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Review Article

Application of Soft Computing to Address Uncertainty in Construction Project Management: A Systematic Literature Review

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Abstract

Decision-making in Construction Project Management (CPM) involves numerous ambiguous information and uncertainties due to the nature of construction project. The Soft Computing (SC) approach, which offers several data processing strategies under uncertainty, has been extensively researched in CPM studies for decision problem solving. Decisions that cannot be adequately handled by conventional computer systems are facilitated by the SC approach. The SC approach encompasses a variety of SC techniques that are constantly developing and becoming more widely used to address real construction challenges. This study aims to conduct Systematic Literature Reviews (SLR) on the development of mainstream SC techniques and their current application in construction projects. Using an inventive SLR technique, 83 CPM papers covering the years 2018 to 2023 were selected for this study and then classified into four primary application themes of SC in CPM. The research trend was then described using bibliometric analysis. Afterwards, a topic-based qualitative analysis was conducted to investigate the application of SC approaches in the construction field. Several potential challenges to current research were then elaborated. It also contributed to suggesting future directions for the advancement of SC techniques that would be advantageous for construction research and practice.

Keywords: Decision; Uncertainty; Project; Construction Management; Soft Computing.

1. Introduction

In general, the construction project phase encompasses the activities of planning, procuring, implementing, monitoring, and evaluating. They are extensive, with ambiguous information and uncertainties. During the implementation of a project, it is common for unforeseen circumstances, such as extreme weather occurrences, to cause abrupt modifications to both immediate and long-term timetables. Additionally, material orders may be shortly cancelled without prior notification, and important information from the site may fail to reach the right people. Under these uncertainties, project managers work to ensure successful project completion in the shortest period and at the lowest cost [1]. Moreover, there are semi-structured to unstructured problems that are often encountered in construction management. Therefore, the implementation of systematic Construction Project Management (CPM) plays an important role in decision-making for success in achieving project goals.

The decision-making process can become very complex when confronted with multiple aspects that necessitate careful consideration and involve a significant degree of ambiguity and uncertainty. Various factors impact decision-making in construction management, including: 1) financial constraints; 2) communication and coordination deficiencies leading to errors and omissions; 3) inadequate assessment of project duration; and 4) design modifications

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requested by the contractor for decision-making [2]. Practitioners should adopt a more outward-focused approach, aggressively address issues faced by external stakeholders, adhere to ethical and sustainable project management practices, and enhance project results [3].

The issue of uncertainty in construction projects becomes increasingly critical in more complicated projects. Some challenges in construction projects cannot be expressed using precise mathematical calculations to determine the intended outcome. Conventional computational or analytical models may not always offer effective answers to practical issues encountered at the project site. This phenomenon can occur due to the presence of numerous circumstances that encompass elements of uncertainty, imprecision, and ambiguity. These complexities can be effectively addressed through the utilization of Soft Computing (SC) methodologies. The SC method offers many techniques for processing data to facilitate decision-making in situations involving uncertainty, which cannot be effectively addressed by conventional computer methods. The SC method allows implementation with a low-cost solution.

The utilization of the SC method within a decision support system in construction management proves highly advantageous in addressing complex interactions and uncertainties inherent in real-world challenges. Implementing this methodology can assist project managers in making well-informed decisions, enhancing designs, and improving the overall efficiency and safety of civil engineering projects [4]. The SC is not an independent problem-solving strategy but rather a harmonious collaboration between several SC techniques, allowing the advantageous parts of each method to actively contribute. Several successful applications of SC in overcoming uncertainty in CPM include project control and monitoring, procurement and contract, risk management, optimization, and scheduling.

The aim of the SC method is to construct intelligent and wiser learning machines capable of performing complex tasks. Smith & Wong (2022) revealed that the majority of research focuses on utilizing the SC method, such as artificial neural networks (ANN) and fuzzy logic (FL) algorithms, for project prediction, management applications, logistics, and design [5]. The application of SC for decision support systems (DSS) in project management has been extensively discussed in various academic works, particularly in the context of software development project management [6–8]. Several SC techniques are constantly developing and becoming more widely used to solve practical construction issues. However, there has not yet been sufficient SLR conducted since 2018 that explicitly investigates the implementation of SC in the field of CPM, which is characterized by a significant amount of uncertainty, lack of confidence, ambiguity, and incomplete data. Systematic Literature Review (SLR) of the SC method may shape the future of the metaverse [9]. Therefore, this paper addresses the problem through a thorough investigation of existing SC methods and a systematic synthesis of their application in CPM.

The aim of the study is to systematically review the application status of the SC method in the CPM. The specific objectives of this study are: (1) to identify the evolution of SC techniques over time and to examine their relationships; (2) to create a new approach for systematically evaluating the use of the SC model in CPM using bibliometric analysis; (3) to identify the primary domains where different techniques within the SC model are applied in CPM; and (4) to assess any potential gaps and propose future directions for SC research in CPM. This literature study is appropriate for scholars and practitioners in the domains of construction management and information technology to peruse. Academics specializing in decision support systems and SC are strongly advised to examine this article. The subsequent sections are organized in a sequential manner to systematically accomplish the study objectives one after another.

There are eight sections to this article. First is the introduction section, which contains the background, objectives, contributions, and structure of the paper. Second, a section that explains SC techniques and the state-of-the-art of SC in CPM. Third, SLR is used in the methodology section, including the theme survey methodology, searching methodology, selection of data sources and papers, and thematic classification. Fourth, it contains a bibliometric analysis of SC in CPM, including: 1) distribution of papers based on year of publication, journal, and author; 2) distribution by CPM stage and field; and 3) distribution by SC techniques and decision model. The topic of applications based on the CPM stage is discussed in the fifth section. The sixth section discusses applications built with SC components. Challenges and directions for further research are included in the seventh. The conclusion is found in the last section.

2. Soft Computing

2.1. Soft Computing Techniques

Numerical modeling and symbolic logic reasoning were the first conventional mathematical techniques employed in the computer-assisted decision-making methodology. Decision-resolution then employs an estimation model, which is predicated on approximative reasoning and modeling, in addition to the intricacy of the issues encountered in decision-making with numerous uncertainty components. Soft Computing (SC) is a well-known term for a method that uses an approximation model, whereas Hard Computing (HC) refers to a methodology that uses a classical mathematical approach. Figure 1 shows the differences between HC and SC [10]. A classic HC approach is depicted in Figure 1a, where the problem is solved using conventional mathematical techniques to obtain an exact model under inquiry. On the other hand, SC provides a solution that is based on approximate reasoning approaches, and Figure 1b illustrates the SC method based on approximation models.

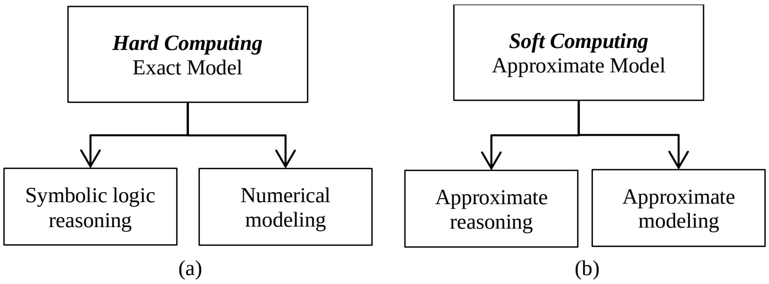


Figure 1. Differences between hard computing and soft computing: (a) Hard computing, (b) Soft computing

In 1965, Lotfi Zadeh presented the concept of fuzzy logic (FL) as a mathematical foundation for approximative models, and then the development of SC officially got underway. Evolutionary Computing (EC), which began with genetic algorithms, started to take shape in the 1960s and 1970s. By using these methods, approximate models for issues with numerous uncertainty components have been made possible. In addition, in the 1980s, new methods utilizing Probabilistic Reasoning (PR) and Artificial Neural Network (ANN) methodologies were applied in several studies. In the 1980s and 1990s, a number of SC techniques evolved into hybrid intelligence systems that could solve complicated issues concurrently and swiftly. The SC technique has been a major player and influencer in several big data-related domains since the 1990s.

The SC method has been widely applied in decision-making that has tolerance for imprecision, uncertainty, and partial realism to achieve accuracy, robustness, low-cost solutions, and a better relationship with reality [10]. Through approximation models, SC seeks to quickly and accurately solve difficult real-world problems. Instead of being a single approach, SC is a hybrid intelligence that integrates a number of techniques, including FL, ANN, EC, and PR. While these techniques do not compete with one another, they can be applied in collaboration to address specific issues harmoniously. The SC paradigm gives people a great deal of freedom in defining real-world issues in computational language. This new strategy aims to maximize usability while minimizing system complexity [11]. The SC application has numerous benefits, including the following: 1) employing a methodology that accepts ambiguity and imprecision; 2) solving problems with uncertain elements, like those in real life; 3) permitting the use of "linguistic variables"; 4) handling problems involving non-statistical data; 5) formulating equations based on overlapping ranges of values rather than strict boundaries.

Numerous innovative techniques, like the fuzzy neural network, fuzzy genetic algorithm, fuzzy system, and genetic fuzzy system, are the result of hybrid intelligence constructed with SC. These techniques can be used to use big data to address challenging tasks. Big data has made it possible for computer systems to learn and adapt on their own. This is accomplished through the utilization of statistical models and algorithms to assess and infer patterns from vast quantities of data. This is commonly known as a Machine Learning (ML) methodology. Machine Learning (ML) is a subset of Artificial Intelligence (AI), which allows computers to identify patterns and anticipate outcomes with little to no human input by learning from data and past experiences. When new data is given to ML applications, they can autonomously learn, adapt, expand, and improve. Because they frequently handle uncertainty and data complexity in a manner comparable to the ideas in SC, ML approaches like neural networks, decision trees, support vector machines, and other algorithms might be seen as components of SC.

2.2. Soft Computing in Construction Project Management

There is a great deal of information uncertainty during the planning, executing, monitoring, and assessing phases of a construction project, which makes it distinctive. This is particularly problematic for long-term plans. Project managers must always be ready for the unanticipated events and uncertainties that arise throughout the execution of construction projects. Several academics in the field of Construction Project Management (CPM) have incorporated fuzzy logic into CPM by utilizing fuzzy inference methods or fuzzy clustering. According to Kuchta & Zabor (2021) [12], the fuzzy approach makes it possible to identify the uncertainty and ignorance around project planning, control, and risk assessments. Using expert information and their subjective opinions, decision-makers can plan and evaluate projects more easily when they use the fuzzy approach. Fuzzy multi-criteria decision making (FMCDM) is a highly effective approach for addressing complex situations that involve conflicting objectives, diverse decision-maker preferences, and a large amount of incomplete yet ambiguous information [13]. Fuzzy clustering has also proven useful for project risk assessment [14].

Artificial Neural Network (ANN) is a technique of SC that utilizes the learning idea. The research community is very interested in using ANN to solve challenging issues in the realm of construction and building (CB) engineering. Over the past three decades, this interest has led to a significant number of scholarly articles in a variety of CB domains [15]. When predicting the cost and time of construction projects, neural network algorithms have a number of advantages over conventional techniques [16]. A better construction market, more knowledgeable and assured clients, effective control, and a higher return on investment are all expected outcomes of accurate initial cost estimates.

Optimization problems can be solved in large part by using Evolutionary Computing (EC) techniques like Particle Swarm Optimization (PSO) and genetic algorithms. Liu et al. (2023) [17] and Bakshi et al. (2012) [18] have noted that evolving computational techniques for scheduling optimization have been the subject of numerous recent research projects. This is because situations with few actions and few resources can only be resolved by the most precise approach.

