Research Type (Review)

Integration of parametric design tools with artificial intelligence in the construction industry - a review

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Abstract

Background: Technology continues to reshape the design and execution of construction projects in today's global scenario.
Objective: The objectives of the research are focused on providing insight into the most prominent Parametric Design (PD) tools in the construction sector, accurately identifying the Artificial Intelligence (AI) techniques and algorithms used in the PD of buildings and structures, and prominently highlighting the benefits derived from the collaboration between these tools and AI in the context of construction.
Methods: The present review is carried out using the Prisma methodology, with a specific search string, and applied to the determined scientific databases, between the years 2015 and 2023 and using exclusion and inclusion criteria.
Results: The research concludes that the integration of parametric tools and AI, with special attention to Rhinoceros 3D + Grasshopper, has a significant impact on building through adaptive and complex models. Collaboration with artificial neural networks (ANN) and convolutional neural networks (CNN) enables detailed simulations and automations.
Conclusions: The benefits are numerous: optimized designs, automation, improved quality and efficient decision-making, all of which drive innovation in construction projects.

1. Introduction

In today's dynamic and ever-changing global scenario, technology continues to be a driving force reshaping the design and execution of construction projects. This paper embarks on an exploration of the intersection of two transformative tools: PD [1] and AI [2]. The main objective of this research is to deepen the scope of the most influential PD tools used in construction [3], [4], with special attention to powerful platforms such as Rhinoceros 3D + Grasshopper [5]. Simultaneously, it aims to uncover the impact of AI algorithms [6], including Artificial Neural Networks (ANN) [7], [8] and Convolutional Neural Networks (CNN) [9], [10], which are reshaping the landscape of design and construction processes. This research goes beyond the mere identification of these leading-edge tools but aims to shed light on the tangible advantages derived from the fusion of PD and AI in the construction industry [11]. These advantages range from design optimization, facilitating the creation of more efficient and sustainable structures, to task automation, thus conserving valuable time and resources [12]. This article explores the immense potential arising from the synergistic integration of PD and AI, ultimately improving decision-making processes, and increasing safety and quality levels in construction projects. In essence, it promises a transformative path for the construction industry.

Different DP tools are integrated with AI to address complex designs and improve the performance of construction projects. For example, in [13], a project developed with DP tools is analyzed and its relationship with daylighting is explored; furthermore, the principles and contests of DP are examined, and it is concluded that its application can be very effective if used with the right tools. In [14], the use of parametric modeling is examined to improve the design of infrastructures, such as roads and bridges, highlighting its flexibility and error-reduction capability. It highlights the importance of sustainability and the identification of research areas for more efficient development, as well as the need for guidelines on the use of parametric models in infrastructure design to address variations and barriers to their widespread adoption. In [15], PD approaches for integrating solar energy into buildings are reviewed and it is shown that PD facilitates multidisciplinary collaboration and efficiency in sustainable solar building design. It also discusses the importance of design elements and addresses a gap in the literature by reviewing existing parametric models. According to [16], there are three types of computational design in architecture: generative, algorithmic, and parametric; in this case, their evolution and the importance of AI and Machine Learning (ML) in the design process are explored. This article resolves that the use of AI and ML streamlines the design process, and the PD allows for better solutions to specialists. Similarly, in [17], it is analyzed how AI is used in the architecture. It is shown that the use of PD and AI tools, together, serves to perform more detailed and accurate simulations and analyses. The study reveals the most important subfields of AI, which provide a better view of its current state. Likewise, in [18], ML in architecture, construction, and engineering is investigated, identifying disciplines, problems, and tools used in this intersection; at the same time, it reveals the growing use of ML methodologies in different areas, such as sustainability, historical and cultural structures, intelligent buildings, etc.

2. Methodology

The present Systematic Literature Review (SLR) research is developed using the Prism methodology [19], which helps to document the information collected from articles that are directly related to the main topic of study. In addition, the methodology presents the analyzed publications comprehensively and accurately, helping stakeholders to make evidence-based decisions. Its structure serves as a guide and ensures that the development of the research is more organized and clearer. The steps of this methodology are:

– Related and important documents related to the topic under study are identified.
– The articles are analyzed, exclusion and inclusion criteria are applied, and duplicate documents are eliminated.
– Eligibility analysis is performed.
– Final papers are selected for in-depth review.

