches for 3D printing (3DP) in architecture. This knowledge can contribute to further research, inform decision-making, and promote the effective integration of AI and 3DP in architectural practice.

The 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 [13]. However, there are still many challenges and opportunities for improvement regarding this technology [14,15], such as low print accuracy or mechanical properties of printed objects. AI tools were recognized as a possible method for overcoming these challenges [16]. The previous state-of-the-art reviews have been found in the fields of 3DP for architectural structures [15,17] and the adoption of AI technologies in the construction industry [18,19] but not for its direct application in the architectural design and fabrication with the exception of a few machine learning (ML) application reviews [20,21].

AI tools, especially ML, are successfully used to optimize 3DP processes in engineering industries, as presented in the study by Goh [22], 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 [23–25], while several ML methods are used for porosity predictions for 3DP structures [26,27]. 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 [18,28].

To the best of the authors' knowledge, no study has provided a comprehensive overview of the application of AI for producing 3D-printed architectural structures up to this point. Regarding the above, the objective of this study is to identify, evaluate, and provide a summary of the data from the results of many individual studies on 3D-printed architectural structures created using AI. The study seeks to synthesize the available knowledge, including research papers, journal articles, conference proceedings, and other relevant sources, to establish a clear picture of the current state of the field. The purpose of the study is to provide a comprehensive understanding of the field, identify research gaps, assess technological advancements, explore design optimization and customization, evaluate performance, and analyze the practical implications for industry adoption.

Furthermore, the study aims to assess the advancements and applications of AI in the context of 3DP for architectural elements. It seeks to understand how AI techniques have enhanced the design, fabrication, and performance of 3D-printed architectural elements/structures. This purpose helps researchers and practitioners stay informed about the latest technological developments and potential applications. Also, the study intends to identify gaps and limitations in the current research related to 3D-printed architectural structures using AI. The research aims to determine areas that have yet to be extensively explored or require further investigation by answering what publishing trends and principal themes are. This analysis can help guide further research directions and identify opportunities for innovation. Finally, the study intends to explore the practical implications and industry adoption of AI in the 3DP of architectural elements. It seeks to answer the question of challenges, barriers, and opportunities for integrating AI into real-world architectural projects. This purpose can inform industry professionals, policymakers, and stakeholders about the potential impact on architectural design, construction processes, and business models.

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 databases search and selection of relevant publications; analyzing the literature sample using quantitative and qualitative methods; summarizing the evidence,

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interpreting the findings, and discussing recognized opportunities and challenges for future research and application of these structures in the industry.

The study provides architects, designers, and researchers with a thorough understanding of the industry's state-of-the-art, inspires innovative design and research ideas, informs material and fabrication decisions, directs structural analysis, supports sustainability efforts, and provides insightful project examples. By exploring the intersection of AI and AM, researchers can shape the future of architecture and construction, creating a more sustainable built environment.

2. Methodology

This study applied the SLR methodology to investigate a domain of knowledge about 3D-printed architectural structures using AI. This methodology was chosen for the study because it provides a systematic approach that ensures objectivity, meticulousness, and transparency while providing theoretical knowledge and insights into current trends and developments related to the research problem [29,30]. The review was carried out in accordance with the PRISMA statement for systematic reviews and meta-analysis [31,32]. Based on these guidelines, a three-step systematic protocol was implemented to generate and evaluate a relevant body of literature consisting of (1) a literature search, (2) literature selection, and (3) literature analysis.

Following the established protocol, a literature sample was collected and refined [33]. A Web of Science (WoS) database was searched in the first step using relevant keyword groups. 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, identified literature sample was then further analyzed using quantitative and qualitative methods to help answer the main research questions, as presented in Figure 1.

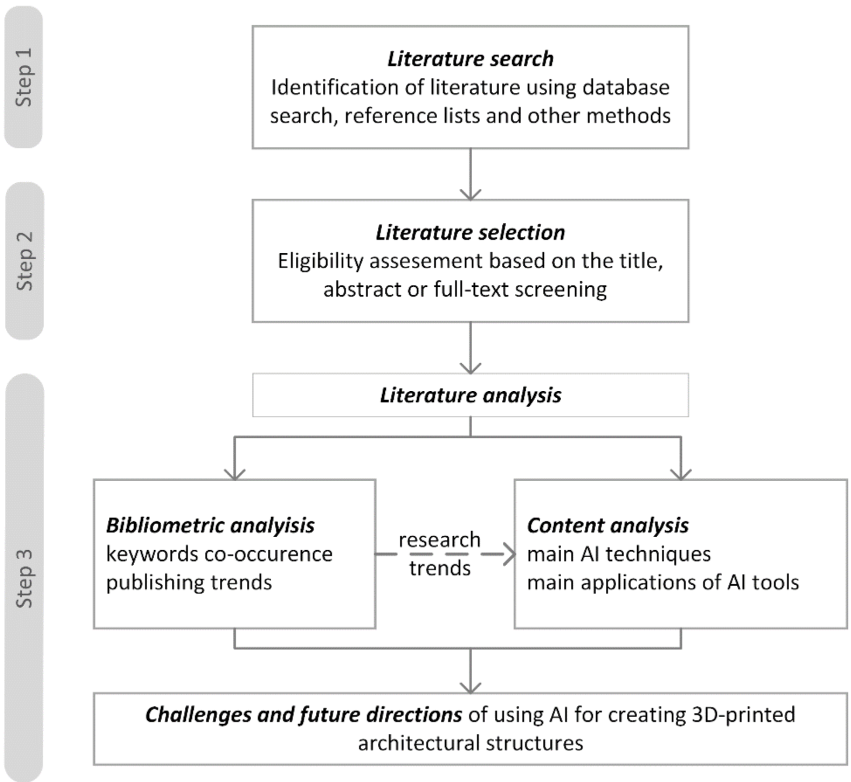

Figure 1. Layout of the research process.