The oldest approach to handling uncertainty is Probabilistic Reasoning (PR). The PR is usually derived using data such as Bayesian networks, Monte Carlo simulations, sensitivity analysis, decision tree analysis, and other historical numerical data [19]. Bayesian networks and probabilistic ontologies are examples of further advancements.

Machine Learning (ML) is the next technique to emerge from the concept of learning. The prediction process's generality, accuracy, and efficiency are significantly increased by the application of ML approaches [20]. In making forecasts, ML and Building Information Modeling (BIM) have a place [21]. By allowing deviation analysis and time and cost estimation during project progress monitoring, ML models for project control under uncertainty expand the earned value framework [22]. While ML is beginning to be used in BIM-based construction projects, it is still not being used effectively to anticipate the effects of design changes.

Moreover, a variety of hybrid approaches have been used to address ambiguity and subjective opinions. CPM uncertainty issues have been successfully resolved using fuzzy hybrids [23]. The combination of Artificial Neural Networks (ANN) with fuzzy systems, known as Neuro-Fuzzy Systems (NFS), enables the explicit representation and modeling of input-output interactions in complex problems and non-linear systems, including those seen in real-world engineering and construction management issues [24]. Various applications, including categorization, regression, prediction, system modeling, and control, can utilize this NFS.

3. Research Methodology

3.1. Survey Methodology

This study is a Systematic Literature Review (SLR), which is a type of literature review. In order to gather and categorize the literature according to specific standards, SLR will methodically map a number of literary works [25]. SLR maintains the principles of transparency and bias reduction while offering a thorough summary of the literature pertinent to the research question and synthesizing earlier research to expand the body of knowledge on a certain subject [26]. The SLR is not an exhaustive examination of all studies; rather, it is a summary of prior research. According to Durach et al. (2017) [27] and Zhu et al. (2021) [28], the steps of the SLR process are as follows: (1) developing questions; (2) identifying research features; (3) sampling possibly relevant material; (4) choosing related literature; (5) synthesizing; and (6) reporting the results.

A review of the application of soft computing techniques in construction management was carried out by Dikmen et al. (2009), that was not conducted in a methodical manner because SC had not progressed as much in that year compared to its current advancements [22]. Unlike other literature reviews currently in use, this study evaluates and compiles prior research using the SLR stepwise process. Additionally, it offers a fair and impartial synopsis of the studies supporting SC's use in CPM. Figure 2 shows specific search and filtering procedures.

3.2. Searching Methodology

This research mainly focuses on the application of SC in CPM. There are four research questions (see Figure 2) that are answered through SLR. Based on a review of the literature on SC in general (see Section 2), 18 keywords were defined, including the main methods used. The string "construction management" was first selected to narrow the search scope. Boolean "OR" logic is then used to combine the following keyword strings: "(TS=(construction management AND (soft computing OR fuzzy OR neural network OR genetic algorithm OR probabilistic OR machine learning OR deep learning OR neuro OR MCDM OR MADM OR multi-attribute OR multi-criteria OR mathematical programming OR predictive OR heuristic OR forecasting OR decision support system))".

3.3. Selection of Data sources and Papers

Scopus and Web of Science were chosen as the primary collections and databases for the literature search. Both are providers of extensive scientific citation indexing services. Potential literature was defined as just journal-published English-language works that were indexed by them. January 2018 to December 2023 was the time frame for article publication. It was selected for a 5-year timeframe because this was when information technology often developed at a quick pace. Of the 137 international journals, a total of 277 papers were acquired. Two criteria were employed for exclusion: 1) the titles and abstracts were screened to remove publications that did not fit within the purview of this study; and 2) the entire text of the articles was examined to remove articles that did not fit within the purview of this study. There were 149 publications in 81 journals after the first set of exclusion criteria was applied. Applying the second set of exclusion criteria, however, produced 83 papers across 58 publications.

Step	Procedure	Content
Step 1 Formulate research question (RQ)	Start Formulate research questions	**RQ1:** What is the bibliometric perspective of soft computing in the construction project management field? **RQ2:** In which research areas and field applications are components of soft computing applied in construction project management? **RQ3:** What are the challenges potentially related? **RQ4:** What are the future research?
Step 2 Determine required characteristics of primary studies	Formulate Keywords Craft inclusion & exclusion criteria	**Inclusion Criteria:** – Timespan: January 2018 – December 2023 – Language: English – Document Types: Peer-reviewed journal article – Index: Scopus and Web of Science **Exclusion Criteria:** – The article outside the research scope after reading the title & abstract – The article outside the research scope after reading the full contents
Step 3 Retrieve sample of potentially relevant literature	Database N = 277; J = 137;	Database: Scopus and Web of Science Searching the keyword Deriving the baseline sample: N = 277, J = 137
Step 4 Select pertinent literatures	EXCL Criteria 1 Database N = 149; J = 81; EXCL Criteria 2 Database N = 83; J = 58;	Reducing the baseline sample to derive the synthesis sample: **Exclusion (EXCL) Criteria 1:** Remove the articles that outside the scope of research after reading the title and abstract **Exclusion (EXCL) Criteria 2**: Remove the articles that outside the scope of research after reading the full articles
Step 5 Synthesize literature	Content cooccurrence analysis	**Coding the synthesis sample** Summarizing the findings (methodological aspects of the primary study should be analyzed) and interpretation
Step 6 Report the results	Apply coding schemes to extract information Result and updating the review Stop	– Descriptive analysis of primary studies – Outlining the knowledge derived from the study synthesis – Keeping the review updated

Figure 2. Steps of literature searching and filtering

3.4. Thematic Classification

This study used co-occurrence analysis to create a distance-based map of phrases in the title and abstract in order to uncover themes related to the application of SC in CPM, as the abstract was thought to be a clear overview of the research content. The map was made using VOSviewer, a bibliometric mapping software application. After deleting a number of broad terms like "construction", "construction management", and "decision support system", a total of 38 terms that appeared more than five times were chosen from 2376 terms. The findings of the content co-occurrence analysis are displayed in Figure 3, where terms are represented by nodes and the degree of association between two nodes is indicated by their distance from one another. Groups to which terms are assigned by similarity analysis are indicated by colors.

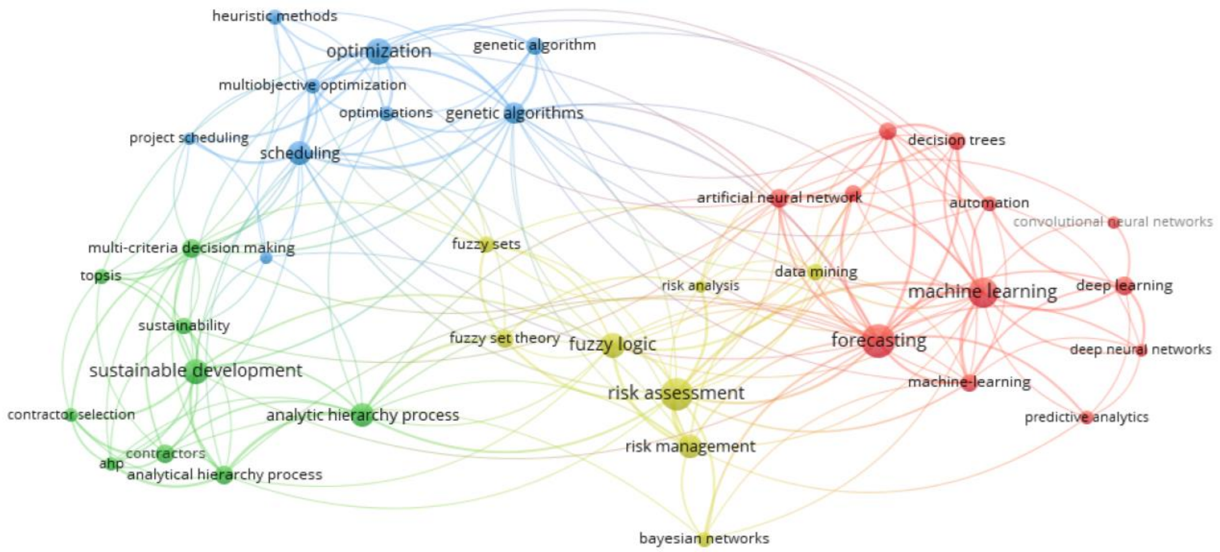


Figure 3. Content co-occurrence analysis of terms in titles and abstracts

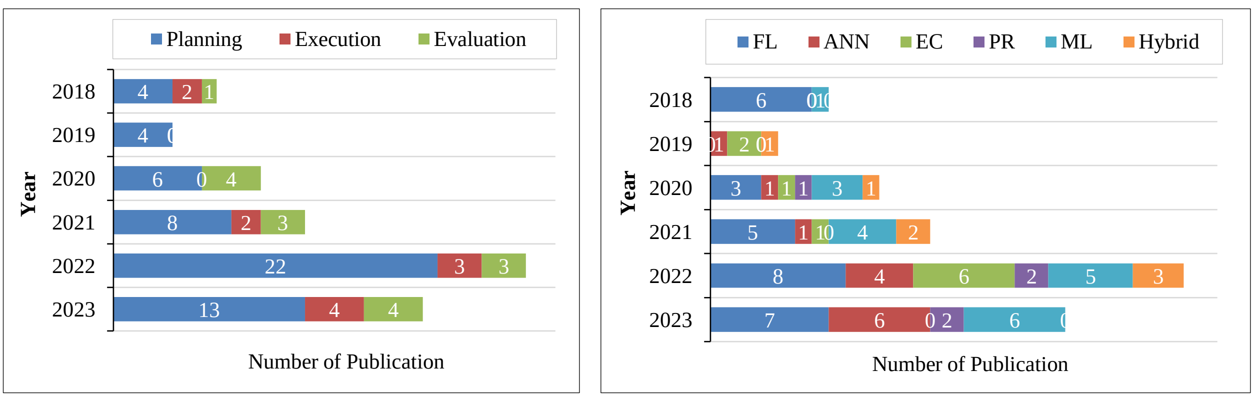
Four main application clusters or themes of SC in CPM emerged, which are as follows: (1) optimization / scheduling / genetic algorithm/ heuristic (blue); (2) forecasting / predictive / machine learning / artificial neural network (red); (3) multicriteria decision making / analytic hierarchy process / sustainable development / contractor selection (green); (4) risk assessment / risk management / fuzzy logic (yellow). It was made a few changes because it could occasionally be challenging to separate these groups. This modification was done in order to categorize based on the definition of each word and the core idea of each theme. There are four categories under this classification. First, there is the CPM stage, which is made up of the phases for planning, executing, controlling and evaluating, and closing. The second is the field of construction science, which includes the selection of contractors, partners, employees, and vendors, as well as procurement and contracts, financing and budgeting, optimization, project control and monitoring, risk and safety management, scheduling, and sustainable performance evaluation. The third group of SC techniques includes hybrid systems, probabilistic reasoning (PR), evolutionary computation (EC), fuzzy logic (FL), artificial neural networks (ANN), and machine learning (ML). Fourth, the decision model includes prediction, scheduling, modeling, heuristics, mathematical programming, factors analysis, and multi-criteria decision making (MCDM).