2.1. Research questions

A review of selected articles and papers investigating PD and its tools is performed. These studies integrate AI techniques and are used in the construction sector for various purposes. To carry out the SLR, the following research questions (RQ) are formulated:

– RQ1: What PD tools are most frequently used in the construction industry?
– RQ2: What AI techniques and/or algorithms are most used in the PD of buildings and structures?
– RQ3: What are the benefits of integrating PD tools with AI in the construction industry?

2.2. Search strategy

To carry out the research, a specific search string is developed, and different filters are applied for each of the databases used, which are: Ebsco Host, IEEE Xplores, Science Direct, Scopus, Springer Link, and Web of Science. The criteria are detailed in Table 1. The search string aims to identify documents related to the research topic and then apply the inclusion and exclusion criteria, detailed in Table according to the Prisma statement, to determine which documents will be selected and used in the article, using an SLR matrix.

Table 1 Search string and filters applied to each database

Data Base	Equation	Filters
EBSCO HOST	("parametric model" OR "parametric CAD" OR "parametric software" OR "parametric tool" OR "parametric design") AND (construction OR architecture) AND ("machine learning" OR "artificial intelligence")	Year: 2015-2023
IEEE Xplore		Year: 2015-2023
ScienceDirect		Refine by: Years: 2015 - 2023. Publication title: Automation in Construction, Engineering Applications of Artificial Intelligence.
Scopus		Year: 2015-2023
Springer Link		Year: 2015 - 2023. Discipline: Engineering. Subdiscipline: Computer-Aided Engineering (CAD, CAE) and Design
Web Of Science		Year: 2015-2023

Table 2 Inclusion, exclusion, and justification criteria

Inclusion criteria	Justification
Include studies related to PD and/or its tools applied to construction projects.	To examine the contribution made to the construction industry and achieve the purpose of this article.

Include studies that apply AI models and/or algorithms along with parametric tools in construction projects.	To examine possible suggestions for improving construction processes and their effects on construction projects.
Include research that has been published in the last nine years (2015-2023).	The most current research possible to obtain the most effective and up-to-date results.
Documents in a reliable database.	Articles from reliable sources to ensure accurate research results.
Exclusion Criteria	**Justification**
Brief documents.	There will be no manuals or similar research.
Items over 9 years old.	Use only recent articles.
Articles that are not pertinent to the subject matter.	They do not contribute to achieving the objective.
Very general articles.	They lack specific arguments to help achieve the objective.
Articles in Spanish	Articles in English are more reliable for research.

Fig. 1 shows the phases of the Prisma statement to select the scientific articles to be used in the development of the research. The first phase consists of identifying articles in selected databases using a search string, resulting in 12,527 articles. In the second phase, the inclusion and exclusion criteria described in Table 2 are applied and those that are duplicated are eliminated, resulting in 465 articles. In the third phase, eligibility, the titles were analyzed for words or phrases directly related to the research objective, leaving 159 articles selected and 306 excluded. In the fourth phase, the articles relevant to the research were chosen by reviewing the abstracts in depth and analyzing their connection with the topic under study, resulting in the exclusion of 113 documents and the selection of 46 relevant articles that will serve as the basis for the research in the following areas:

- The PD tools most used in the construction sector.
- The AI techniques and/or algorithms most used in the PD of buildings and structures.
- The benefits of integrating PD tools with AI in the construction sector.

