Artificial Intelligence-Based Decision Support Systems in Project Sustainability

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Decision support systems (DSS) is a computer-based aid, which is designed to assist project managers in decision making when the tasks at hand are of a complex nature. Artificial intelligence (AI) is “the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages”. The use of artificial intelligence (AI)-based decision support systems (DSS) has been gaining in popularity. AI technologies are becoming powerful tools throughout the world for improving project management; however, the advancement of construction management is still in its infancy and is adapting to the use of AI at a much slower pace than other sectors

Keywords: decision support system ; construction ; artificial intelligence ; machine learning ; sustainability

1. Introduction

Project management in the construction sector has its own unique challenges, which have a clear impact on project success. These challenges relate to each project having variations in location, personnel, the equipment and logistics, as well as other factors such as economics and cost variations [1]. These can increase the degree of uncertainty during project planning and implementation, which can result in overspending, project delays, and disputes between the customer, employees, and contractors. In addition, traditional project management methods that are used by current construction companies rely heavily on the experience of project managers, while data are collected manually in a variety of non-digital formats through decentralized storage [2][3]. This leads to the use of delayed, flawed, or incomplete information during decision making, which jeopardizes process improvement. Relying heavily on empirical knowledge rather than a systematic approach often leads to wrong conclusions with substantial consequences.

Moreover, the critical success factors (CSFs) of project management are changing alongside the technological advancements. In particular, the CSF evolution is obvious in construction project management due to key changes in societal needs at the start of this century. The goals of construction project management have moved on from focusing on cost and profit, scheduling, and quality to also consider other tangible and intangible factors as well [4]. This trend motivates the measurement of project success with respect to the goals of economic, environmental, and social sustainability.

1.1. Decision Support Systems

A DSS can be defined as a computer-based aid, which is designed to assist project managers in decision making when the tasks at hand are of a complex nature [5][6]. Early DSSs could be defined as passive ones that would do what the users explicitly direct them to do, with a narrow range of decision-making capability [5]. In more recent years, the introduction of AI techniques has increased the capability of DSSs in construction. The basic structure of a DSS can be seen in **Figure 1**. This involves a user interface to support human-machine interaction, such as inputting data for analysis and receiving the guidance or recommendations in a human-readable format. The inference engine is the brain of the system, which utilizes AI algorithms to perform reasoning and computing. Hence, decisions or solutions to a problem can be derived based off the historical data stored in the knowledge base and the inputted data from the user. The knowledge base is where useful decision-making logics and historical data are stored to support the inference engine. The knowledge base will also be updated with new information/knowledge from interacting with users and resolving real-life issues. This will increase the sophistication of knowledge base and the intelligence of the system.