4. Bibliometric Analysis of Soft Computing in CPM

4.1. Distribution by Publication Years

Figure 4(a) displays the distribution of publications by CPM stage for each year. In 2023, the highest number of publications (28) was recorded compared to any other year. Meanwhile, in 2019, only four papers were published, and all articles focused on topics in the planning stage. Additionally, the planning stage consistently took precedence as the main topic of discussion each year.

The distribution of publications by year according to SC techniques is displayed in Figure 4(b). During these periods, FL was the most frequently discussed issue. Unfortunately, in 2019, FL was not discussed at all. After the current development of ANN and ML, it is obvious that the application of ANN in conjunction with ML is growing fast along with the advancement of big data and data mining technologies.



(a) (b)

Figure 4. Distribution of publication by year based on: (a) CPM stage; (b) SC techniques

4.2. Distribution by Journals

There were 58 journals left in this study for the literature evaluation after the screening process. A list of 16 carefully chosen periodicals with at least two papers is shown in Table 1. First place goes to the Engineering, Construction, and Architectural Management journal, which contributes 8.43% of the chosen articles. The bulk of selected publications are published in journals focusing on construction, civil engineering, or construction management/engineering. Soft computing-related journals are limited to one publication.

Table 1. Distribution of Journals

No.	Journal Title	Frequency	Percentage	Cumulative Percentage
1	Engineering, Construction, and Architectural Management	7	8.43%	8.43%
2	Journal of Construction Engineering and Management	4	4.82%	13.25%
3	Journal of Civil Engineering and Management	3	3.61%	16.87%
4	Journal of Engineering, Design and Technology	3	3.61%	20.48%
5	Advances in Civil Engineering	2	2.41%	22.89%
6	Applied Sciences (Switzerland)	2	2.41%	25.30%
7	Applied Soft Computing	2	2.41%	27.71%
8	Asian Journal of Civil Engineering	2	2.41%	30.12%
9	Automation in Construction	2	2.41%	32.53%
10	Construction Innovation	2	2.41%	34.94%
11	Innovative Infrastructure Solutions	2	2.41%	37.35%
12	International Journal of Construction Management	2	2.41%	39.76%
13	Iranian Journal of Science and Technology - Transactions of Civil Engineering	2	2.41%	42.17%
14	Journal of Management in Engineering	2	2.41%	44.58%
15	Journal of Soft Computing in Civil Engineering	2	2.41%	46.99%
16	Symmetry	2	2.41%	49.40%
17	Others	-	50.60%	100.00%

4.3. Distribution by Authors

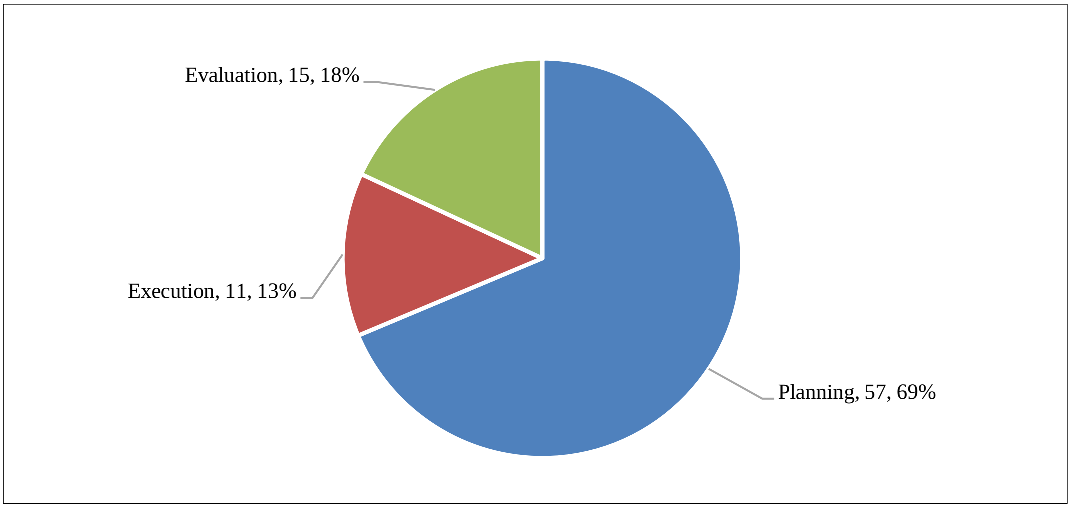
The top five authors can be seen in Table 2, with at least two publications on the use of SC in CPM, based on Google Scholar that offers information on author names, their articles, and citation counts. Fin C.L has three articles, and the others have only two articles. Guimaraes F.G. has accumulated 5,955 citations as of February 2024.

Table 2. Distribution of Authors

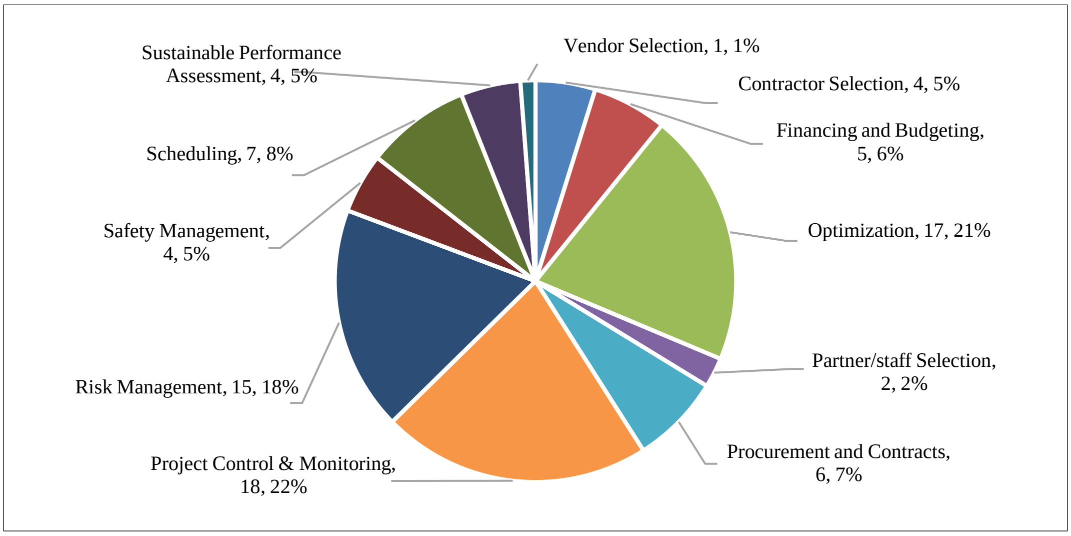
No	Author	No of articles	No of citations
1	Fan C.L.	3	187
2	Guimaraes F.G.	2	5955
3	Nguyen P.T.	2	1033
4	Faraji A.	2	179
5	Oliveira B.A.S.	2	178

4.4. Distribution by CPM Stage and Field

Planning is the CPM stage that receives the greatest discussion (57 publications or 69%), while execution receives the least discussion (11 publications or 13%), as illustrated in Figure 5(a). Regarding the subject of research, vendor selection received the least amount of discussion (1 publication or 1%), while project control and monitoring received the most (18 publications or 22%), as presented in Figure 5(b).



(a)

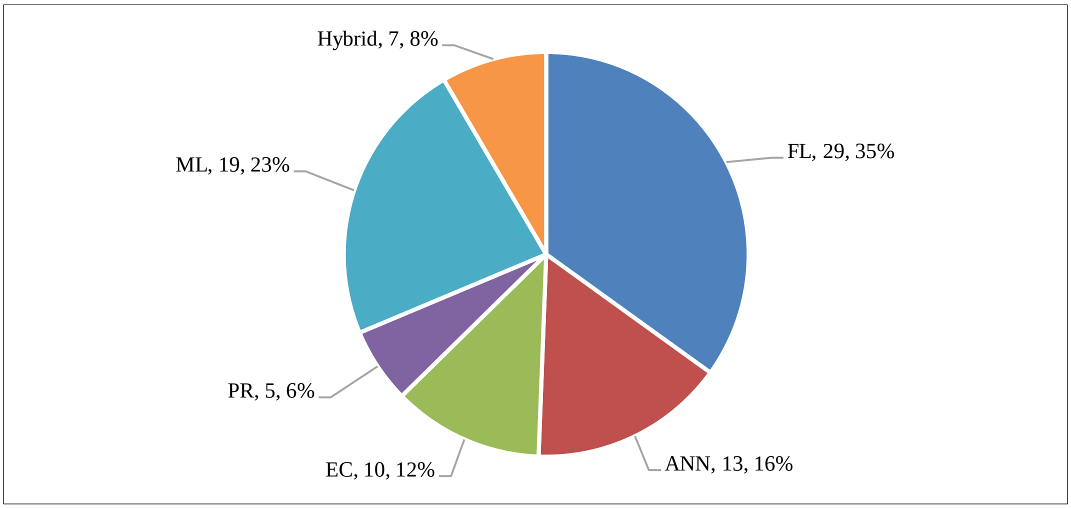


(b)

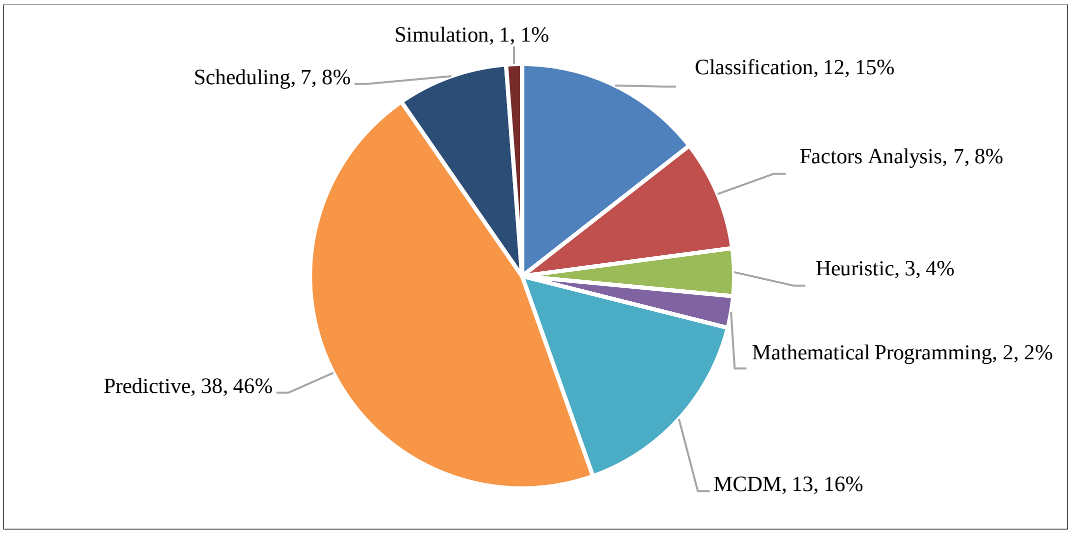
Figure 5. Distribution of publication based on: (a) CMP stage; (b) Field

4.5. Distribution by SC Techniques and Decision Model

Figure 6(a) depicts the distribution of SC techniques, in which Probabilistic Reasoning (PR) is mentioned the least (5 publications or 6%), and fuzzy logic (FL) is discussed the most (29 publications or 35%). According to the decision model's distribution as described in Figure 6(b), the predictive model receives 46% of the attention, while the simulation model receives 1% of the attention.