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2.1. Forming Literature Sample

The application field of AI tools for 3D printed structures is wide, encompassing several engineering disciplines that often overlap and collaborate; this poses a challenge in searching for the relevant body of literature. The first exclusion criterion that needed to be implemented was to limit the database search results to research categories relevant to this study. Three main categories were chosen (1) Architecture, (2) Engineering, Civil, and (3) Construction & Building Technology, as they all refer to build environments, and relevant papers can be expected to be found there. 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 the 11 July 2023, following the set search criteria presented in Table 1.

Table 1. Search criteria.

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

2.1.1. Literature Search

The initial search and collecting of papers were done in the WoS database, which includes leading peer-reviewed publications with bibliometric data. Other databases, such as Scopus, were also considered for this research, especially because Scopus offers a more comprehensive sample pool than WoS. 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. Also, WoS was chosen as the primary literature source because this limitation was applicable using built-in categorization of papers by research categories. Meanwhile, the Scopus search engine is more keywords 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 commonly used AI tools and the other referring to the terms commonly used for AM in architecture. The AM and design set mostly consist of synonyms often used to describe 3DP technologies and several architectural design terms in order to cover the whole design and fabrication process. On the other hand, the topic of AI tools covers a wide range of different technologies which 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 relevant categories and publication date range, as shown in Figure 2.

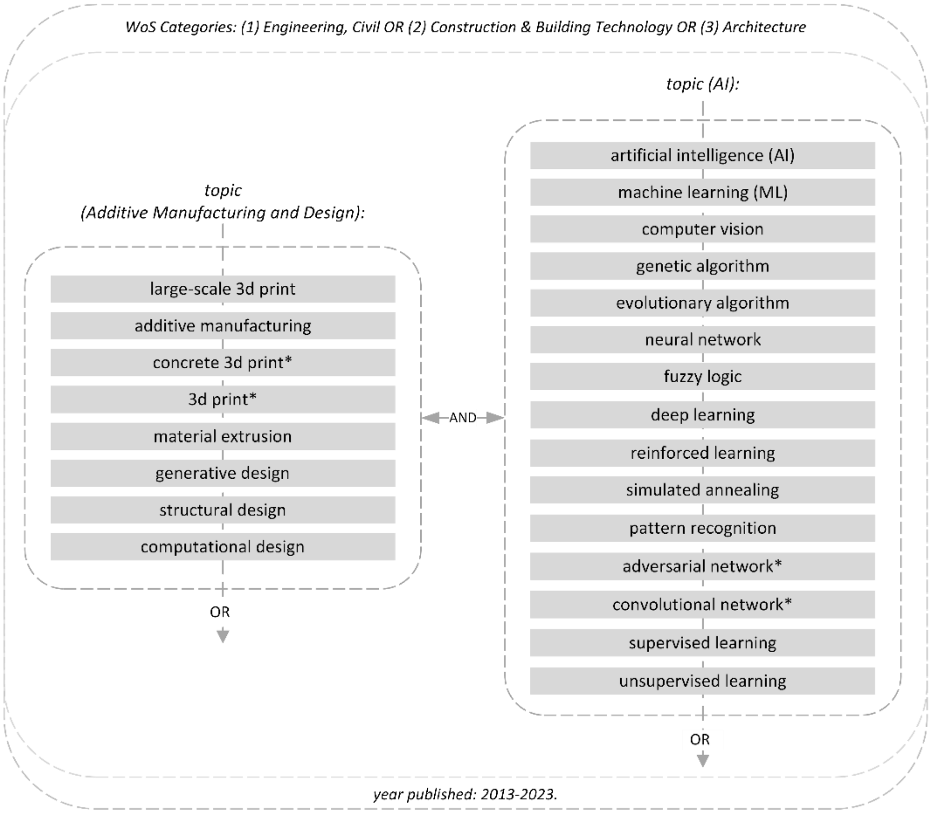

Figure 2. Illustration of the literature search frame/domain and topics.

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

2.1.2. Literature Selection

The identified literature sample was then screened following the defined inclusion criteria in Table 2. First, as many papers still belonged to multiple research categories, all categories unrelated to the building industry were excluded. Then, only papers in English were identified and kept, resulting in 287 items eligible for screening from the database search. These documents were then screened based on the titles and abstract content based on the relevance to the research topic. After this step, 64 papers were remaining that needed to be further screened in full. The final screening step consisted of a full-text assessment to verify their relevance for this review. In this step, another 37 papers were eliminated as they would not directly contribute to research questions as the focus of the studies was more centered on other disciplines, such as computer science or material science, exploring the in detail technological processes relating to AI or 3DP that wouldn't directly contribute to this study.