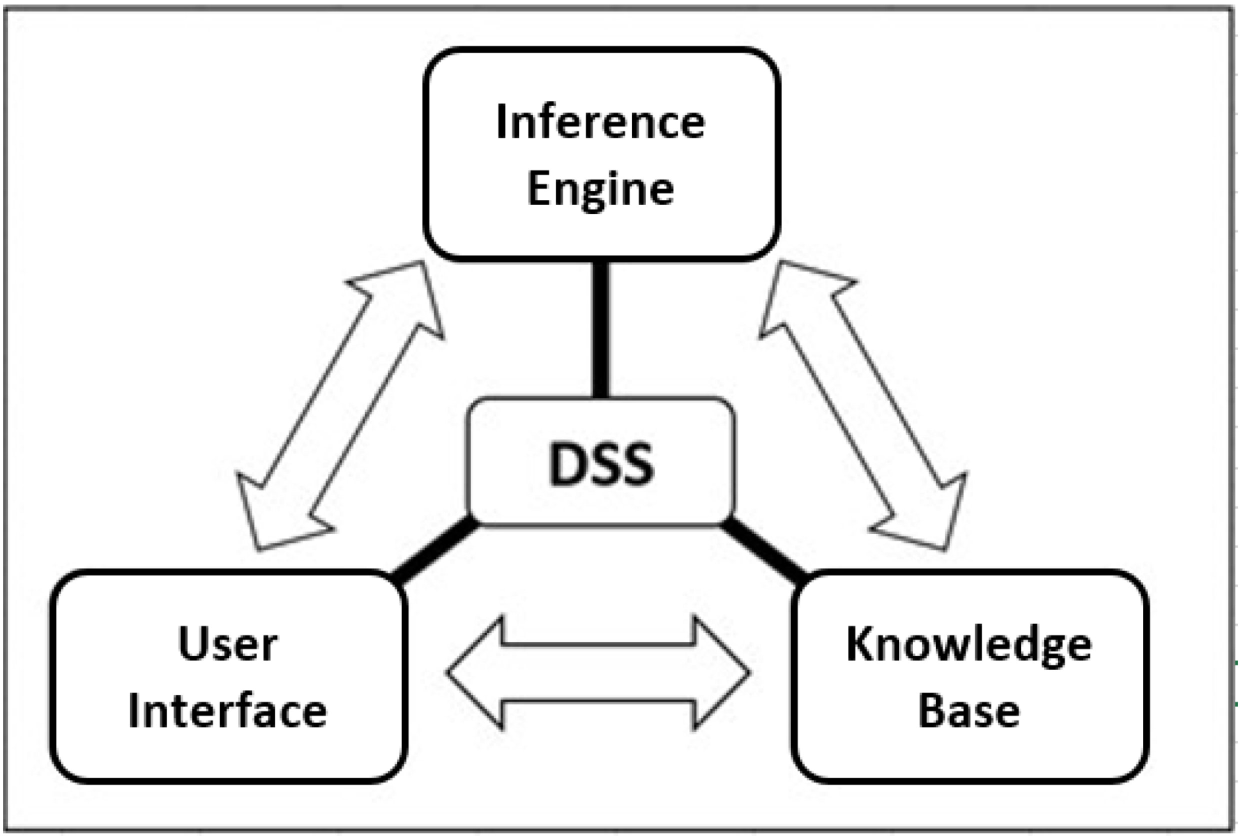

Figure 1. The three key components of a DSS: the user interface, the inference engine, and the knowledge database.

1.2. Sustainability in Construction

Project sustainability relies on the notion that the project should meet the present as well as future needs without compromising the others' interests. A widely accepted view on sustainability is the idea of the three pillars of sustainability, which are defined as the economic, environmental, and social goals [7]. These are more informally defined as the consideration of the three Ps: profit, planet, and people [8].

Economic Sustainability

The primary goal of economic sustainability is providing financial return compared to the utilized resources, adding value, and making financial profits while saving through minimizing expenditure [9]. Examples of this would include efficient project management, compliance with standards and regulations, and effective risk management and mitigation.

Environmental Sustainability

Looking further than the business alone, the goal of environmental sustainability is to minimize the negative impact of operations on the environment and to maintain and improve the environment. This includes reducing energy usage, limiting material usage, and utilizing environmentally friendly materials [10]. The goals of environmental sustainability have often gone together with economic sustainability, as the reduction of waste materials and compensating for inefficient working methods will reduce financial waste and increase profits.

Social Sustainability

The goal of social sustainability is to maintain and improve the quality of human life. This includes customers, employees, contractors, and all other parties who may be affected by the work carried out during a project. This can be through improving health and well-being, better training, and development; improving workplace diversity; and contributing to the betterment of society [11]. The benefits of social sustainability are the improvement of the morale and well-being of company personnel; improving relations with suppliers, customers, and the affected parties; as well as improving reputations both locally and internationally.

1.3. Artificial Intelligence

Machine Learning

This is the process of developing computer programs that learn from past data to make predictions without being explicitly programmed to do so. The learning methods consist of supervised data; learning from labelled datasets for both the input and desired result and unsupervised learning; for structuring unlabeled data and reinforcement learning (RL); and mapping from situations to actions to maximize the reward [12]. Examples of machine learning algorithms include multivariate-linear regression (MLR), logistic regression (LR), support vector machine (SVM), decision tree (DT), random forest (RF), K-means, Bayesian inference (BI), and artificial neural network (ANN).

Fuzzy Logic

In the real world, especially in project management, there are situations in which human reasoning is required for decision making, which may have a level of uncertainty for what the right choice may be. A tool to combat these situations is fuzzy logic (FL), first introduced in 1965 by Lotfi Zadeh [13]. This is a technique that can measure the degree of correctness of uncertain data, and it has been widely adopted in real-world systems to tackle ill-defined and complex problems that have incomplete and imprecise information [14]. Rather than measure something to be true or false, fuzzy logic is used to quantify the level of truth. Fuzzy logic is used primarily for quantifying the knowledge of experts from ranked questionnaires [15], capturing human reasoning for various applications in decision making.