(a)



(b)

Figure 6. Distribution of publication based on (a) SC techniques. (b) Decision model

5. Discussion about Application based on CPM Stage

5.1. Project Planning

Contractor/Vendor/Staff/Partner Selection

In CPM, selecting a contractor is a routine procedure. This is a crucial task since choosing the wrong contractor might have disastrous results. By using the Kano Fuzzy Model (KFM) and TOPSIS, tactical and strategic criteria for contractor selection can be categorized into three Kano categories: must-be quality, one-dimensional quality, and attractive quality. The weighting of these categories is determined by the developer satisfaction index [29]. To get around the drawbacks of the conventional "lowest bid price" approach, contractor selection models can also be based on the Best-Worst Method (BWM) and the fuzzy-VIKOR technique [30]. It has also been demonstrated that using the Fuzzy Analytic Hierarchy Process (FAHP) model can improve the effectiveness of contractor bidding decisions [31]. Employing ANN, a thorough examination of buildings linked to the expenses and length of construction projects has also been done to select contractors [32].

Selecting vendors is as important as choosing contractors in order to reduce time and risk and encourage effective supply chain management. In projects involving Industrialized Building Systems (IBS), multi-attribute decision-making employing Fuzzy TOPSIS can be used to choose vendors [33]. The results have shown improved decision-making processes that are comparable to existing IBS vendor selection techniques.

Project management leadership factors also have a big impact on how effectively a construction project turns out. What kind of management style in construction organizations will motivate which employees has been studied [34]. This study looks at how a leader's style affects employee productivity using ML. Three distinct algorithms have been used for classification: the ANFIS hybrid algorithm (ANFIS-HB), the ANFIS backpropagation algorithm (ANFIS-BP), and the ANFIS genetic algorithm (ANFIS-GA). Additionally, studies on a number of facets of leader behavior have been conducted [35]. This study has used the Artificial Bee Colony (ABC) algorithm as a feature selection method to forecast the perceptions of leadership among construction workers.

Procurement and Contracts

Procurement operations are frequently a focus of attention during the planning phase. The tasks and obligations of participants in a building project are outlined in the Project Procurement Method (PPM). A framework for knowledge visualization to support construction PPM decision-making has been investigated [36]. Interval-valued intuitive fuzzy sets (IVIFS) in multi-criteria decision making (MCDM) are commonly used to address this issue [37]. Fuzzy set theory has been used in this study to overcome uncertainty. Small and medium-sized firms (SMEs) are able to enhance their competitiveness and increase their chances of winning contracts by utilizing fuzzy logic models [38].

Combining ANN with Time Series (TS) can improve the precision of predicting low bid ratios for three distinct contract categories (mechanical, electrical, and building) before auctions [39]. Machine learning can objectively assess contract complexity [40]. By utilizing ML and the K-Nearest Neighbors (KNN) technique, it is possible to forecast the construction price index using socioeconomic data [41].

Scheduling

Scheduling is a crucial responsibility in developing project management. Studies have shown that Genetic Algorithms (GA) are able to be used to address resource-constrained project scheduling issues [42]. This method has combined the immunity algorithm (IA) and GA [43].

Evolutionary Algorithms have been utilized to develop robust baseline plans that cover a sufficient duration to counteract the negative impacts of uncertainty using actual building project data [44]. The cooperative coevolutionary genetic algorithm has been introduced by Yin et al. (2022) to address the service schedule optimization model for several tower cranes operating in overlapping areas and ensure collision-free outcomes [45]. Genetic Algorithm-based optimization models are beneficial for construction management engineers and contractors to minimize the time and cost of earthmoving activities [46].

The optimization of the distribution and inventory of building materials during the construction stages has been made feasible through the use of automated systems [47]. This study has developed optimal material supply plans by integrating Evolutionary Algorithms with multi-layer perceptron. This automated strategy assists contractors in procuring building supplies at the optimal price while avoiding any overstock or shortage of any particular product. The authors Kaveh & Rajabi (2021) have utilized a fuzzy multi-mode limited resource-time-cost-resource optimization model to address trade-offs between time, cost, and resources in project management [48].

Financing and Budgeting

To help property owners and financial investors make decisions and manage their investments in the erratic construction business, budgeting and financial management are critical. The prediction of building construction expenses has been achieved by the application of Bayesian regularization and a multilayer feed forward ANN model [49]. Survey data from professionals and specialists in the building sector can be analyzed using a fuzzy inference method to evaluate overestimation of costs drivers [50].

It has been proven that a hybrid model that blends ANN and ML methods can correctly forecast pile foundation costs [51]. Using a data analysis technique and cost overrun factors as predictors, it was demonstrated that the k-Nearest Neighbor (k-NN) and ANN models were straightforward, understandable, and accurate enough to anticipate project time and cost overruns [52]. A Fuzzy Cognitive Map (FCM) can be used to perform what-if scenario analysis, predictive, diagnostic, and sensitivity analysis as well as dynamic interactions between elements impacting the costs of prefabricated buildings [53].

Optimization

The requirement to optimize construction management technique-related operations is caused by limited resources, time, and cost constraints. Using symmetric or non-symmetric fuzzy integers, the time-cost trade-off can alternatively be represented as a fuzzy linear programming problem [54]. Mathematical model of fuzzy constrained programming combined with the characteristics of the information cloud structure can be used to complete a comprehensive analysis of production uncertainty and customer demand in public system management in the construction industry [55]. The synergy between Lean Construction (LC) techniques and BIM systems can be effectively defined by combining FAHP and FTOPSIS. Additionally, this combination can be utilized to assess and identify the most critical applications and infrastructure in building projects [56].

Using pseudo resistivity image datasets, it was demonstrated that the Bayesian convolutional neural network (BCNN) could accurately and efficiently classify fake subterranean cavities [57]. It has been demonstrated that the ANN algorithm can estimate time and cost with perfect weight values [58]. It has also been possible to apply AI technology by merging deep learning modeling of construction management systems with 3D reconstruction [59, 60]. Deep learning autoencoders were created as a way to deal with small data sets in construction management by augmenting and creating synthetic data [61]. In the realm of geotechnical engineering, ANN has demonstrated the ability to resolve a number of construction management issues [62].

The material specific energy of three widely used building materials, including fly ash, copper slag, and phospho-gypsum, has been demonstrated to be calculable using the Particle Swarm Optimization (PSO) model [63]. The analysis of many conceptual possibilities for low-CO_2, low-cost, and safe construction management is done using the Non-dominated Sorted Genetic Algorithm II (NSGA-II) [64]. Based on a quantum genetic algorithm, a multi limit and multitarget construction optimization model with the lowest period and cost is developed [65]. It has been demonstrated that genetic algorithms, particle swarm optimization, and differential evolution techniques work well for solving the time-cost trade-off problem [66].

Project Control and Monitoring

Construction project management also requires control and monitoring plans. The success elements of building projects can be ranked using Fuzzy TOPSIS [67]. Fuzzy logic can be used to evaluate significant aspects influencing the construction price index in an unpredictable setting [68].

Modular building objects can be detected using single shot multi-box detectors (SSD) and region-based convolutional neural networks (faster RCNNs) [69]. Data mining methods are also used to examine the link between faults, quality levels, number of contracts, project categories, and progress in inspection projects. These algorithms include Neural Network (NN), Support Vector Machine (SVM), and decision tree (C5.0 and QUEST) algorithms [70].

Risk Management

Combat risk management is crucial for preventing hazards in building projects. The identification and study of potential risk sources in engineering, geology, equipment, management, and accidents can be done with fuzzy logic. The system takes into account the impact of several aspects, including the experience and skill of the decision maker [71]. It has been demonstrated that a system constructed using the fuzzy normal distribution and linear weighted combination method can assist decision-makers in risk management and help stakeholders manage hydroelectric project risks thoroughly, cooperatively, and effectively [72]. Time buffers for concrete gravity dams and hydropower projects can also be precisely calculated using fuzzy logic [73]. Criticality in project networks with activity length is measured using fuzzy set theory [74]. Additionally, risk variables that could impair the performance of Built Operated Transferred (BOT) toll projects in India can be identified and evaluated using fuzzy probabilistic models [75].

For evaluating the danger associated with deep-buried tunnels, Bayesian networks constructed using expert knowledge and historical data can also be employed [76]. Project managers can take proactive steps to maintain their projects on time by using probabilistic reliability analysis in conjunction with BIM to estimate the risk of schedule delays [77]. It has been determined that multistate Dynamic Bayesian Network (DBN) evaluation is capable of precisely controlling the danger of tunnel collapse [78]. Based on normal cloud theory and Bayesian Networks (BN), it is also possible to evaluate the failure probability of tunnel collapse [79].

Key risk indicators and construction quality can be predicted using AHP and ANN models [80]. Dam building project delays and their severity can also be predicted using Multilayer Perceptron Neural Network (MLP-NN) models [81]. In order to forecast project risk management suggestions, a decision support system based on an ontology has been developed [82]. This framework models integrated Project Risk Management (PRM) knowledge by utilizing the capabilities of semantic ontologies. Natural Language Processing (NLP) techniques are employed in the enrichment process. Ontology and Case-Based Reasoning (CBR) techniques can be used to assess the safety concerns associated with subway construction [83]. Swiss Cheese Model (SCM) combined with hybrid machine learning has been used to identify construction flaws [84]. In this case, hybrid machine learning uses a combination of Bayesian networks and association rule mining to find correlations between defect likelihood and defect occurrence. Using a Computer Vision (CV) based non-contact technique, K-Means and modified k-NN fusion machine learning models can be utilized to directly identify indicators of falls [85].

5.2. Project Execution

Optimization

Optimization is frequently done during the execution phase to provide outcomes that are both efficient and successful. It has been demonstrated that fuzzy AHP can be utilized to identify the root cause of ineffective pavement drainage systems that quickly deteriorate roads [86]. For hydraulic structure engineering projects, the Particle-Swarm Optimization (PSO) technique and a fuzzy multi-mode approach are suggested as models [87].

The mapping function between the diaphragm wall's duration and its influencing elements has been generalized in terms of foundation construction through the use of the Firefly Algorithm (FA) and Least Squares Support Vector Machine (LS-SVM) [88]. Recurrent Neural Networks (RNNs) have been used in the development of a machine learning model to forecast time series of labor resource utilization levels at the work package level [89]. This study makes it easier to prioritize and allocate resources, which enhances the performance of the project as a whole.

Project Control and Monitoring

Team performance is also significantly impacted by member behavior. In order to enhance cooperative work in project teams, fuzzy logic can be utilized to evaluate significant behavioral indices [90]. It has been demonstrated that fuzzy fault tree analysis can be utilized to determine the variables affecting the productivity of construction workers [91]. It has been shown how deep learning models contribute to automation. In order to evaluate the effects of implementing automation in construction, deep learning models were also applied to track the placement of reinforcement by validating finished reinforcement ties [92].

Safety Management

The primary objective of safety management is to ensure and safeguard employees' health and safety by preventing occupational illnesses and accidents. Applying multi-layer fuzzy logic to rules including of building and weather conditions, worker data from IoT devices, and other construction-related environmental aspects can infer worker safety indices [93].

In construction work, four types of injuries can be predicted by applying ML models: upper limbs, lower limbs, head/neck, and back/trunk [94]. It has been demonstrated that the Partial Least Square–Back Propagation Neural Network (PLS-BPNN) used in the creation of smart helmets for construction work is capable of correcting the temperature measurement findings of smart helmets [95]. For object detection and building feature extraction, ANNs and a combination of text and picture feature extraction techniques can be applied [96]. The Term Frequency-Inverse Document Frequency (TF-IDF) or Latent Dirichlet Allocation (LDA) method can be given priority if the building sample is a document. Convolutional Neural Networks (CNN) provides the optimum processing effect when the construction samples are images.

