AI-DRIVEN BLOCKCHAIN SOLUTIONS FOR ENHANCING DECISION-MAKING IN COMPLEX ENGINEERING PROJECTS

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ARTICLE INFO

***Article history*:**
Received:13.09.2024.
Received in revised form: 11.03.2025.
Accepted 12.03.2025.

Keywords:
AI-Driven
Blockchain
Complex Engineering Projects

DOI: https://doi.org/10.30765/er.2632

Abstract:

The current state of technology is causing a surge in high-end technical items, which in turn are causing a wide range of client needs. As a result, engineering system design projects are expected to become more complicated. Consequently, engineers working on large-scale design projects need designers adept at collaborating across disciplines and solving complex challenges. The inefficiency of team communication and the execution of complicated projects is directly impacted when firm managers appoint designers with multi-disciplinary knowledge to such projects. This is because designers need more excellent knowledge in each area, which will lead to communication issues. Futuristic technologies such as AI and blockchain have the potential to optimize and greatly improve procedures in the ever-changing realm of complicated engineering projects. This study delves into AI-driven Blockchain Solutions for Enhancing Decision-Making in Complex Engineering Projects (AI-BC-CEP) by examining the combined impact on efficiency, cost reduction, and data integrity. The particular artificial intelligence models used include Reinforcement Learning (RL) for decision-making optimization and machine learning (ML) for predictive maintenance, together with the steps taken to train and test these models using real-world or simulated data. The technological setup and smart contract systems used to record project decisions and data and the integration of blockchain technology guarantee secure and transparent communication across multidisciplinary teams. Blockchain technology generates a decentralized, immutable ledger of all monetary transactions to lessen the possibility of fraud and errors. Analytics powered by artificial intelligence may help with predictive maintenance, demand forecasting, and decision-making, which can improve operational efficiency and resource allocation. Some of the limitations and challenges mentioned in the article are privacy, interoperability, and scalability. This research delves deeply into whether blockchain technology and artificial intelligence collaborate to take on the complexities of modern engineering tasks. The experimental results demonstrate that the proposed AI-BC-CEP model increases the cost reduction ratio by 21.2%, predictive maintenance ratio by 95.6%, decision-making ratio by 85.3%, and demand forecast by 97.4% compared to other existing models.

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1 Introduction

Digital technology has revolutionized several industries, including complex engineering projects. In particular, artificial intelligence (AI) and blockchain have emerged as powerful tools for enhancing the engineering project decision-making process. Integrating blockchain and AI may help solve inefficiency, lack of transparency, and security risks in selecting challenging engineering projects [1-2]. As a result of its decentralized and immutable ledger structure, blockchain technology offers unparalleled transparency and traceability. Due to blockchain's safe and verifiable record of transactions, all parties involved may rest assured that the information is correct and consistent. To address issues like fraud, counterfeiting, and anomalies in decision-making, it is crucial to foster trust among participants via this transparency [3-4]. On the other hand, artificial intelligence has capabilities that make decisions and operations more efficient. Using artificial intelligence, massive amounts of data may be sorted to improve decision-making in complex engineering projects, monitor inventory levels, and predict demand. Machine learning is a subfield of AI that has the potential to learn from new data to make better, more accurate decisions over time [5-6]. Blockchain and AI show great decision-making potential when applied to complex engineering projects. Blockchain's secure data environment may help AI systems by making data more trustworthy, leading to more significant insights and predictions [7-8]. On the other side, AI has the potential to streamline decision-making by organizing and comprehending the complex data stored on blockchain networks. Using these technologies to boost efficiency, transparency, and security, this paper seeks to explore blockchain solutions driven by AI to enhance decision-making in complex engineering projects [9–10].

This essay will examine the present applications of these technologies, discuss their benefits and drawbacks, and finally lay forth a plan for their potential integration. The impact of blockchain and AI on decision-making is examined in this study to shed light on how these technologies may transform intricate engineering projects and drive innovation [11]. This study's complex engineering project design primarily aims to tackle the complexity of multi-disciplinary engineering project designs. Challenges abound for designers working on big engineering projects due to the inherent complexity of the systems and settings. As a result, interdisciplinary design knowledge exchange issues arise when complex engineering project companies recruit designers with diverse design knowledge, theoretical and methodological backgrounds, and experience levels to engage in and solve project problems actively. Because of this critical interdepartmental communication and cooperation issue, design firms must immediately implement a system to pick the most qualified multi-disciplinary designers for intricate engineering projects [12-13]. Consequently, this study's AI-BC-CEP overarching goal is to provide a procedure for selecting designers for complicated engineering projects that considers the designers' competency, the project's necessary level of fundamental technical competence, and the importance of designers' ability to communicate across disciplines.