Natural Language Processing

Natural language is what humans use to communicate information as opposed to computer programming languages, examples being English or Mandarin. In order for natural language to be interpreted by a computer, a tool known as natural language processing (NLP) is applied [16]. This is concerned with creating computational models that will resemble the linguistic capability of human beings. This includes reading, writing, listening, and speaking [17]. NLP is used to convert natural language into computer readable language for applications in social media, customer service, e-commerce, education, entertainment, finance, and healthcare [18]. In relation to construction project management, the processing of typed documentation and reporting can be computed, and knowledge can be gained through the use of NLP. Examples being the evaluation of accident reports in the construction sector for determining the precursors for accidents [19].

Evolutionary Algorithms

Evolutionary algorithms are a tool that relates biology, artificial intelligence, numerical optimization, and decision support for a diverse field of engineering applications. These algorithms utilize models based on organic evolution for intelligent optimization [20]. The task of intelligent optimization involves searching for the best result to minimize or maximize an objective function subjected to defined constraints [21]. An example of this type of algorithm would be the genetic algorithm (GA). This can be used for the optimization of the results of a system to improve model performance in decision making for construction project management [22].

Construction Project Lifecycle

The construction industry can be defined as the construction, extension, installation, repair and maintenance, renewal, removal, alteration, dismantling or demolition of any building or structure, transport infrastructures, power, and water services [23]. This covers both commercial and industrial applications, residential buildings, as well as infrastructure items, such as transport routes, water service stations, and the connecting pipelines. Over this wide field of construction, projects can be categorized into five stages. These stages are initiation, planning, execution, controlling, and closing [24]. A flowchart explaining each stage of the project lifecycle is given in **Figure 2**.

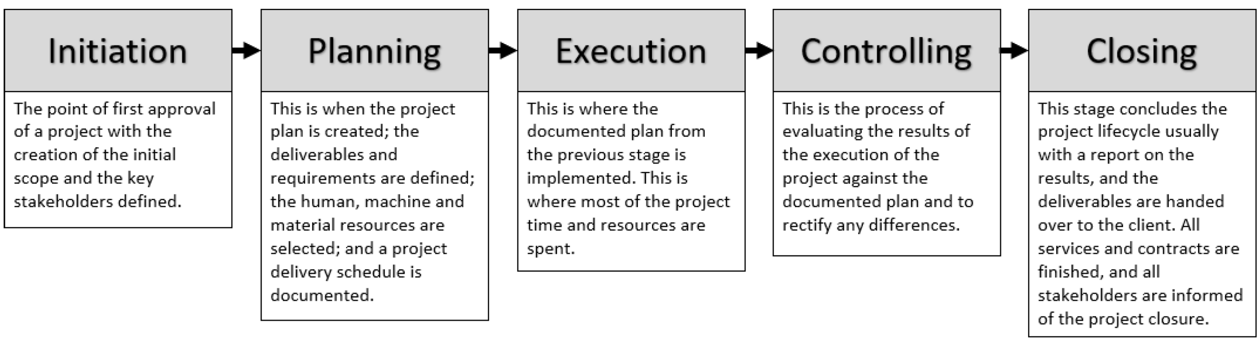

Figure 2. A flowchart of the five stages of the project lifecycle.

2. Artificial Intelligence-Based Decision Support Systems in Project Sustainability

2.1. Categorizing the Task of the DSSs

Contractor and Supplier Evaluation

An area of research where DSSs have been applied with sustainability criteria using AI is for evaluating suppliers. Ref. [25] refined sustainability criteria for the selection of suppliers with the assistance of academics and industry experts for defining the importance of applicability of criteria taken from the literature. Fuzzy preference programming was then used to allocate weights to each of the sustainability criteria, resulting in graded levels of importance reducing from economic to environmental to social criteria. Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) was then used for supplier selection. Others have also used a similar approach, with [26] also using fuzzy logic for weight definition but using VIKOR for the selection of the projects. Another example is [27], who used VIKOR for project selection but with analytical hierarchy processing for the weight definition. The sustainable selection criteria in all these studies are great examples of a drive towards sustainability, and these are just some examples of the few studies into supplier selection in manufacturing [26]. It can be seen in these studies that all the evaluation criteria are defined through subjective opinions of experts related to the work, and there is a lack of quantitative data. Combining these two data types may prove beneficial for supplier selections. These are all focused on the manufacturing industry, which does have a different format from the construction industry for supplier selection and would have differences in the selection criteria based of the unique aspects of construction projects when compared to manufacturing.