Table 2. Inclusion criteria.

Inclusion criteria	Value
Papers belong to research categories unrelated to construction industry	Exclude
The paper is 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

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Full text is relevant to the research question	Include

Another 22 potential 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).

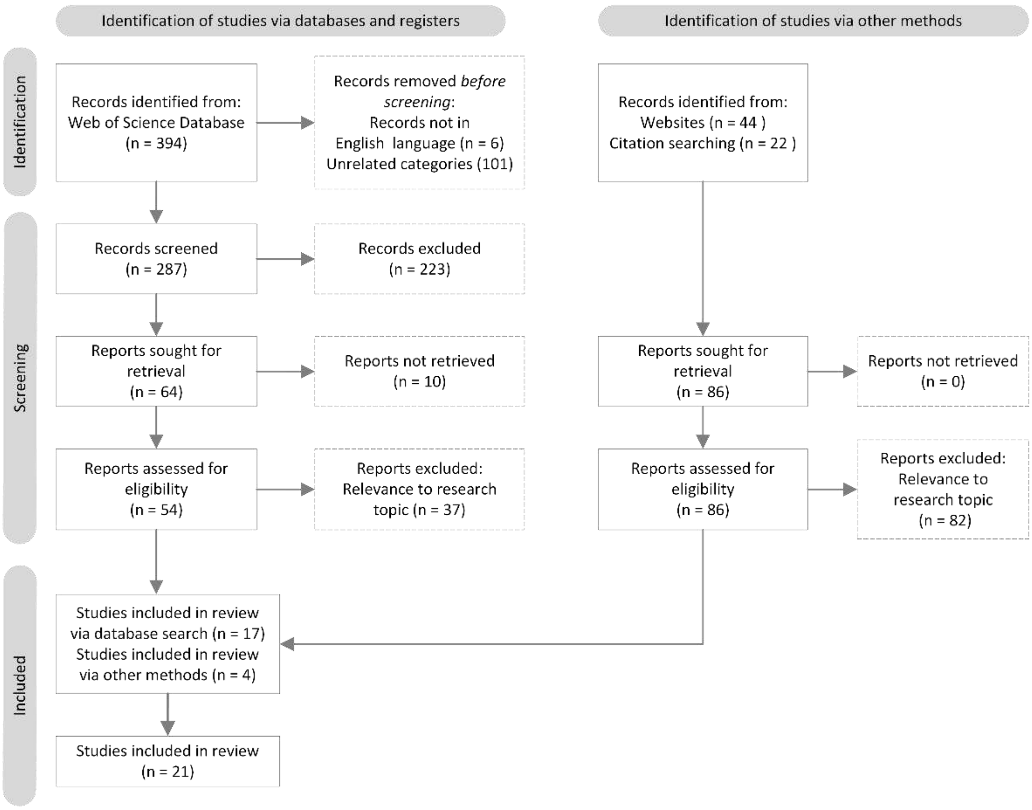

Figure 3. PRISMA flow diagram of literature review.

2.2. Analyzing Literature Sample

The selected literature sample was then analyzed using quantitative and qualitative methods. Quantitative analysis was performed to gain insight into the collected sample characteristics relating to the publication trends and main research topics. Previous was achieved using a bibliometric analysis method, an applied mathematical analysis of bibliographical units [34]. By analyzing publication data, citations, and keywords, this method systematically represents citation patterns and publication trends within a specific field or across several disciplines [35].

A group of authors performed a described three-step research process. Two researchers were assigned the first two steps, literature search, and collection, with the third author overseeing and reviewing the collected sample and process to ensure the quality of research. The searches were 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 titles and abstracts 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

A network analysis, a bibliographic technique, was performed for this research. This method relies on the analyses of bibliographic data to visualize the connections between different articles based on the citations, publications, or keyword co-occurrences. By forming these connections, data is systematized, and research trends are uncovered. This analysis was performed using the software VOSviewer, which is designed for constructing and visualization of bibliographic networks [36] and which application proved to be beneficial in previous studies [37,38]. The literature sample data was imported, and a keywords network was created based on the found keyword co-occurrence to gain insight into trends in the researched field.

2.2.2. Content Analysis

After the quantitative study, the collected sample was qualitatively analyzed to systematize and assess the findings based on the bibliometric analysis results. This step provides a deeper understanding of the principal themes uncovered during the quantitative portion of the study. These principal themes are further explored through content analysis. Furthermore, content analysis was used to identify and explore 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 found in the literature to assess the state-of-the-art in the field along with the main challenges.

3. Results

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

3.1. Bibliometric Analysis

3.1.1. Publishing trends

The direction of developments in the researched field can be better understood by observing publishing trends of the collected literature sample. First, 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 of the papers collected in the sample were published in the last six years, showing a rapid 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 also underlines the need for this kind of study as all available literature is contemporary and comprehensive reviews in the field have not been conducted.