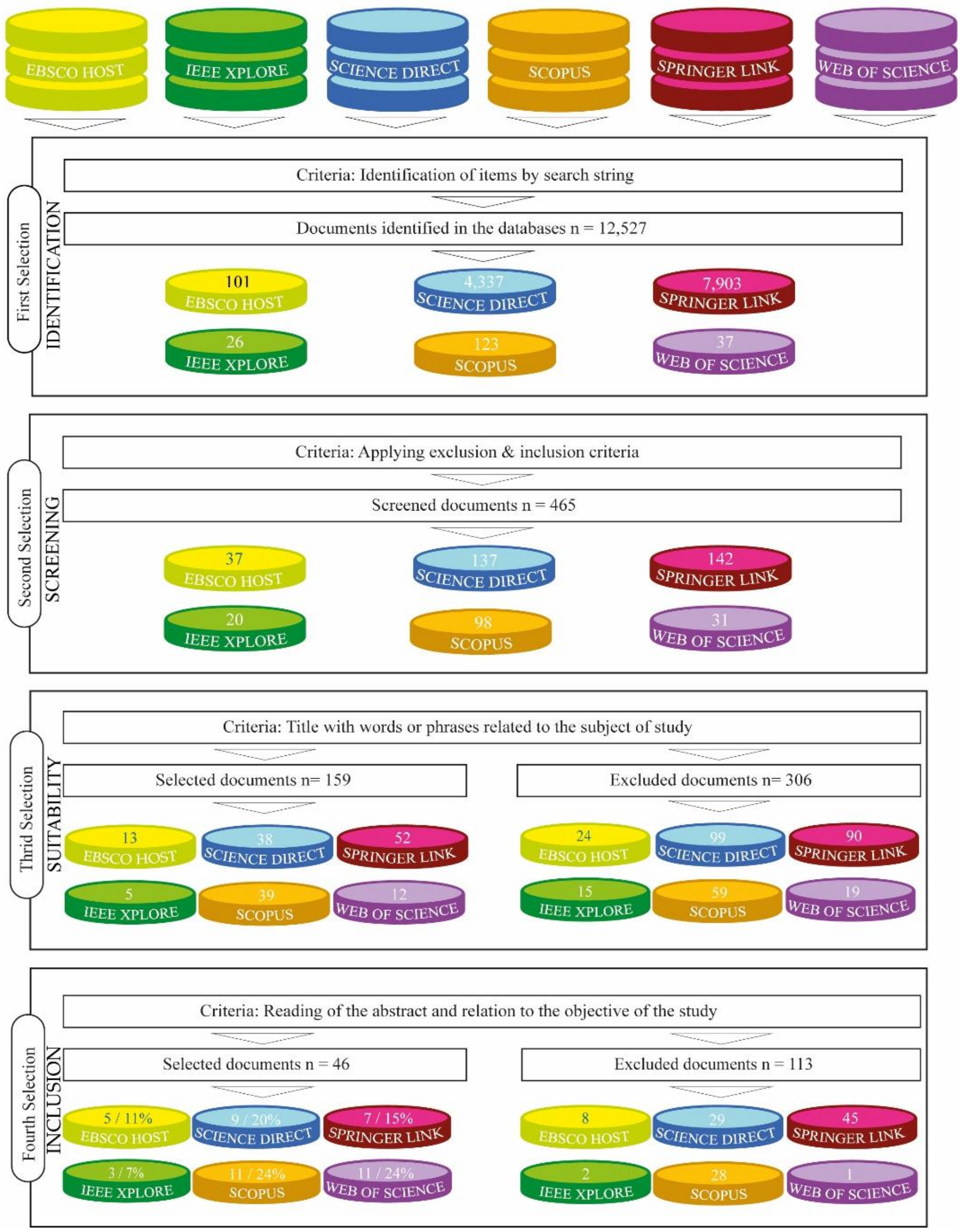

Fig. 1 Diagram of the scientific steps for the selection of scientific articles according to the PRIS-MA methodology

3. Results and Discussion

The first section of the text delves into a bibliometric analysis, meticulously examining 46 articles. The second part explores PD tools, AI techniques implemented in PD, and the advantages of integrating both tools for effective construction project management.

3.1 Bibliometric analysis

VOSviewer is a program that performs bibliometric analysis and shows the connections between journals, researchers, or publications through citation data. By examining the use of keywords, this study sheds light on the relationship between PD tools and AI in the construction sector. of Fig. 2 shows the bibliometric map with the connections and associations between 18 groups of keywords. The most used keywords are DP, ML, IA, and Architectural Design; each with 17, 7, 6, and 4 occurrences each respectively.