Design Optimization

Ref. [28] highlighted ongoing research into the use of DSSs for sustainable building material selection in the design stages, with a key focus on incorporating criteria for the environmental goals of sustainability. Ref. [29] developed a DSS for helping design engineers to choose sustainable materials during the planning stage of construction for pavement design. This method not only considers economic, environmental, and social goals during the project lifecycle but also for the maintenance of the materials during the lifecycle of the product. An example of AI being used for DSSs for design optimization would be [30], who developed a DSS for concept-design decision making in the construction industry. They adopted a Markov decision process (MDP) and RL for this DSS. The aim of this model was to implement value engineering from the manufacturing section into the construction design phase. The focus was to achieve optimization against environmental, economic, and social criteria. Utilizing the MDP approach was especially useful, as the structure of this approach has similarities to the decision-making system that engineers manually carry out in the concept-design stage of construction projects. The method was tested using the concept design of a house, and the design was optimized, which showed a positive result; however, there is area for improvement by adding feedback complexity and representing the interdependencies between different decisions at different stages of design.

Early-Stage Project Predictions

The most popular application for a DSS from the last ten years is for making predictions of project performance at the initiation and planning stages of the project lifecycle. This can be for project cost prediction, project delays, and for risk in project selection. These areas of study all follow the same approach of utilizing historical project performance data and key parameters to train an algorithm for predicting the resultant performance given the same input parameters for a new test project. This is an especially useful tool, as it provides the project manager with a quantifiable method for selecting which projects to choose during the initiation stage of the lifecycle or how best to plan for a project prior to execution. The most popular algorithms to be used are ANNs and more recent models, which include hybrids with FL for quantifying qualitative data and genetic algorithms (GA) for optimizing the weights of the parameters [22][31][32][33]. Case-based reasoning (CBR) has also been studied, utilizing previous similar cases of projects to make predictions [34][35][36][37][38]. It has been observed that most of the research into project predictions examine the economic pillar of sustainability with 76% of all EPP research solely focusing on the economic sustainability goals. Research considering environmental and social goals is the minority, equating to approximately 25% of studies.

Dynamic Performance Prediction

The authors of [22], who proposed the evolutionary fuzzy hybrid neural network (EFHNN) for project cost prediction at early stages, clearly understood the benefits of creating a dynamic performance-prediction tool. This hybrid is a combination of FL for dealing with uncertain data, a high-order ANN for making predictions, and GA for optimizing the results. The same authors published a paper on their dynamic prediction performance method [39], which used the same hybrid AI algorithms to classify the performance of projects throughout the lifecycle. This classified project performance into four levels ranging from successful to disastrous, with inputs related to 10 time dependent variables, including change order data, weather impact, owner commitments, contractor commitments, recorded incidents, and overtime work. This model is classified with a high accuracy; however, the method was only validated against the highly similar evolutionary fuzzy neural inference model (EFNIM) and with only 12 projects for training and 3 projects for testing.

Safety Risk Assessment

In the application of improving safety through the project lifecycle, there have been studies into the use of natural language processing (NLP) for analyzing injury reports. Ref. [40] used NLP to structure data from accident reports into attributes of incidents and the safety outcomes and then used random forest and stochastic gradient tree boosting for prediction. The models were able to have better predictive capability for defining the injury type, energy type involved, and the injured body part with a higher likelihood than at random, which gives evidence to the use of quantitative and empirical methods for evaluating safety compared to that of expert opinion and subjective judgment. One of the authors then took the study further, such as [19], which introduced a method for automatically determining valid accident precursors for accidents in the oil and gas sector. Three different ML techniques were used and compared. These are convolutional neural network (CNN), hierarchical attention network (HAN), and term frequency-inverse document frequency representation with support vector machine TF-IDF-SVM, which were used for NLP. All predictions of precursors performed better than random selection, and the TF-IDF + SVM method proved to be the most accurate. The data collected for these reports were quantitative in nature, and circumstantial and environmental information that contribute to hazards in the workplace were not considered.

Site Logistics

Site logistics can be defined as the control of the movement of people, equipment, and materials related to a work site. The category for site logistics covers all the DSSs, which focus on improving site logistics with the use of AI and sustainability criteria. Ref. [41] developed a digital twin and DSS, which applied heuristic optimization and clustering for the purposes of silo replenishment on various construction sites during project execution. The purpose of this software tool is to predict the best routes for resupply vehicles to optimize vehicle usage and minimize work site stoppage times. Over a 3-year period, this reduced logistic costs by up to 25% and with every kilometer of transport saved having a positive impact on the development of CO_2 emissions. The complexity of the digital twin and refill truck cost had a large effect on the cost reduction, which has left area for improvement.