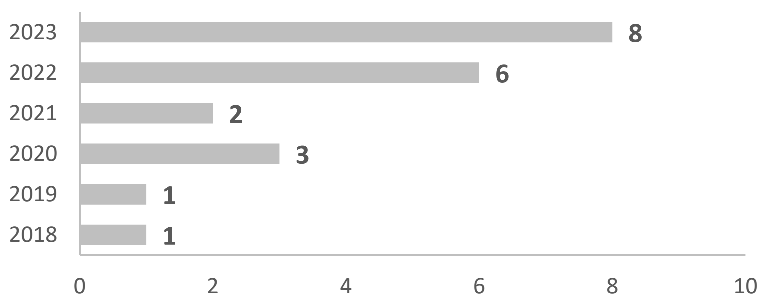

Figure 4. Number of articles published per year.

The relevance of the research problem is also shown by analyzing the source journals for the retrieved sample. The source journals are the journals that published selected papers. In the final sample, only two were conference proceeding papers [39,40]; the rest were journal articles. This study

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includes 19 articles published in 13 different journals. Table 3 summarizes the source journals by a number of reviewed papers and journals' impact factors. One journal, *Construction and Building Materials* had a considerably higher occurrence rate than the rest, with 4 published papers on the topic [41–44]. Previous shows a recent focus on using AI tools to analyze structural material properties in construction. Another 3 journals had more than one published article selected, *Cement and Concrete Research*, *Buildings*, and *Automation in Construction*. The previous study [45] showed that these journals actively publish research on the 3DP technology application in architecture. However, it can be noted that they are also supporting the interest in implementing AI tools in these processes.

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 interest and support trend for the 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 exceptionally high impact factors. Four of the identified journals, publishing 6 (28.5%) of the reviewed papers, had significantly high impact factors values above 10.

3.1.2. Keywords Analysis

A network analysis was performed based on the keywords co-occurrence rates visualizing a map showing 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 [36]. For this study, the second method was implemented because it can provide a clearer picture of the principal themes discussed in the literature, as predefined keywords usually correspond with the main themes presented in the research. As the literature sample was collected through multiple sources, bibliographic metadata for this analysis was obtained from the reference manager software and subsequently imported into VOSviewer for analysis.

Two possible methods for counting keyword occurrence rates are full counting and fractional counting [46]. For this study, the network was generated by a 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 two times. 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. Identified keywords, co-occurrence rate and link strength.

Keyword	No. occurrences	Link-strength
compressive strength	6	28
concrete	5	22
machine learning	6	21
3d printing	5	18
artificial neural networks	4	17
performance	4	15
construction	4	14
additive manufacturing	3	12
cementitious materials	3	11
artificial intelligence	2	11
design	4	10
mix design	2	10
prediction	2	10

Identified keywords are strongly topically related, with most of them referring to the 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 [44,47,48]. Another highly present term was "machine learning," the indicating increased use of ML tools in the field. Previous can be better observed in Figure 5 which visually presents a keyword network grouping related keywords in four clusters.

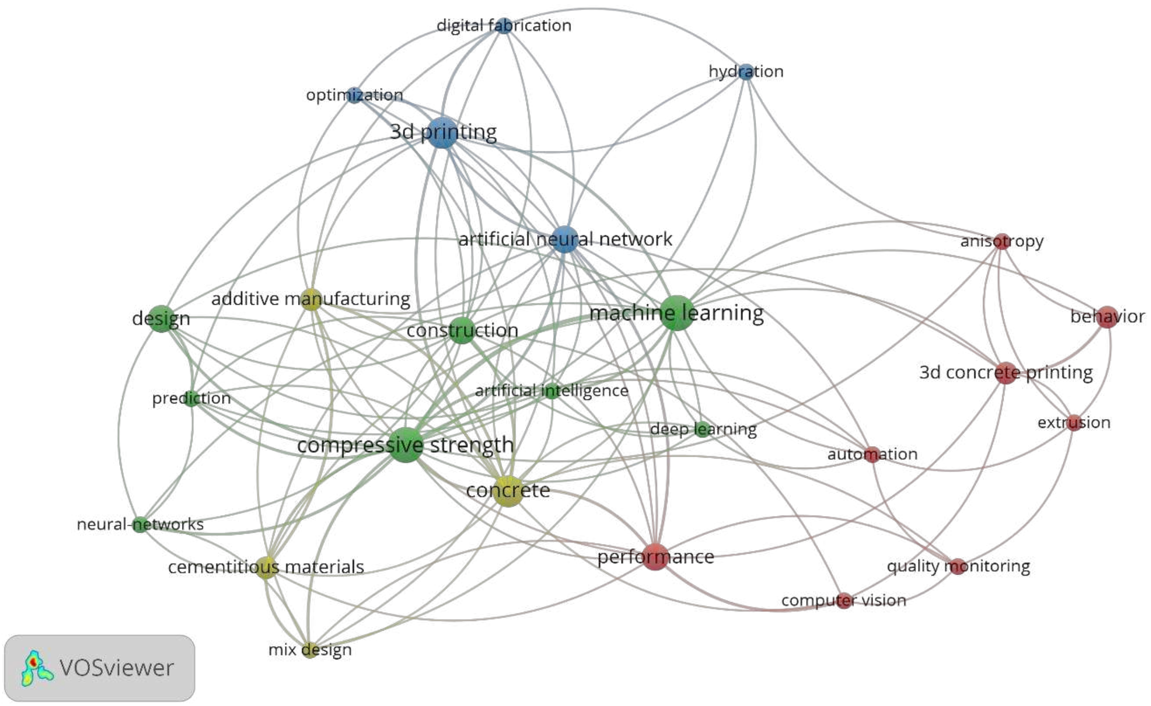

Figure 5. Visualization of keywords network.