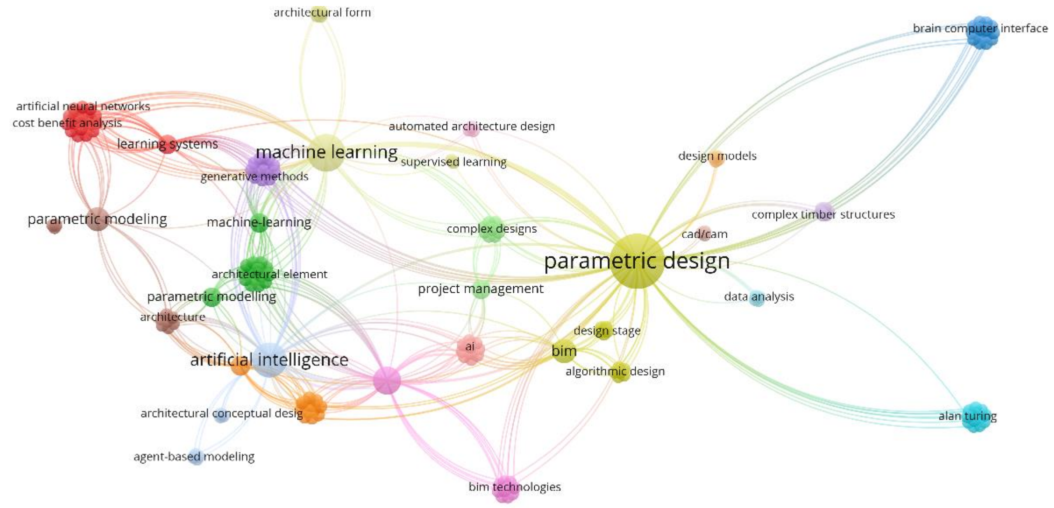

Fig. 2 Bibliometric map of the relationships between keywords

3.2 Manuscript analysis

Six databases were chosen for the article selection process: EBSCO Host, IEEE Xplore, Science Direct, Scopus, Springer Link, and Web of Science. The initial search yielded 12,527 articles, but after applying the agreed criteria and using the Prisma methodology, 46 relevant articles were obtained and included in the research. Scopus and Web of Science had the highest number of articles selected, with 11 documents each, representing 48% of the total. This information is illustrated in Fig. 1.

Figure 3 shows an upward trend in the number of research conducted on the topic at hand since 2018, with a slight decrease in 2023 because only part of the year has elapsed. 2019 and 2022 saw the highest peaks in the number of relevant articles published, with nine articles each. The year 2021 also witnessed a significant contribution, with eight relevant articles, and it is worth mentioning that the Web of Science database had the highest number of articles that year, with four papers. These results suggest a growing interest in the subject among researchers and, in addition, the field is expanding with new knowledge and discoveries.

China and the United States have the highest number of publications, with 12 and 10 articles, respectively, followed by Italy and Australia, with 4 and 3 articles, respectively. The other countries have only 1 to 2 publications each. In addition, Asia and Europe have the highest number of published articles, with 17 and 13 respectively. On the other hand, America, Oceania, and Africa have 11, 4, and 1 publication respectively. All this is shown in Fig. 4.