5.3. Project Evaluation

Project Control and Monitoring

The process of monitoring and controlling can include regular project evaluations. The construction productivity of building projects is investigated using a Bayesian network model under the influence of possible factors [97]. From the standpoint of developing nations, an assessment of the elements that support stakeholder management's performance throughout the project planning phase is required [3]. To accomplish this, several methods such as fuzzy synthetic assessment techniques, factor analysis, and mean scoring are employed.

Data mining techniques such as association rules, K-Means, and fuzzy logic can be employed to explore the correlation between different types of faults and the level of quality inspection in public construction projects [98]. The Analytic Network Process-Fuzzy Comprehensive Evaluation (ANP-FCE) model can be used to assess the Lean Construction Management Performance (LCMP) of engineering projects [99]. Change Order Management (COM) implementation performance in the construction industry can be assessed quantitatively using the Adaptive Neurofuzzy Inference System (ANFIS) [100]. Project systems can be analyzed using ANFIS from the standpoint of modeling variables and dynamic behavior [101].

To give more accurate labor productivity projections using historical data, ANN-based prediction intervals (PIs) were also applied [102]. Deep learning approaches have demonstrated the ability to effectively automate the monitoring of feeder construction automation at electric power substations [103]. It has been demonstrated that construction project work sites can be monitored through the use of deep learning and single shot detection in image recognition [104]. To enhance the administration and oversight of substation construction through remote monitoring, deep learning is also employed for classification [105]. The relationship between three target variables (engineering level, project cost, and construction progress) and defects has been demonstrated to be predictable by ML algorithms like Support Vector Machines (SVM), ANN, Decision Trees (DT), and Bayesian Networks (BN) [106].

Sustainable Performance Assessment

Over the past few decades, building manufacturing has had serious environmental impacts, despite its role in national economic growth. Therefore, in developing strategic plans for economic growth, the government considers the implementation of environmentally friendly building and manufacturing technologies as a key factor towards a greener economy and lower carbon emissions. Guidelines for selecting and promoting optimal practices in environmentally friendly building manufacturing have been carried out using the fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) in Malaysia [107]. The integration of BIM with a decision-making and problem-solving approach using Fuzzy TOPSIS is used to efficiently optimize the selection of sustainable building components at the conceptual design stage of building projects [108]. A decision support model to assist managers in understanding the concept of sustainability in selecting construction projects and choosing the best project was developed using the MCDM approach. This model is integrated with Fuzzy Preference Programming (FPP) as a modification of the Fuzzy Analytical Hierarchy Process (FAHP), with the Fuzzy Inference System (FIS) as a fuzzy rule-based expert system [109]. Multi-Criteria Decision-Maker based on time and cost saving factors correlated with ANN methods can be used to evaluate sustainable hybrid materials [107, 110]. During the conceptual design stage of building projects, the selection of sustainable building components is effectively optimized by the integration of BIM with a decision-making and problem-solving method employing Fuzzy TOPSIS [108]. Using the MCDM approach, a decision support model was created to help managers comprehend the concept of sustainability while selecting construction projects and picking the best project. This model is combined with the Fuzzy Inference System (FIS), a fuzzy rule-based expert system, and Fuzzy Preference Programming (FPP), a variant of the Fuzzy Analytical Hierarchy Process (FAHP) [109]. Sustainable hybrid materials can be assessed using the MCDM, which is based on time and cost-saving variables associated with artificial neural network techniques [110].

6. Discussion about Application based on Soft Computing Components

Studies have demonstrated how these SC methods improve CPM decision-making. Managing uncertainty, recognizing patterns and prediction, optimization, multivariate analysis, adaptation and learning, and dynamic decision-making are a few techniques that can be used. Construction project managers can reduce risk and enhance project performance by employing these SC strategies to make better decisions that are more accurate, efficient, and of high quality.

The 83 articles reviewed for this paper are shown in Table 3 in which Fuzzy Logic is the SC technique that is used the most frequently. In contrast, the hybrid system is the component that is utilized the least.

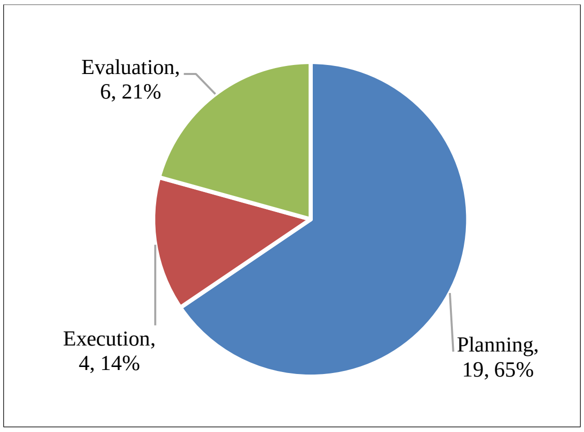
Table 3. Publication list

Components	Stages	Field	Model		Authors	Year
FL	Evaluation	Project Control & Monitoring	Classification	1	Lin & Fan [80]	2018
FL	Evaluation	Project Control & Monitoring	Factors Analysis	2	Oppong et al. [3]	2021
FL	Evaluation	Project Control & Monitoring	Predictive	3	Li et al. [98]	2020
FL	Evaluation	Sustainable Performance Assessment	MCDM	4	Fallahpour et al. [109]	2020
FL	Evaluation	Sustainable Performance Assessment	MCDM	5	Fazeli et al. [108]	2022
FL	Evaluation	Sustainable Performance Assessment	MCDM	6	Yadegaridehkordi et al. [107]	2020
FL	Execution	Optimization	MCDM	7	Alaneme et al. [86]	2021
FL	Execution	Project Control & Monitoring	Factors Analysis	8	Shoar & Banaitis A [91]	2018
FL	Execution	Project Control & Monitoring	Predictive	9	Ellis et al. [90]	2023
FL	Execution	Safety Management	Predictive	10	Xu et al. [93]	2023
FL	Planning	Contractor Selection	MCDM	11	Cai et al. [29]	2023
FL	Planning	Contractor Selection	MCDM	12	Leśniak et al. [31]	2018
FL	Planning	Contractor Selection	MCDM	13	Vardin et al. [30]	2021
FL	Planning	Financing and Budgeting	Factors Analysis	14	Luo et al. [53]	2022
FL	Planning	Financing and Budgeting	Factors Analysis	15	Obianyo et al. [50]	2022
FL	Planning	Optimization	Mathematical Programming	16	Gong et al. [55]	2022
FL	Planning	Optimization	MCDM	17	Moballeghi et al. [56]	2023
FL	Planning	Optimization	Predictive	18	Elkalla et al. [54]	2021
FL	Planning	Partner/staff Selection	Classification	19	Keles et al. [35]	2023
FL	Planning	Procurement and Contracts	MCDM	20	Zhao et al.[36]	2022
FL	Planning	Procurement and Contracts	Predictive	21	Khouja et al. [38]	2023
FL	Planning	Project Control & Monitoring	Factors Analysis	22	Nguyen et al. [68]	2021
FL	Planning	Project Control & Monitoring	Predictive	23	Maghsoodi & Khalilzadeh [67]	2018
FL	Planning	Risk Management	Classification	24	Zhang et al. [71]	2022
FL	Planning	Risk Management	Heuristic	25	Li et al. [72]	2023
FL	Planning	Risk Management	Predictive	26	Ammar M.A.; Abd-ElKhalek S.I. [74]	2022
FL	Planning	Risk Management	Predictive	27	Balta et al. [73]	2018
FL	Planning	Scheduling	Scheduling	28	Kaveh & Rajabi [48]	2022
FL	Planning	Vendor Selection	MCDM	29	Omar et al. [33]	2018
ANN	Evaluation	Project Control & Monitoring	Classification	30	Oliveira et al. [103]	2023
ANN	Evaluation	Project Control & Monitoring	Predictive	31	Nasirzadeh et al. [102]	2020
ANN	Evaluation	Sustainable Performance Assessment	MCDM	32	Albasri & Naimi [110]	2023
ANN	Execution	Safety Management	Predictive	33	Li et al. [95]	2021
ANN	Execution	Safety Management	Predictive	34	Zhao [96]	2022
ANN	Planning	Contractor Selection	MCDM	35	Ujong et al. [32]	2022
ANN	Planning	Financing and Budgeting	Predictive	36	Arabiat et al. [52]	2023
ANN	Planning	Financing and Budgeting	Predictive	37	Chandanshive & Kambekar [49]	2019
ANN	Planning	Optimization	Classification	38	Xia et al. [57]	2023
ANN	Planning	Optimization	Predictive	39	Challa & Rao [58]	2022
ANN	Planning	Procurement and Contracts	Predictive	40	Almohsen et al. [39]	2023

ANN	Planning	Risk Management	Predictive	41	Lin et al. [80]	2022
ANN	Planning	Risk Management	Predictive	42	Shirazi & Toosi [81]	2023
EC	Planning	Optimization	Heuristic	43	Kanyilmaz et al. [64]	2022
EC	Planning	Optimization	Mathematical Programming	44	He and Shi [65]	2019
EC	Planning	Optimization	Predictive	45	Chassiakos & Rempis [66]	2019
EC	Planning	Optimization	Predictive	46	Ronghui & Liangrong [63]	2022
EC	Planning	Partner/staff Selection	Classification	47	Kaya Keles et al. [35]	2021
EC	Planning	Scheduling	Scheduling	48	Asadujjaman et al. [43]	2022
EC	Planning	Scheduling	Scheduling	49	Liu et al. [42]	2020
EC	Planning	Scheduling	Scheduling	50	Milat et al. [44]	2022
EC	Planning	Scheduling	Scheduling	51	Shehadeh et al. [46]	2022
EC	Planning	Scheduling	Scheduling	52	Yin et al. [45]	2022
PR	Evaluation	Project Control & Monitoring	Classification	53	Khanh et al. [97]	2023
PR	Planning	Risk Management	Heuristic	54	Wang et al. [76]	2020
PR	Planning	Risk Management	Predictive	55	Meng et al. [79]	2022
PR	Planning	Risk Management	Predictive	56	Ou et al. [78]	2022
PR	Planning	Risk Management	Predictive	57	Zhang & Wang [77]	2023
ML	Evaluation	Project Control & Monitoring	Classification	58	Fan [70]	2022
ML	Evaluation	Project Control & Monitoring	Classification	59	Lung et al. [104]	2023
ML	Evaluation	Project Control & Monitoring	Classification	60	Oliveira et al. [105]	2021
ML	Execution	Optimization	Predictive	61	Cheng & Hoang [88]	2018
ML	Execution	Optimization	Predictive	62	Golabchi & Hammad [89]	2023
ML	Execution	Project Control & Monitoring	Predictive	63	Watfa et al. [92]	2022
ML	Execution	Safety Management	Predictive	64	Alkaissy et al. [94]	2023
ML	Planning	Financing and Budgeting	Predictive	65	Deepa et al. [51]	2023
ML	Planning	Optimization	Predictive	66	Davila Delgado & Oyedele [61]	2021
ML	Planning	Optimization	Predictive	67	Wang and Hu [59]	2022
ML	Planning	Optimization	Simulation	68	Pour Rahimian et al. [60]	2020
ML	Planning	Procurement and Contracts	Predictive	69	Nguyen [41]	2021
ML	Planning	Procurement and Contracts	Predictive	70	Zhang et al. [40]	2023
ML	Planning	Project Control & Monitoring	Factors Analysis	71	Fan [70]	2022
ML	Planning	Project Control & Monitoring	Predictive	72	Liu et al. [69]	2022
ML	Planning	Risk Management	Classification	73	Fan [84]	2020
ML	Planning	Risk Management	Classification	74	Liu et al. [85]	2023
ML	Planning	Risk Management	Predictive	75	Jiang et al. [83]	2020
ML	Planning	Risk Management	Predictive	76	Zaouga & Rabai [82]	2021
Hybrid: ANFIS	Evaluation	Project Control & Monitoring	Predictive	77	Naji et al. [100]	2022
Hybrid: FL & PR	Planning	Procurement and Contracts	MCDM	78	Su and Li [37]	2021
Hybrid: FL & PR	Planning	Risk Management	Factors Analysis	79	Patel et al. [75]	2020
Hybrid: FL & PSO	Execution	Optimization	Predictive	80	Meye et al. [87]	2022
Hybrid: GA & ANN	Planning	Optimization	Predictive	81	Uncuoglu et al. [62]	2022
Hybrid: GA & ANN	Planning	Scheduling	Scheduling	82	Golkhoo & Moselhi [47]	2019
Hybrid: Neuro Fuzzy	Evaluation	Project Control & Monitoring	Predictive	83	Faraji [101]	2021