The keywords are divided into clusters based on the interconnections, but these agglomerations can help better understand the principal themes in current research. The biggest 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 and performance and

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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 additive without the inclusion of specific AI tools.

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

Table 5. Principal research themes.

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

3.2. Content Analysis

The scientometric analysis provided insight into the most often researched topics, AI tools and techniques, their application and their correlations. To fully grasp the relationship between AI, 3DP and architecture, a more in-depth analysis of the discovered data is given further in the study.

3.2.1. Overview of Techniques

Among the reviewed publications, the four most often researched AI categories include (1) ML, (2) ANN, (3) a combination of ML and ANN and (4) computer vision. Brief definitions of the significant AI concepts and main characteristics are provided to better comprehend the presented results.

ML, as a field of computer science, relates to algorithms that learn to solve complex real-world problems from given datasets. The most common problems met by ML include (1) classification, (2) clustering and (3) prediction [49]. The generally accepted types of ML, distinguished by significant functional differences, include (1) Supervised Learning, which uses input data for identification and fulfillment of certain tasks, among which classification and regression are the most well-known, (2) Unsupervised Learning, which is mostly concerned with identifying groups and organization patterns within unlabeled datasets, with the common task of clustering, (3) Semi-Supervised Learning, which learns from both labeled and unlabeled data, commonly used for classification and clustering purposes and (4) Reinforcement Learning, that functions within a reward-punish system where the algorithm automatically evaluates the best behavior patterns and takes further actions to optimize the system [50]. Deep learning (DL) is a subset of ML with key features represented in (1) numerous layers or stages of nonlinear information processing and (2) supervised or unsupervised learning of feature representation at progressively higher, more abstract layers [51]. Determining the definition of ANN in the scientific and practical domains remains challenging [52]. The architecture and functionality of artificial neurons forming ANN are based on biological neurons. These networks function by processing information in its fundamental constituents—artificial neurons—in a non-linear, distributed, parallel, and local manner [53]. 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 (1) visualization, (2) image formation, (3) control of irradiance, (4) focusing, (5) irradiance resolution, (6) tracking, and (7) processing and analysis [54].

Out of the 21 reviewed studies, ML is found to be the topic of 6 studies with the application ranging from design, optimization to diagnostic purposes for 3DP structures [21,40,48,55–57]. ANN as a technique is found to be present in 9 studies overall, with applications belonging in the diagnostic domain [39,43,44,47,58–62]. ML and ANN combined application is found in the total of 4 studies, where the use is focused around optimization and diagnostics [42,63–65]. Lastly, computer vision algorithms are present solely in the diagnostic domain and cover a total of 4 papers [40,41,47,66]. Figure 6 overviews the identified AI techniques, their domains of application, and the correlated references.