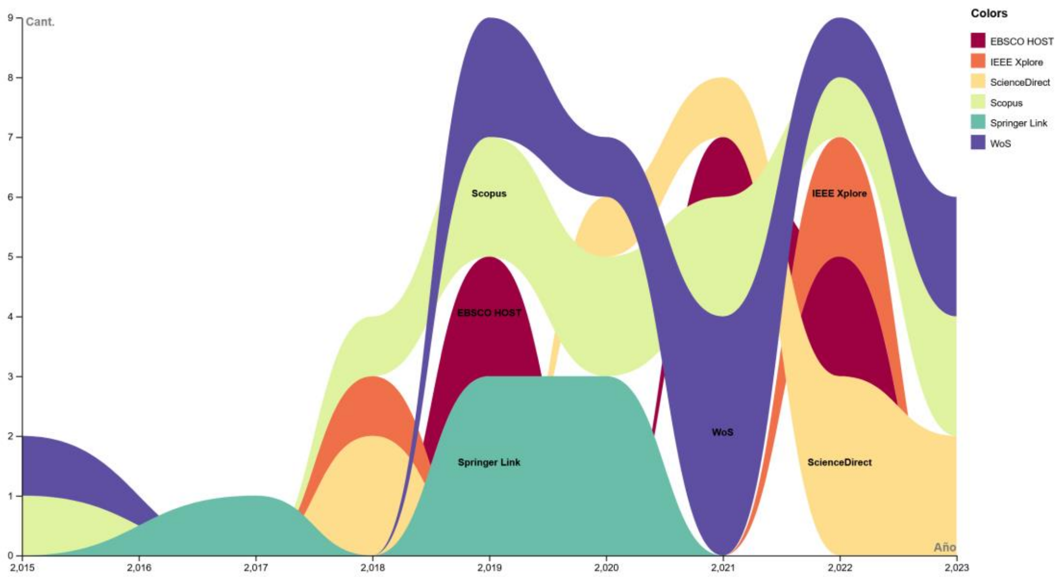

Fig. 3 Number of articles by year of publication

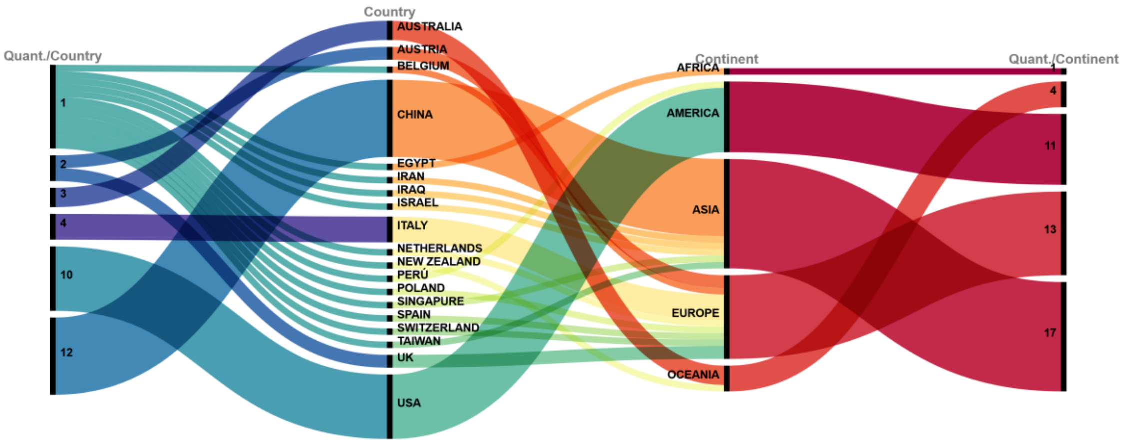

Fig. 4 Number of Articles by country and continent

3.3 PD tools are most frequently used in the construction industry

PD tools allow designers to create digital models that can be modified according to changes in design parameters. This allows them to explore various possibilities and efficiently generate complex shapes and structures. In [14] the following PD tools are identified: Autodesk Inventor, Siemens NX, Dassault CATIA, OpensCAD, Rhinoceros 3D + Grasshopper, Auto-desk Revit + Dynamo. In [13], programs such as CATIA, 3D Studio Max, and Rhinoceros 3D+ Grasshopper are used together with the plugins: Diva, Ladybug, Honeybee, and Galapagos. In [18], various PD tools are shown, and it is concluded that Rhinoceros 3D + Grasshopper is the most demanded design tool in the construction sector. Similarly, SLR identifies Rhinoceros 3D + Grasshopper as the most used PD tool in construction, with the highest impact on the results, followed by Autodesk Revit + Dynamo, as shown in Table III. In addition, 37 of the 56 occurrences related to the use of Rhinoceros software use various plugins to achieve the design objective, as seen in Table 3.

Table 3 Parametric design tools

Item	PD Tool	Occurrences	%	References
1.00	AutoCAD 3D	1	1%	[20]
2.00	CATIA	3	4%	[21], [22], [23]
3.00	TopSolid	1	1%	[24]
4.00	ArchiCAD	1	1%	[25]
5.00	ArchiCAD + PARAM-O	2	2%	[26], [27]
6.00	Autodesk Revit	6	7%	[20], [25], [28], [29], [30], [31]
7.00	Autodesk Revit + Dynamo	12	15%	[20], [21], [22], [26], [32], [33], [34], [35], [36], [37], [38], [39]
8.00	Rhinoceros 3D + Grasshopper	56	68%	(**)