2.2. Observations and Trends Related to AI

The overall trend in AI shows that complex prediction in the form of ANN and quantifying expert opinion using FL have had the most focus, which covered 37% and 31% of papers, respectively. GA is also popular for the optimization of models, with 12% of studies considering this. CBR, which focuses on the use of previous cases to advise project managers on how to progress in future projects, and two other machine learning algorithms, namely MLR and SVM, have been involved in approximately 10% of all studies. In total, 46% of the studies used hybrids of multiple AI algorithms; this was not an increasing trend, though. As the quantity of papers increased over the decade, the ratio of hybrid models decreased. This reduction in the ratio of hybrid models does coincide with the increase in studies for other applications of DSSs than EPP. In all, 50% of all studies are focused on EPP, which can lead to a bias of the overall results towards the EPP research.

Contractor and supplier evaluation papers have used only FL for quantifying expert opinion [25][42] while overlooking the potential of using machine learning techniques to examine empirical data alongside the opinion of experts. Design optimization and site logistics have only a few studies that use AI, and there is no obvious trend, but these two categories were published within the last six years, suggesting an increase in interest; hence, the potential of AI has not been fully explored in these areas. EPP is the most popular field of study and has been investigated with a wide variety of AI models. The most popular are the ANN and FL, with CBR, MLR, and GA also used in a considerable number of studies. DPP has also been involved a wide variety of AI models, the most common being ANN, followed by DT, FL, and SVM.

2.3. Observations and Trends Related to Sustainability

It must be noted that this coincides with the increase in papers focused on design, site logistics, safety, and both supplier and contractor evaluation as shown in **Figure 3**. These studies have been noted to have a high percentage of consideration for the environmental and social goals of sustainability. EPP primarily focuses on the economic goal of sustainability when viewing bidding, claims, and cost prediction; however, there has been an area of EPP focused on project risk, of which most studies consider the three sustainability goals [43][44].

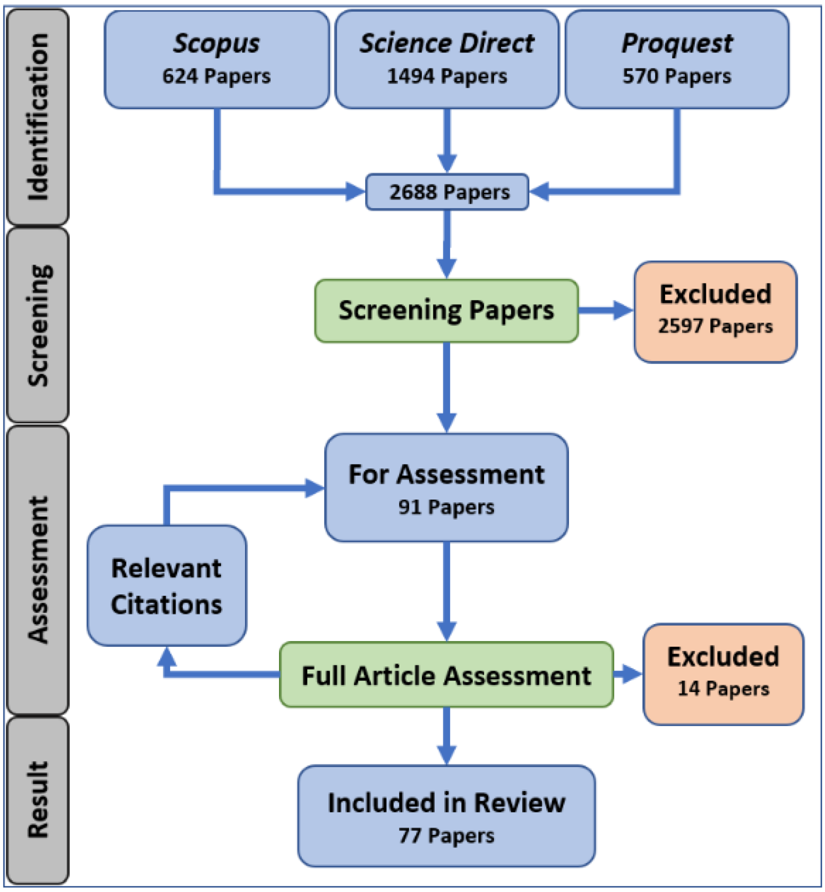

Figure 3. The count of each DSS category examined in papers by year of publication.

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