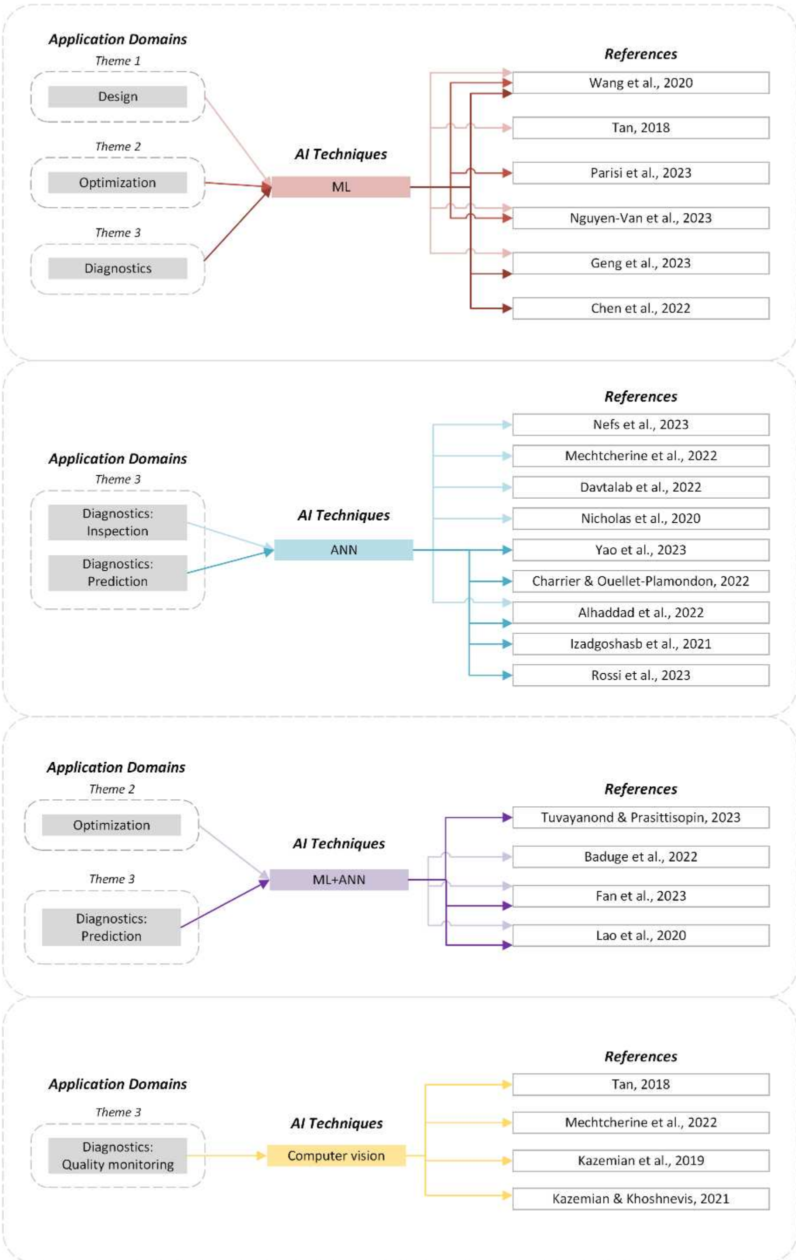

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Figure 6. Overview of AI techniques and main applications in 3DP in architecture.

3.2.2. Applications

This subsection provides an extensive review of the (1) design, (2) optimization, and (3) diagnostics (including inspection, simulation, prediction and quality assurance) of 3D-printed architectural structures, with a particular focus on the key challenges of the methods ML, ANN, ML+ANN, and computer vision.

- **Theme 1. AI-driven design of 3DP architectural structures**

AI integration in the 3DP design process is delivered by different techniques and is mainly focused on the issues of material design and design optimization of the 3DP printing mixes since 75% of the classified papers deal with that specific topic. Of the 4 papers, 2 are in the form of literature review articles, one is a case study, and one is a conference paper that gives a framework for combining AI and construction 3DP. Wang et al. [57] deliver a systematic review of the emerging digital technologies used for off-site construction leading towards Industry 4.0, where among the 15 reviewed technologies, AI and 3DP are elaborated on separately, each representing an important factor for the future development of the construction sector. Nguyen-Van et al. [48] review the development of predictive modeling and design optimization 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. Geng et al. [21] 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 the study, Tan proposes a framework for AI and 3DP combinations in five specific aspects, including (1) 3DP materials, (2) automation design, (3) digital construction, (4) 3DP robots, and (5) 3DP BIM platform [40]. An overview of the discovered AI models in 3DP for design purposes is presented in Table 6.

Table 6. Overview of specific techniques, applications, research conclusions and challenges of AI-driven design for 3DP.

Applications	AI techniques	Main challenges and conclusions	Author(s) References
Design for topology analysis of prefabricated elements	ML	Time consuming preparations of topology analysis	Wang et al. [57]
Design automation for 3DP	ML	AI can help establish decision making models, provide various alternatives, compare, and judge various schemes to achieve the maximum benefits	Tan [40]
Conceptual design and design optimization	ML, ANN	(1) Small amount of research can be found on the topic of Design for Additive Manufacturing (DfAM) for construction (2) The research which was conducted has not been implemented in the building industry	Tuvayanond & Prasittisopin [65]

- **Theme 2. AI-driven optimization of 3DP architectural structures**

Defined as one of the tasks of intelligent algorithms, optimization is a process executed using different algorithms, ranging from ML based optimization with several studies containing the combination of ML and ANN models.

Among the papers which explore ML applications for the optimization of 3DP, the study by Parisi et al. [56] delivers an approach towards intelligent AI controlled tower crane 3DP, with optimization of the extruder toolpath. Wang et al. [57] explore the ML based optimization targeted at specific construction tasks in off-site construction applications. Nguyen-Van et al. [48] present an overview of the current state-of-the-art development of modeling and design optimization tools for 3D concrete printing (3DCP), highlighting the possibility of reducing printing time, improving

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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. [63] 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. [64] explored optimized nozzle shapes for delivering high-quality surface finish 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 [42]. Table 7 summarizes the key features of the optimization-related studies.

Table 7. Overview of specific techniques, applications, research conclusions and challenges of AI-driven optimization for 3DP.

Applications	AI techniques	Main challenges and conclusions	Author(s) References
Printing process optimization through model segmentation and extruder toolpath optimization	ANN		Baduge et al. [63]
	DLR	The tower crane 3D printer and the extruder can be properly controlled by AI which allows its effective use in the construction industry	Parisi et al. [56]
	ML	Intelligent toolpath generation has potential to reduce printing time, therefore optimizing the printing process	Nguyen-Van et al. [48]
Optimization and prediction of the construction tasks	ML	Large amounts of data needed that is not readily available for prediction methods	Wang et al. [57]
Material distribution optimization	ML	The application of AI methods and ML algorithms in practice of AM are still limited to checking printability and modularization for prefabrication techniques	Baduge et al. [63]
Optimized material mixture design	ML, ANN	Limited research on the micro characteristics of the UHPC material	Fan et al. [42]
	SL	SWOT analysis of ML applications for construction 3DP is given in the review article	Geng et al. [21]
	ML	Handling large amounts of data in the integration process of ML into AM poses challenges	Nguyen-Van et al. [48]
		The advantage of ML algorithms is that the failed experimental data can also be used as input for next, and then the algorithms are refined	Tan, 2018 [40]
Finding a proper nozzle shape for production of designated extrudate geometries	ML, ANN	The proposed approach offers the improvement of the surface quality on structures with different curvatures	Lao et al. [64]

- **Theme 3. AI-driven diagnostics for 3DP architectural structures**

The reviewed articles include several approaches towards the predictive tasks for the 3DP processes, based on (1) ML-driven prediction, simulation, and inspection, (2) ANN- based inspection

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and prediction, (3) combined use of ML and ANN for prediction, and (4) computer vision technology used for inspection and quality monitoring purposes.