Table 4 Grasshopper plugin occurrences

Item	Plugin	Occurrences	%	References (**)
1	Rhinoceros 3D + Grasshopper	19	34%	[21], [23], [25], [26], [32], [33], [34], [35], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48]
2	Rhinoceros 3D + Grasshopper + Biomorpher	2	4%	[27], [34]
3	Rhinoceros 3D + Grasshopper + Colibri	1	2%	[34]
4	Rhinoceros 3D + Grasshopper + Conduit	1	2%	[34]
5	Rhinoceros 3D + Grasshopper + Crow	1	2%	[34]
6	Rhinoceros 3D + Grasshopper + DIVA	1	2%	[49]
7	Rhinoceros 3D + Grasshopper + Dodo	1	2%	[34]
8	Rhinoceros 3D + Grasshopper + Galapagos	6	11%	[34], [36], [50], [51], [52], [53]
9	Rhinoceros 3D + Grasshopper + Generator	1	2%	[34]
10	Rhinoceros 3D + Grasshopper + Genoform	1	2%	[34]
11	Rhinoceros 3D + Grasshopper + Goat	1	2%	[34]
12	Rhinoceros 3D + Grasshopper + Honeybee	4	7%	[22], [49], [53], [54]
13	Rhinoceros 3D + Grasshopper + Karamba	1	2%	[54]
14	Rhinoceros 3D + Grasshopper + Ladybug	5	9%	[22], [49], [53], [54], [55]
15	Rhinoceros 3D + Grasshopper + Lunchbox	1	2%	[34]
16	Rhinoceros 3D + Grasshopper + Monkey	1	2%	[24]
17	Rhinoceros 3D + Grasshopper + Octopus	3	5%	[34], [53], [54]
18	Rhinoceros 3D + Grasshopper + Opposum	1	2%	[34]

19	Rhinoceros 3D + Grasshopper + Owl	1	2%	[34]
20	Rhinoceros 3D + Grasshopper + Silvereye	1	2%	[34]
21	Rhinoceros 3D + Grasshopper + StormCloud	1	2%	[34]
22	Rhinoceros 3D + Grasshopper + TT Toolbox	1	2%	[34]
23	Rhinoceros 3D + Grasshopper + Wallace	1	2%	[34]

3.4 AI techniques and/or algorithms most used in the DP of buildings and structures

The integration of PD tools and AI is used to perform more detailed and accurate simulations and analyses. In [17], the most important subfields of AI are studied, such as expert systems, ML, evolutionary design, generative design, Mult objective optimization, and Deep Learning (DL) together with its techniques and algorithms: ANN and CNN. Likewise, in [18], the growing interest in the use of new technologies related to AI, ML, and its various techniques such as ANN, Distributed Constraint Optimization Problem (DCOP), CNN, Convolutional-Deconvolutional Neural Networks (CD-NN), Random Forest (RF), Support Neighbor Machines (SVM), Decision Tree, Fast Forest Regression and Fast Tree Regression; all of them are integrated to the DP tools detailed in the previous point. The present research reveals the different algorithms and their respective subfields of operation; in addition, it highlights the architectures and algorithms most used by designers in the construction sector, namely ANN, Genetic Algorithm (GA), and CNNs; those are presented in Table 5.

Table 5 AI algorithms and their most used fields in parametric design of buildings and structures

IA Field	AI Techniques and/or Algorithms	Occurrences	References
Deep Learning (DL)	Convolutional Neural Networks (CNN)	6	[24], [33], [46], [51], [53], [55]
	Deep Neural Networks (DNN)	1	[56]
	Generative Adversarial Networks (GAN)	4	[24], [43], [53], [57]
Machine Learning (ML)	Artificial Neural Networks (ANN)	16	[25], [31], [33], [38], [41], [47], [50], [51], [53], [56], [58], [59], [60], [61], [62], [63]
	Backpropagation Neural Network (BPNN)	2	[45], [58]
	Decision Tree	3	[38], [45], [51]
	Extremely Randomized Trees (ERT)	1	[45]
	Fuzzy C-means	1	[37]
	Genetic Algorithm (GA)	9	[22], [29], [36], [40], [50], [51], [53], [54], [62]
	Gradient Boosting Regression Trees (GBDT)	2	[45], [47]
	Interactive Evolution Algorithm	2	[27], [34]
	K-means	1	[25]
	K-Nearest Neighbors (KNN)	2	[51], [64]
	Logistic Regression (LR)	1	[51]
	Random Forest (RF)	3	[38], [45], [47]
	Support Vector Machine (SVM)	5	[42], [45], [47], [51], [64]
	Xtreme Gradient Boosting (XGBoost)	1	[51]
Optimization	Adaptive Genetic Algorithm (AGA)	1	[64]
	Adaptive Particle Swarm Optimization (APSO)	1	[64]
	Covariance Matrix Adaptation with Evolution Strategy (CMA-ES)	1	[38]
	Evolutionary Programming	1	[51]
	Evolutionary Strategies	1	[51]
	Genetic Programming	1	[51]
	Interactive Genetic Algorithm (IGA)	2	[27], [50]
	Particle Swarm Optimization (PSO)	2	[50], [51]
	Simple Genetic Algorithm (SGA)	1	[50]
	Simulated Annealing Algorithm	1	[50]