6.1. Fuzzy Logic

FL is most frequently used during the planning phase, particularly for project control and monitoring. This is consistent with studies conducted in the field of project planning and control by Kucha et al. (2021) who found that FL can be used to handle uncertainty problems [12]. When considering decision models, MCDM is the model that has been studied the most. According to research by Chen & Pan (2021), Fuzzy Multicriteria Decision Making (FCDM) is becoming more and more well-liked as a successful method for resolving complicated and ambiguous issues Review fuzzy multi-criteria decision-making [13]. Figure 7 presents the distribution of articles on FL components.



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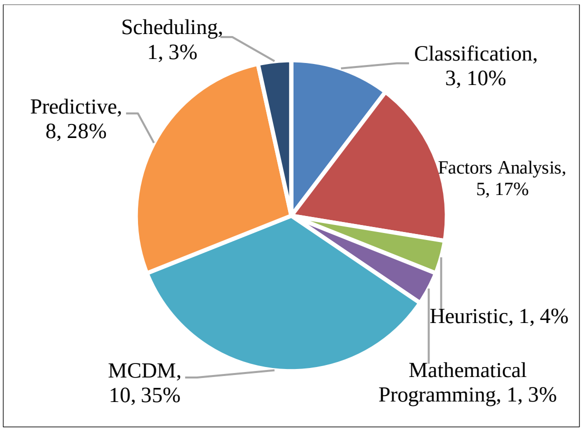

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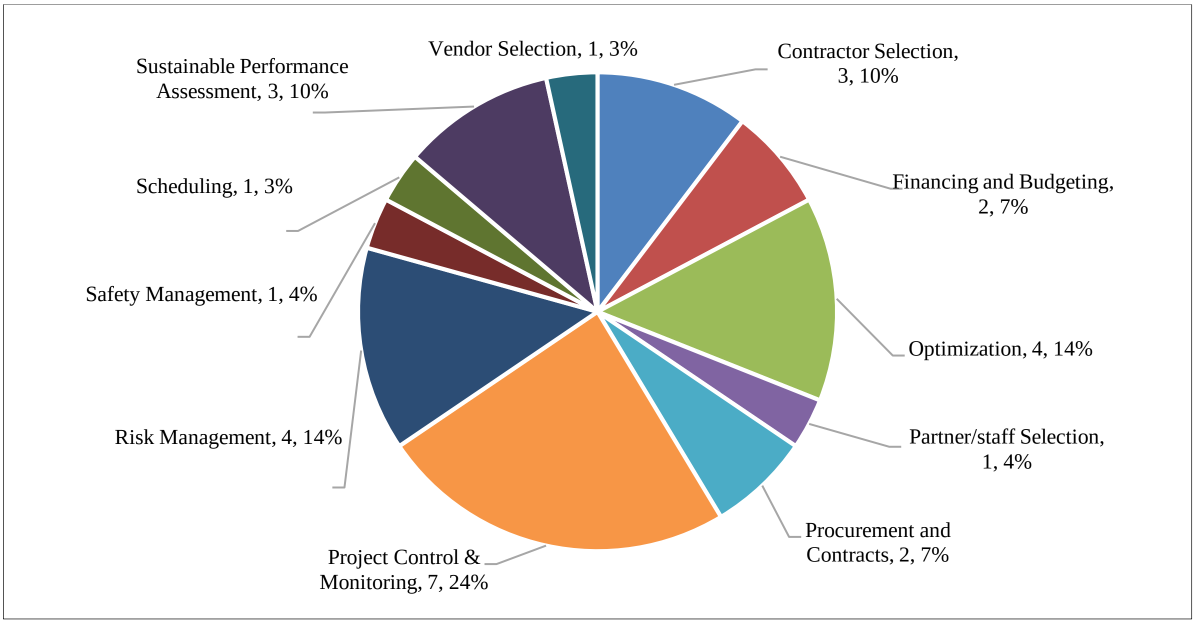
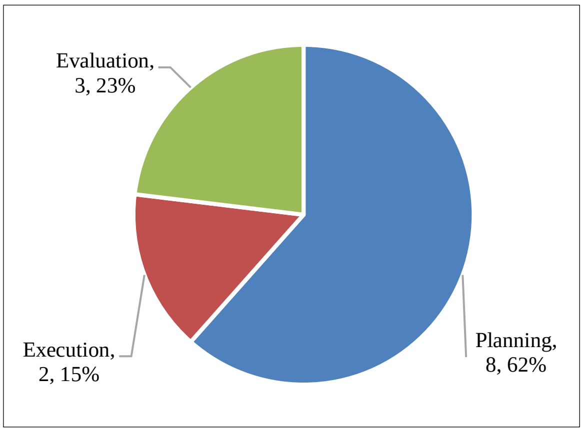


(c)

Figure 7. Distribution of articles on FL components based on: (a) stage; (b) decision model; and (c) fields

6.2. Artificial Neural Network

ANN is most frequently used during the planning phase, particularly for budgeting and funding. ANN offer improvements over traditional methods in the prediction of building project costs [16]. The predictive model is the most studied model when looking at decision models. According to Marzouk et al. (2024), ANN has been widely employed in the field of construction engineering to address complicated challenges. Figure 8 describes the distribution of articles on ANN components [15].



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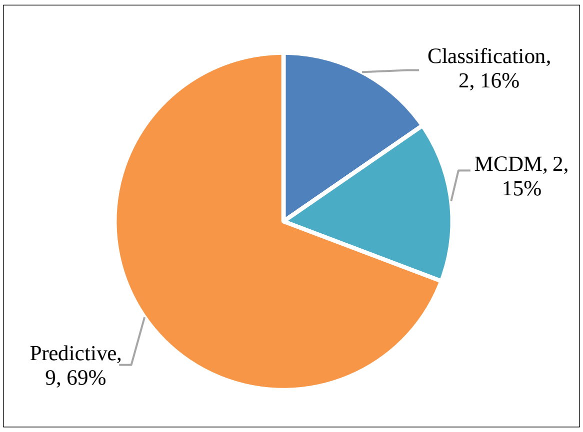

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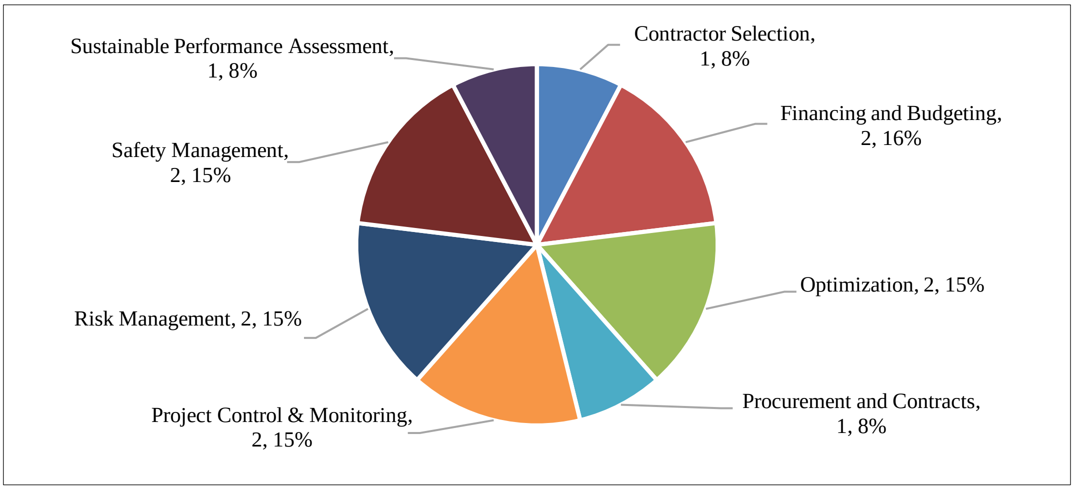

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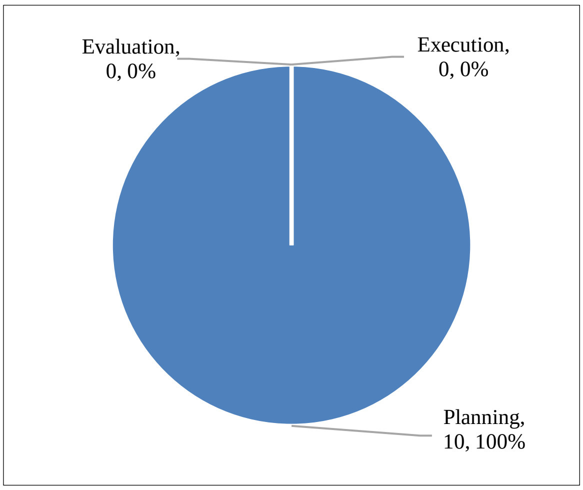
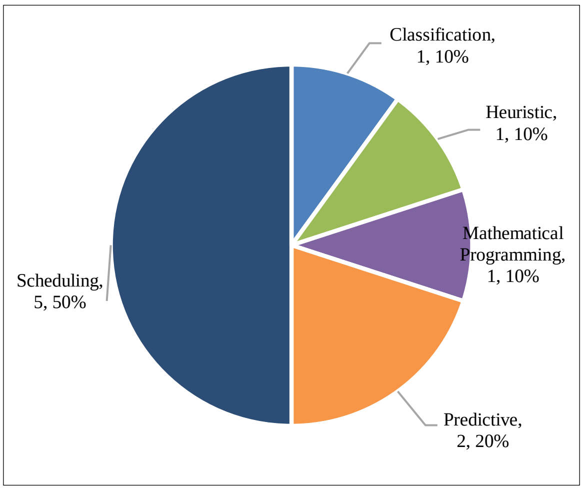
Figure 8. Distribution of articles on the ANN components based on: (a) stage; (b) decision model; and (c) fields

6.3. Evolutionary Computation

The planning stage of the study occurred when all of the Evolutionary Computation (EC) applications were implemented. The most frequently brought up subject is scheduling. This is in line with research done by Liu et al. (2023) [17], and Bakshi et al. (2012) [18] who claimed that the development of evolutionary computing techniques is frequently used for scheduling optimization. Figure 9 illustrates the distribution of EC components.