Among the selected papers, a systematic review [57], a case study [21], and an original paper stating the new method of 3DP parts inspection [55] are found. A variety of ML techniques are utilized for predictive and inspection purposes, ranging from supervised, unsupervised, semi-supervised, and reinforced learning, with applications explored in the domain of material design optimization, control printing accuracy, printing defects detection and classification, state differentiation of the printing process, anisotropic behavior analysis, printing products classification in relation to the deformations, printing costs estimation, compensation of printing material deformation, printing process planning correction, large-scale printing product customization and other [21] Additionally, a deep-learning module of a preexisting Dragonfly software was used to extract the axes of the steel fibers in the X-ray micro-computed tomography (X-CT) images and evaluate their three-dimensional orientational distribution statistics and coefficients [55].

ANN models used for the inspective tasks in 3DP rely on several algorithm types, which differ in functionality and purpose. DCNNs have been explored in 3 out of 6 papers [43,47,60], representing the algorithms that excel in processing organized arrays of data, such as images, as their primary functional characteristic [67]. Another explored type of ANN includes Conditional Generative Adversarial Network (cGAN) [62], whose main characteristic is the fact that they constitute a pair of networks, known as the forger/generator and expert/discriminator, which compete with each other in the parallel training process [68]. 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 [58]. Similarly, specific types of ANNs are employed to predict the characteristics of 3DP structures. Yao et al. explore the effect of steam curing conditions' effect on the performance properties of 3DP materials in various ages of curing [44], 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 strength of the researched materials [58,59,61]. Additionally, Rossi et al. [39] 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 toward employing both terms. Among the papers presented in this subgroup, two papers represent reviews of the research status [42,65], whereas one paper presents an original methodology for finding the proper nozzle shape in the 3DP process [64].

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 [40,47], whereas the other two papers develop novel methods for this purpose. Kazemian et al. [66] 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 [41].

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

Table 8. Overview of specific techniques, applications, research conclusions and challenges of AI-driven diagnostics for 3DP.

Applications	AI techniques	Main challenges and conclusions	Author(s) References
Prediction of the construction tasks	ML	Large amounts of data needed that is not readily available for prediction methods	Wang et al. [57]
	Computer vision	The principal applications of state-of-the-art AI methods in 3DP process are identified	Tan [40]
Identification of the micro-structural	DL + U-Net module	U-Net is a newly approved neural network in the ML field where the computer is allowed to	Chen et al. [55]

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objects of 3DP fiber-reinforced materials		segment according to the semantics of the images, used for identification of steel fiber reinforcements based on the X-CT images	
	DCNN + U-Net module	Successful identification of fibers oriented in arbitrary directions, which eliminates the time-consuming task of a human expert to manually annotate these data	Nefs et al. [43]
Geometrical accuracy and fidelity measurements for 3DP elements	DCNN Computer vision Image processing	The preliminary data imply the great potential of the shown techniques, both for automated inspection and as-built measurements during the 3DCP process	Mechtcherine et al. [47]
Quality monitoring and automated inspection systems	DCNN	Quality monitoring and inspection of large-scale AM have not been as extensively researched as printing material design or software issues	Davtalab et al., [60]
Real-time quality control and monitoring	Computer vision	The obtained results revealed the high precision and responsiveness of the developed extrusion monitoring system under the experimental conditions	Kazemian et al. [66]
		The vision-based technique has the highest precision and responsiveness to material variations	Kazemian & Khoshnevis [41]
Structural performance simulations and predictions for 3DP structures	cGAN	The workflow proves the ability to use an entirely digital proxy dataset to train a Neural Network that would predict the behavior of physically fabricated panels	Nicholas et al. [62]
	ANN	(1) The accuracy and performance largely depend on the ANN hyperparameters (2) The construction of a suitable ML model with high precision and dependability is laborious and time-consuming	Yao et al. [44]
Mechanical properties simulations and predictions for material design	ANN	ANNs can predict the fresh properties of cementitious materials according to different admixtures	Charrier & Ouellet-Plamondon [59]
		The model can be used as a credible guideline for the designers and researchers to manufacture FRP of optimal mechanical properties, which results in saving efforts and financial resources The developed ANN model accurately predicts the UTS of FRP	Alhaddad et al. [58]
		(1) The difficulty of this method is that the accuracy of the model depends on the number of patterns (2) Limited amount of research on patterns concerning 3DP concrete's compressive strength	Izadgoshasb et al. [61]
	ML, ANN	Insufficient predicting accuracy when using common AI models for predicting UHPC properties	Fan et al. [42]
Prediction of printing errors due to curing conditions	ANN	(1) Instead of having to post-process the prediction to extract fabrication-relevant effects, the authors can target their predictive model towards an application scenario by selecting a	Rossi et al. [39]