Fig. 5 shows the domains of artificial intelligence, focusing specifically on DL, ML, and optimization. Each domain has its own set of algorithms, which are characteristic of their functions. This visual representation provides a clear and concise illustration of the level of interconnectedness between the use of each algorithm and its relationship to various domains. In addition, Fig. 6 provides a graphical representation of the percentage of occurrences of the algorithms identified in the research. These have been classified according to specific fields of artificial intelligence, providing a visual perspective that highlights the frequency of use of each algorithm in their respective domains. This visual analysis reveals the prevalence and strategic distribution of these algorithms, providing a clear view of their impact in various AI domains.

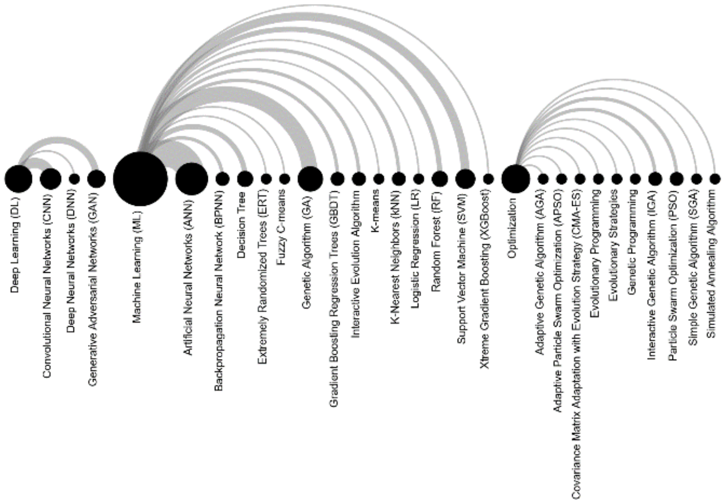

Fig. 5Relationship between AI fields with their algorithms

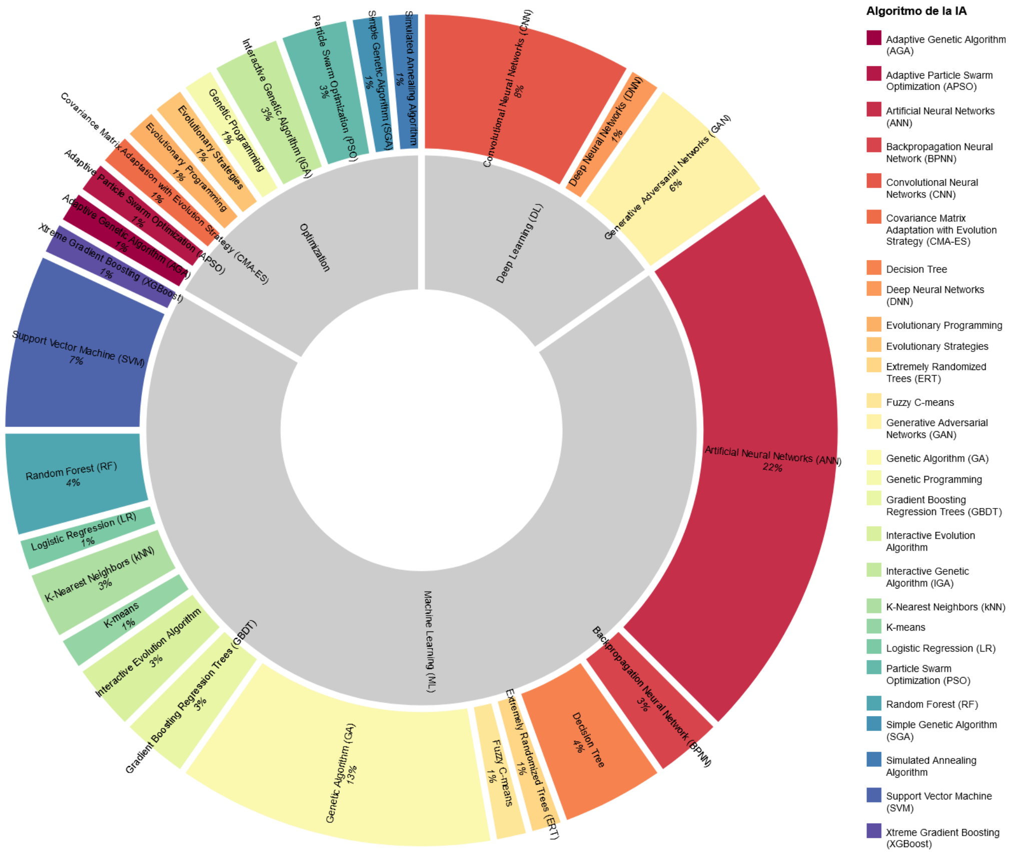

Fig. 6 Algorithms and their percentage of occurrence in the research

3.5 The benefits of integrating PD tools with AI in the construction industry

The integration of PD tools with AI is radically transforming the construction sector. In [16], it is highlighted that the synergy of these tools optimizes the design process and achieves better quality results; likewise, it generates automation in the processes or specific tasks with greater precision and occupies less time and resources. Similarly, in [13], [15], [17], the flexibility to automatic changes and immediate updates of the digital model when the design parameters are modified according to the user's needs are highlighted, allowing the development of a variety of optimal solutions more efficiently. Based on the results of the present research, Table 6 classifies the benefits that encompass all the advantages resulting from the collaboration between PD tools and AI into seven groups.

Table 6 The advantages of integrating PD tools with AI

Benefits	References
Design Optimization: The combination of PD and AI allows a wide range of design options to be automatically explored and optimized. Algorithms can search for solutions that meet multiple criteria, such as energy efficiency.	[22], [24], [25], [26], [27], [29], [31], [34], [35], [36], [38], [40], [42], [45], [50], [51], [53], [54], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65]
Advanced analysis and classification: AI can analyze large data sets from PD tools to identify patterns and trends, helping to make informed decisions and anticipate problems in the design phase.	[22], [26], [33], [36], [37], [41], [45], [46], [55], [56], [58], [63], [65]
Automated Generation: AI can automatically generate designs based on set parameters and constraints, which speeds up the creative process and allows designers to explore more options in less time.	[24], [25], [26], [27], [29], [31], [34], [38], [40], [41], [42], [43], [46], [47], [51], [57], [59], [60], [61], [62], [63]