(a)



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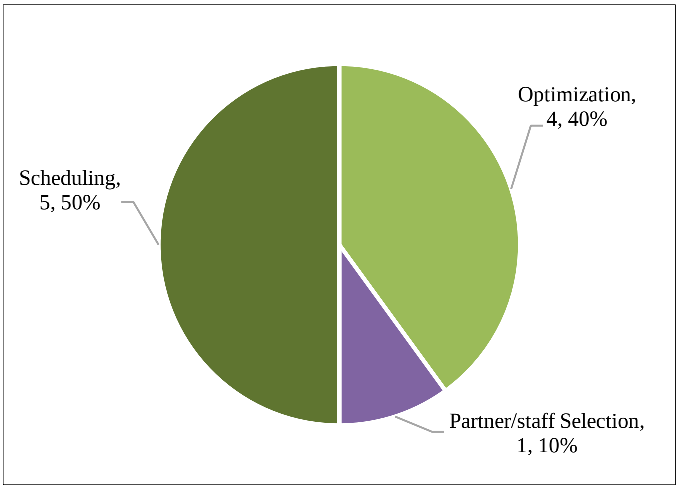


(c)

Figure 9. Distribution of articles on EC components based on: (a) stage; (b) decision model; and (c) fields

6.4. Probabilistic Reasoning

Especially in risk management, Probabilistic Reasoning (PR) is most frequently used for prediction during the planning phase. This is consistent with study by Khodabakhshian et al. (2023), who reported that a common method for evaluating construction risk is probabilistic reasoning [19]. Figure 10 illustrates the distribution of articles on PR components.

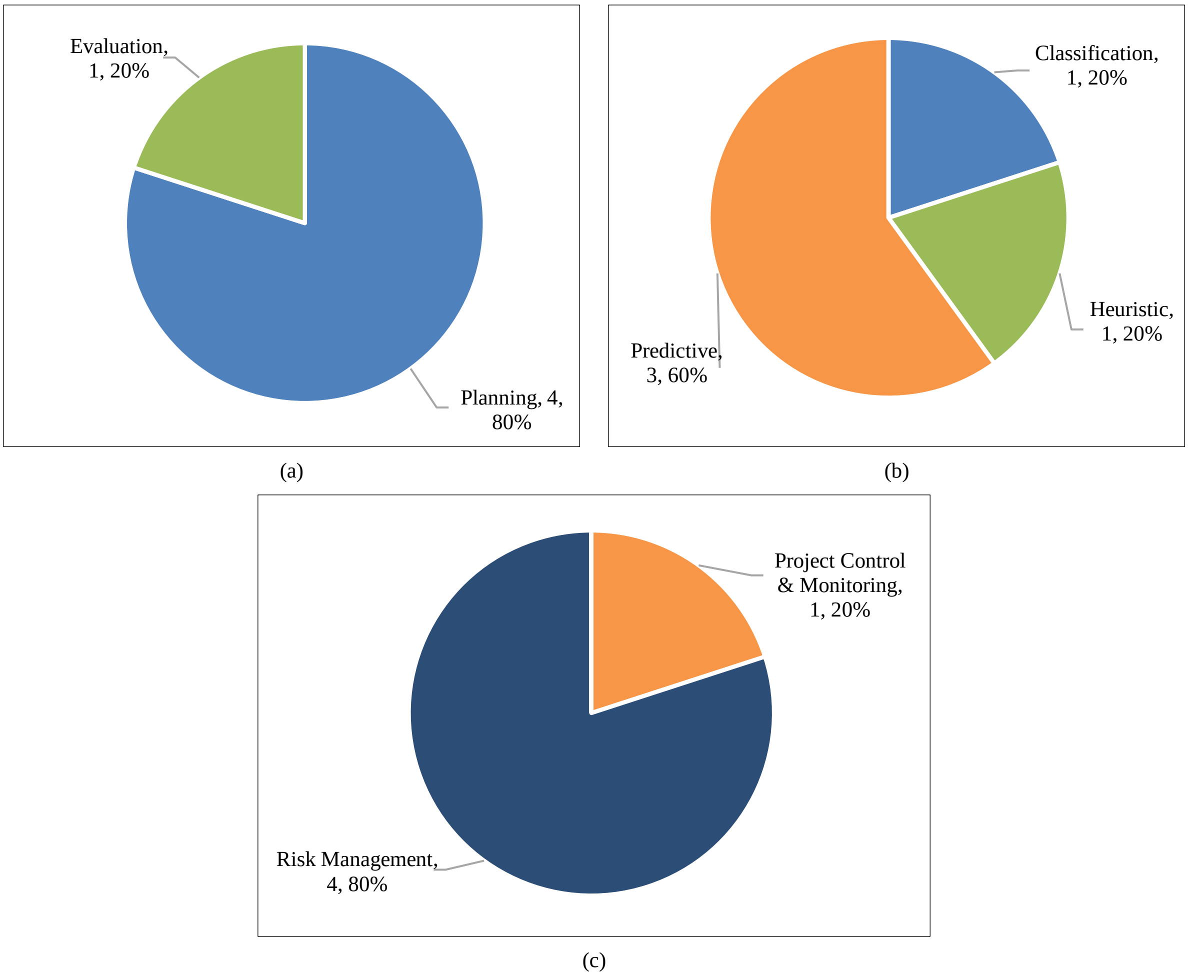
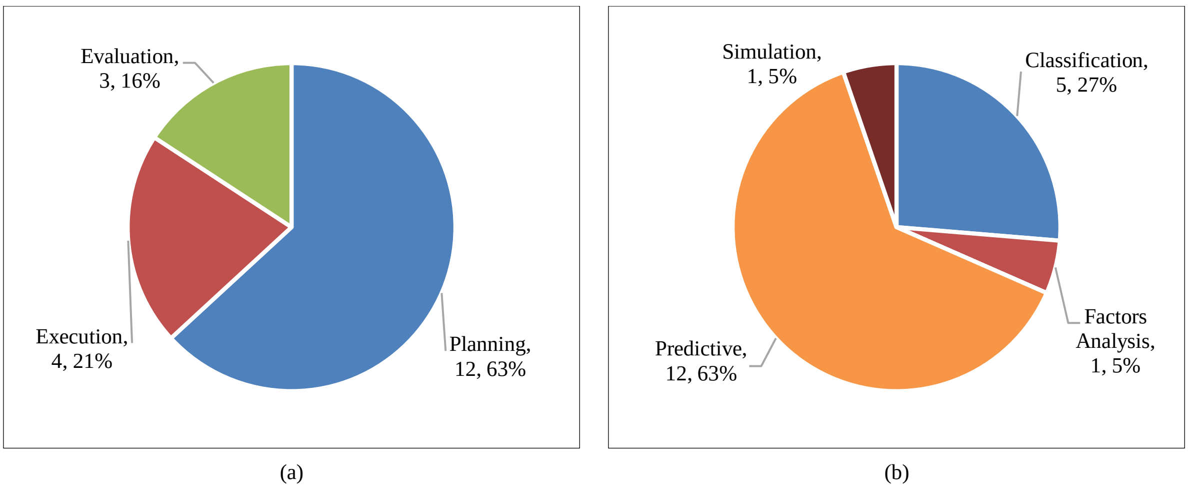
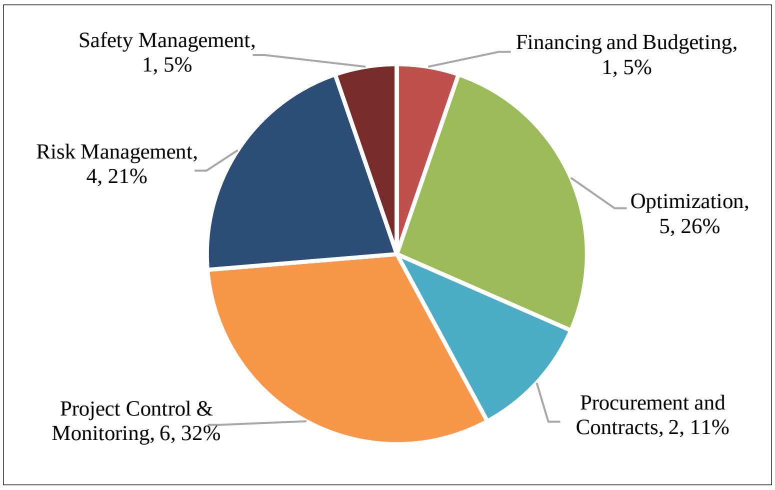


Figure 10. Distribution of articles on the PR components based on: (a) stage; (b) decision model; and (c) field

6.5. Machine Learning

In project control and monitoring in particular, Machine Learning (ML) is most frequently used during the planning phase. This is consistent with studies from Dikmen et al. (2009), who claim that ML models make it possible to analyze time and cost estimations while tracking the status of a project [22]. From the standpoint of decision models, the most popular model is the predictive model. Research by Abdulfattah et al. (2023) and Lin et al. (2023) is supported by this [20, 21]. Figure 11 depicts distribution of articles on ML components.



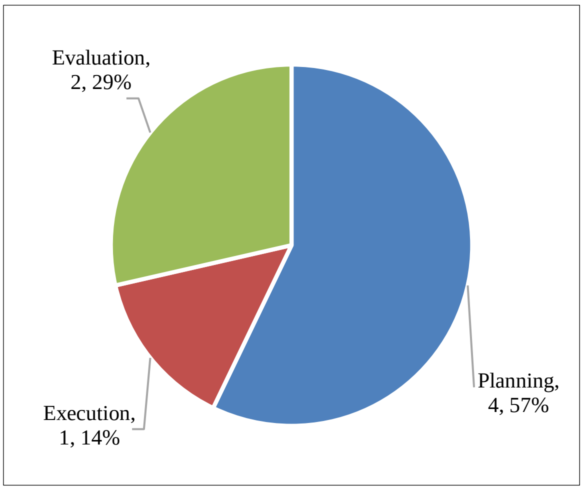


(c)

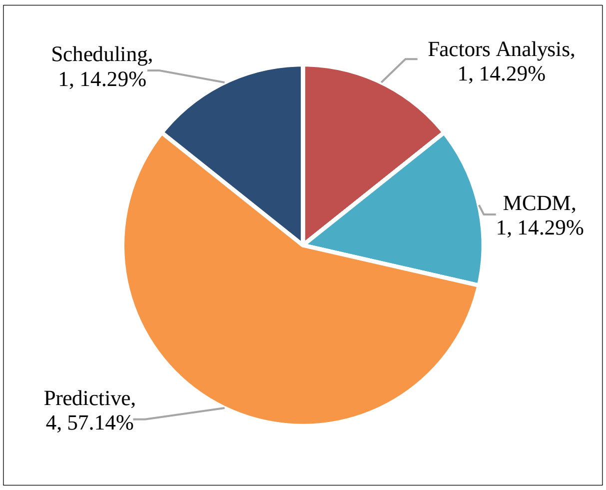
Figure 11. Distribution of articles in ML components based on: (a) stage; (b) decision model; and (c) fields

6.6. Hybrid System

The most common use of Hybrid Systems (HS) is during the planning phase, particularly for project control, monitoring, and optimization. The model that uses HS the most frequently is the predictive model. Research by Nguyen et al (2022) and Tiruneh et al. (2020) indicates that ML has been used to manage uncertainty, particularly for prediction and control [23, 24]. Figure 12 shows distribution of articles on the HS components



(a)