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	processed feature extraction approach coupled with simple ML models as opposed to a raw rich data approach and complex models (2) The dataset size is a constant constraint for getting good predictions out of physically generated datasets, even with straightforward statistical "off the shelf" models

4. Discussion and Conclusion

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 3D-printed architectural structures produced using AI was performed on the representative literature sample, which included 21 relevant papers examined using bibliometric and content analyses. A bibliometric analysis shows that papers on the topic have been published over the past five years, with a growth trend in the number of publications in the past two years. Additionally, bibliometric analysis revealed that journals covering engineering, fields, and architecture and construction are where articles on the issue are most frequently published. Moreover, co-occurrence network analysis discovered keywords 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 3D-printed architectural structures – AI-driven design, optimization, and diagnostics. Keywords co-occurrence analysis also isolated AI techniques (including ML, ANN, and computer vision) commonly applied in the production of architectural structures by 3DP. Further, full-text content analysis on 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 study produced a synthesis and summary of existing published research papers related to the application of AI technologies in the production of 3D-printed architectural structures. Consequently, the study helps consolidate the current state of knowledge in the field and provides a comprehensive overview of the subject matter. Moreover, the study sheds light on how 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 perspective use. By synthesizing the literature, the study offers insights into techniques and integration strategies relevant to architectural production. The study recognized the capabilities, limitations, and potential of AI technologies that support the production of 3D-printed architectural structures. 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. The study explored how AI can contribute to design optimization and customization of 3D-printed architectural elements. Examining literature, methodologies, algorithms, or frameworks utilizing AI to design or optimize designs for structural integrity, aesthetics, energy efficiency, or other criteria are identified. The study also inquired how AI can enhance structural performance, material efficiency, and environmental sustainability. Previously helped perceive the benefits and limitations of AI-based approaches in achieving desired outcomes. The study also includes gap analysis and identifies areas of further research within the subject matter domain. 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. This review can be a source of inspiration and help generate new ideas and approaches. 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 authors strictly followed the PRISMA statement [31,32]. Previously aimed at minimizing bias or chance results and production of reliable findings. However, the study has some limitations, and when it was practical, these issues were taken into account. First, the analysis is performed on the limited data sample and depends on data provided by databases (principally WoS). Additional papers are included in the sample through manual and reference list searches to provide a more thoughtful overview and overcome this limitation. Second, the review may have been limited due to retrieval and linguistic biases. Thirdly, the keywords applied in the search needed to be standardized, and some authors used distinct keyword variations. Finally, one should be mindful of the authors' bias and that no formal risk-of-bias evaluation was done when using the research's findings. Nevertheless, an authors' expertise in the field provides context for interpreting bibliometric analyses.

4.3. Future Directions

Directions for future research will probably focus on advancing various aspects of AI and 3DP technologies and their integration with architectural practice. Future research for 3D-printed architectural structures using AI will undoubtedly advance all three application domains – design, optimization, and diagnostics.

More research on conceptual design, specifically the DfAM in architecture, is needed [65]. 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. Research can focus on developing AI tools that assist designers in the creative design process. However, it is essential to investigate the ethical implications of AI-driven architectural structure design and ensure the technology aligns with human values.

Checking printability and modularization for prefabrication procedures is currently the extent of AI methods applications in AM practice [63]. Future research can explore more advanced AI algorithms and generative design techniques to optimize the performance and functionality of 3D-printed architectural structures. Previous involves developing AI models that can consider multiple design objectives, constraints, and user preferences to generate optimized and efficient designs. Additionally, exploring AI-driven algorithms for multi-scale, multi-material 3DP can create new opportunities in architectural design. 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. In order to produce complex and customized architectural structures, researchers can investigate how AI can be utilized to control printing processes involving numerous materials with different qualities and scales. Also, the effectiveness and scalability of 3D printing in architectural construction

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can be increased by studying the integration of AI with construction robotics and automation. For example, research in this area can consider developing AI-controlled robotic systems for on-site 3D printing and assembly of large-scale structures. However, further research is needed in the field of data collection as the lack of readily available data sets in the construction industry poses challenges for the wider implementation of AI-driven tools [48,57].

Although numerous research concern inspection, simulation, and prediction of 3D-printed structural performances using AI, more research in the domain of diagnostics could be done. As addressed in the literature, the effectiveness and quality of printed structures can be increased by integrating AI systems that offer real-time feedback and adaptation during the 3DP process. Further research in this area can 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 [60]. Another interesting area is the advancement of AI-based techniques for structural analysis and verification of 3D-printed architectural structures. Developing AI models that can efficiently analyze the structural performance of complex designs will help architects ensure safety and make informed decisions.

Future studies can also focus on AI-driven approaches to circular economy concepts and sustainable design in 3D-printed architectural structures. Previous 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 3D-printed architectural structures become more prevalent, it is important to study the legal and regulatory implications of their design, fabrication, and implementation [45]. With this respect, research can focus on understanding intellectual property rights, liability issues, building codes, and safety standards for AI-driven 3DP in architecture. Moreover, future research can 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. Knowledge from this research can inform policymakers, industry professionals, and stakeholders in making informed decisions and outlining future policies.

In conclusion, future research should emphasize interdisciplinary collaboration between architects, engineers, material scientists, computer scientists, and other experts. Such collaborations can 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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