Customization and Adaptation: AI can tailor DPs to meet specific customer needs and preferences, resulting in unique personalized designs.	[27], [31], [35], [58], [63]
Resource Optimization: Combining PD and AI can optimize the use of resources such as materials and energy, resulting in more sustainable and efficient designs.	[33], [36], [37], [38], [46], [47], [51], [53], [59], [62], [64]
Predictions and Simulations: AI can simulate and predict based on historical and real-time data, making it useful for forecasting how a building will perform under different conditions and anticipating potential problems.	[26], [36], [37], [41], [42], [45], [47], [50], [51], [53], [54], [55], [57], [60]
Error reduction: AI automation and pattern detection can help identify potential design errors before construction, saving time and resources.	[25], [36], [38], [40], [43], [50], [60], [62]

4. Conclusions (Times New Roman, 11 pt, Bold)

The present SLR is developed with the Prisma methodology, in which after applying the search string in the determined databases and, between the years 2015 and 2023, it yields 12,527 articles at first, the same that are submitted to the inclusion and exclusion criteria, resulting in 46 relevant articles that will be included for the research. In the in-depth analysis of the manuscripts collected, the great potential that the integration of the tools under discussion allows is identified.

According to the results of this research, it is concluded and determined the great influence of PD tools and the integration of AI in the construction sector. PD tools allow designers to create adaptive and complex models, with Rhinoceros 3D + Grasshopper being one of the most widely used. Collaboration with AI, which encompasses techniques such as ANNs and CNNs, revolutionizes the design process by enabling detailed simulations and task automation. The benefits of this synergy are grouped into seven categories, including design optimization, task automation, quality improvement, and decision-making efficiency, ultimately driving innovation and efficiency in construction projects. These findings underscore the importance of adopting these technologies in the construction sector to achieve more efficient and higher-quality results.

Limitations of this research include the need for greater depth in explaining how AI algorithms are applied in the construction industry, the generalization of benefits that may vary with circumstances, the lack of quantitative impact assessment, and the possibility that technological advances have changed the relevance of the findings. These limitations point to areas for future research that can provide a more complete and updated understanding of the integration of these technologies in the construction industry.

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