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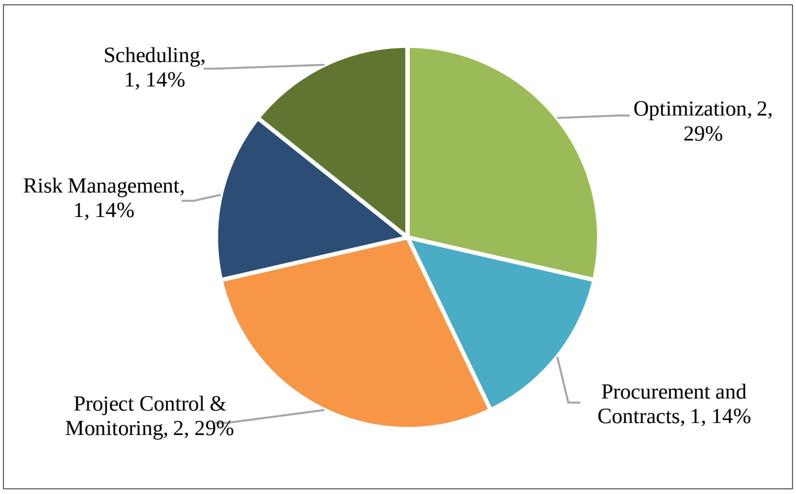

(c)

Figure 12. Distribution of articles in Hybrid Systems components based on: (a) stage; (b) decision model; and (c) fields

7. Challenges and Future Research Directions

7.1. Challenges and Knowledge Gaps in CPM

This research identifies a number of common issues and knowledge gaps in the implementation of SC in CPM, based on the statistical analysis in Section 4 and the discussion in Section 5. First, the beginning and closing phases of CPM are not covered in any articles. Despite the possibility of uncertainty in the issues at these two levels. For instance, we may use SC to forecast potential hazards early on in a project to mitigate them. As the project comes to an end, SC can be used to assist in creating a knowledge management system based on information gathered during project execution.

Second, only 8% of systems are now implemented in a hybrid fashion. The same is true for the use of ML (23%). In the meantime, the predictive model (46%) is the most frequently discussed choice model. In reality, a growing number of disciplines have started to adopt hybrid methods to solve predictive challenges in the past five years. One may argue that there is still a disconnect between the application of hybrid systems in other industries and the CPM field. On the other hand, some combinations of SC components exist, such as FL & ANN, FL & EC, FL & PR, and ANN & EC. Meanwhile, ML has made room for the merging of PR and ANN.

Third, the ML approach at the planning stage yielded only one simulation model. In actuality, CPM makes extensive use of simulation models. It is also extremely possible to use SC to uncertainty-containing simulation models. The current state of computer vision technology and its rapid evolution offer the possibility to visualize this simulation and generate easily comprehensible output for people. Examples include utilizing simulation and visualization techniques for tasks such as architectural design, scheduling, budgeting, and facility planning.

Fourth, it is imperative to establish a seamless interaction between the Decision Support System (DSS) and the pre-existing systems, such as Building Information Modeling (BIM). Reducing data redundancy is crucial as it directly contributes to increasing uncertainty. This integration is crucial for maximizing the utilization of data in the process of decision making.

Fifth, MCDM is widely recognized as the predominant approach for resolving selection dilemmas. Regrettably, the research undertaken in this literature review did not include a substantial number of decision-makers. Implementing a significant construction project typically involves multiple stakeholders who make key decisions. Hence, the model of the group decision support system poses a significant problem.

Sixth, employing simulation models and integrating BIM and DSS with SC present a number of unique issues, including: 1) Because BIM produces vast volumes of data, it must be extracted, cleaned up, and validated before being seamlessly integrated into the simulation model; 2) The system must be accurately represented in simulation models, hence care must be taken to make sure the model accurately depicts real-world circumstances; 3) Scalability emerges as a crucial factor to take into account as project size grows; 4) Insufficient access to highly qualified personnel and in-depth understanding of many disciplines, such as artificial intelligence, civil engineering, and information technology; 5) It's necessary to provide platform interoperability in order to facilitate data transfer without losing crucial information; 6) It is essential to guarantee that the information accessed, saved, and transferred amongst systems is safe and shielded from online dangers; 7) It is important to confirm that the results produced by simulation models utilizing this method satisfy the dependability and precision requirements necessary for sensible decision-making; 8) Because there is a lack of expertise, the staff members in charge of the creation and management of this system need to receive sufficient training.

7.2. Future and Studies

SC has generally been used during the CPM phase. There are still a number of challenges and future studies ahead, as presented in Table 4.

Table 4. The research challenges and future studies

Issue	Research challenges	Future studies
CPM stages	Application of SC at the initiation and closing stages	Big data analysis using machine learning
		Development of a knowledge management system (KMS) model
SC components	More varied implementation of the hybrid system	Development of a hybrid system that supports business intelligence
Decision models	Application of simulation models in various fields of study	Application of vision systems and IoT technology
Integration	BIM and DSS integration	BIM and DSS integration
Decision-maker	Group decision-makers	Development of a group decision support system model

Integration between BIM and DSS is an area that needs more research and development. This has been initiated by a number of investigations, including those conducted by Moballeghi et al. (2023) [56], Abdulfattah et al. (2023) [21], and Fazeli et al. (2022) [108]. For the BIM data to be used as knowledge in the DSS as effectively as possible, this integration is crucial. As a result, the DSS being produced will always have current information.

Future research will also examine the role of multiple decision makers in the resolution of a problem. In MCDM, this model is particularly prevalent. The majority of research has not taken into account the existence of a group decision support system, even though MCDM weights have been objectively calculated by a pairwise comparison matrix, as in the studies of Ujong et al. (2022) [32], Lin et al. (2022) [80], Alaneme et al. (2021) [86], and Fallahpour et al. (2020) [109]. In order to get decision makers to agree, another option is to employ fuzzy preference relations.

Future research should focus on strategically developing Knowledge Management Systems (KMS) to facilitate the transfer of knowledge among internal stakeholders inside a corporation. The time efficiency of the decision-making process will be enhanced by utilizing this Knowledge Management System (KMS) to facilitate the completion of tasks assigned to staff, especially new hires. Consequently, the organization will be able to reduce the time spent on training.

Construction projects necessitate the development of a Business Intelligence (BI) system to enable higher management to easily assess the status of the organization. Therefore, it is necessary to conduct studies on business intelligence (BI) models that provide help for managing uncertainty. A reliable learning machine is necessary to enhance the optimization of information and decision support provided to managers. A thorough research into the novel hybrid system paradigm is necessary.

Conducting research on the use of big data, machine learning (ML), and the Internet of Things (IoT) in the field of project management is imperative, alongside the progress made in these three technologies. In their study, Xu et al. (2023) utilized fuzzy logic to deduce a worker safety index by employing rules composed of construction ambient data linked to IoT sensors [93]. The study conducted by Li et al. (2021) involved the utilization of Partial Least Square–Back Propagation Neural Network (PLS-BPNN) to develop an intelligent helmet. Further research should be conducted to enhance worker safety management [95].

Research can be conducted on vision system technologies to monitor construction progress in real-time. Construction operations can be recognized utilizing SC to assess progress and detect any potential delays. Building sites can employ automated personnel identification and monitoring systems to ensure strict compliance with safety procedures. Images and videos can be analyzed to ensure compliance with building quality standards. Researchers are studying virtual simulations of building projects to aid project teams and stakeholders in experiencing and understanding the ultimate appearance of the project. Through the utilization of virtual reality simulations, construction workers can enhance their preparedness and proficiency in dealing with a broader spectrum of emergencies and scenarios.

The CPM field's implementation of SC approaches looks to have an upward trend due to their tight integration with new technologies like big data analysis and the IoT. We can use SC techniques like ANN and FL to create accurate predictive models for various aspects of CPM. This involves risk assessment, project completion schedules, and cost projections. Data integration from the IoT can strengthen this model by providing access to real-time information about projects and environmental conditions. Construction planning, including resource allocation, task scheduling, and material supply routes, can be optimized using SC. Optimization algorithms can yield more effective and flexible solutions by utilizing big data, including data from previous projects and IoT data pertaining to field situations. By analyzing complicated environmental conditions and historical data, SC can assist in identifying and mitigating hazards associated with construction projects. ANN techniques can identify patterns that are hard for conventional techniques to interpret, and FL helps handle uncertainty in risk modeling. Real-time data collection from sensors put on building sites is made possible by IoT integration. SC is able to quickly estimate the requirement for maintenance or repairs by analyzing this data. Through the integration of IoT and big data analytics data with SC methodologies, construction management systems can enhance their adaptability and responsiveness to dynamic project requirements, shifting environmental conditions, and developing issues. Decision-making can be done more quickly and intelligently as a result.

8. Conclusions

Uncertainties arising from difficulties in the CPM field are unavoidable. Soft Computing (SC) refers to a collection of methods specifically developed to tackle uncertainties. This study has collected a total of 83 publications pertaining to CPM that were scrutinized using the Systematic Literature Review (SLR) approach and published throughout the timeframe of 2018 to 2023. Several inferences can be made from the analysis of relevant literature, as outlined below:

- The number of publications about the utilization of SC in the domain of CPM has had a substantial annual growth, particularly in the year 2022. The majority of the selected works were published in journals that focus on construction management/engineering, civil engineering, or construction. Soft computing-related journals have a restriction of only allowing one publication.
- Every year, the planning phase becomes the focal point of the discussion. FL, with a 35% demand rate, is the most sought-after SC procedure. ANN and ML are always advancing approaches. This is made feasible by the progress in data mining, Internet of Things (IoT), and big data technology. Project control and monitoring is the most widely studied field, accounting for 22% of articles. The predictive model is the decision model that is most commonly mentioned, accounting for 46% of the discussions.

- The most prevalent stages in the FL technique are articles regarding the planning stage, the project control and monitoring study area, and the MCDM model, at 65%, 24%, and 35%, respectively.
- The most common stages in the ANN technique are 62%, 16%, and 69% of papers, respectively, concerning the planning stage, financing and budgeting study areas, and prediction models.
- The most widespread stages in the EC technique are articles regarding the planning stage, the field of scheduling research, and the scheduling model, at 100%, 50%, and 50%, respectively.
- The most common stages in the PR technique are articles about the planning stage, study areas for risk management, and predictive models, at 80%, 80%, and 60%, respectively.
- The most dominant stages in the ML technique are the planning stage (63%), project control and monitoring study areas (62%), and predictive models (63%).
- The stages with the highest percentages of articles in the hybrid component were those concerning the planning stage, project control & monitoring, optimization research areas, and predictive models, at 57%, 29%, and 57%, respectively.

The adoption of SC in the field of construction management has been found to encounter several challenges. These include difficulties in using simulation models, integrating Building Information Modeling (BIM) and Decision Support Systems (DSS), forming DSS groups, and implementing SC at the beginning and concluding stages. This provides recommendations for additional investigation, such as developing a framework for a collective decision support system, implementing an Internet of Things (IoT) enabled visual system, and establishing a knowledge management system

9. Declarations

9.1. Author Contributions

Conceptualization, S.W. and S.K.; methodology, S.W. and S.K.; software, S.K.; validation, S.K. and Y.Y.; formal analysis, S.K.; investigation, S.K.; resources, S.W.; writing—original draft preparation, S.W. and S.K.; writing—review and editing, S.W. and S.K.; visualization, S.W.; supervision, S.W.; project administration, S.W.; funding acquisition, S.W. All authors have read and agreed to the published version of the manuscript.

9.2. Data Availability Statement

Data sharing is not applicable to this article.

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9.5. Conflicts of Interest

The authors declare no conflict of interest.

10. References

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