This paper will utilize a design group's Total Average Communication Level (TACL) value to quantify multi-disciplinary communication and cooperation efficiency inside a designer's portfolio. Design firms, particularly those working on complicated engineering projects, might benefit from the suggested strategy when it comes to selecting interdisciplinary design teams that are both productive and cooperative [14-15]. By analyzing sensor data using machine learning algorithms, Siemens has introduced AI-driven predictive maintenance in its production facilities. This has greatly reduced maintenance costs and downtime by predicting equipment problems before they happen. Similarly, Walmart has improved visibility and traceability by using blockchain technology to monitor food items moving through the supply chain. Using this method, they can swiftly determine where items came from in case of a safety risk, speeding up problem resolution and guaranteeing high-quality products. With AI for demand forecasting and blockchain for smart contract execution, JP Morgan can streamline transaction procedures, reduce operating costs, and revolutionize the financial sector. This study presents a new way to improve the efficiency of real-time decision-making, transparency, and AI-driven communication models to integrate with blockchain technology. The model's adaptability addresses challenges in engineering project management to changing project needs and emphasizes enhancing communication and multi-disciplinary cooperation. In addition, this study is particularly relevant to the needs of the industry since it incorporates predictive maintenance, cost reduction, and prompt decision-making into the framework. This helps to reduce operational inefficiencies and improve overall project results.

Here are three research questions for the study:

- "How can AI-driven decision-making models optimize communication efficiency and collaboration across interdisciplinary teams in complex engineering projects?"
- "What role does blockchain technology play in ensuring data integrity and transparency during the execution of engineering projects, and how does it influence decision-making processes?"
- "How does integrating AI and blockchain technologies contribute to cost reduction, predictive maintenance, and adherence to project timelines in engineering projects?"

In complex engineering projects, which often include several disciplines, short timeframes, and unpredictable changes, the ongoing difficulty of improving communication, decision-making, and operational efficiency is the target of this study. Few studies have examined the potential of integrating AI with blockchain to improve decision-making, guarantee data transparency in real-time, and foster multidisciplinary cooperation, despite both technologies having come a long way. The existing methods address AI and blockchain separately, which does not address the problem of creating a cohesive system that can adjust to changing project needs and handle unexpected obstacles. To address this, this study will try to merge blockchain and artificial intelligence to streamline project communication, save expenses, and guarantee on-time delivery, all of which will improve the result.

Objectives of Study

- This article aims to improve cross-disciplinary communication and teamwork effectiveness in a designer-led portfolio, employing the TACL value as a criterion.
- AI-BC-CEP evaluated the proposed system, stating that an open environment for exchanging material information improves decision-making and decreases material delays, total material costs, legal problems stemming from material delays, and overall material costs.
- Because of blockchain's decentralized and transparent platform, all parties involved in a transaction may see the same data. This fosters better cooperation and trust among participants, which, when paired with insights generated by AI, leads to more effective decision-making.

This paper is structured as follows for the rest: Section 2 provides an overview of the relevant literature and context. Section 3 provides a comprehensive outline of Methods for Improving Engineering Decisions. Section 4 describes a scenario to illustrate the experiments' specifics and the simulations' outcomes. In Section 5, they review the whole conversation and come up with some proposals for further research.

2 Literature Review

For construction engineering projects,

- Jeen Guo et al. [16] came up with the fuzzy technique and created an Interference Fuzzy Analytical Network Process (IF-ANP) method using a decision-making trial and evaluation laboratory (DEMATEL) approach. The paper includes a break in the capital chain, ineffective decisions, potential regulatory and legal issues, economic decline, and stakeholder disputes. The findings revealed that additional hazards, only symptoms rather than the illness itself, originated with the policy and legal risk.

Included in this contribution is the work of

- Robert Woitsch et al. [17] on supporting decision-makers, particularly with the Democratic AI-based Decision Support System (DAI-DSS) developed and deployed in the EU-funded FAIRWork project. The FAIRWork project suggests an AI-enhanced model-based method for formally describing decision processes, improving current modelling approaches. This approach aims to improve the usefulness of conceptual models throughout their production and usage.
- Long Li et al. [18] proposed a multi-attribute group choice model that is information fusion-driven in a fuzzy environment to enhance decision-making processes. MTI's decision-making would be more sustainable with this methodology. This work uses intuitionistic fuzzy weighted averaging (IFWA) to aggregate information. This paper creates a knowledge-fusion-driven two-level decision model that

promotes knowledge fusion across domains, decreases information fuzziness and uncertainty, and has practical applications.

- Seng Hansen et al. [19] presented a context-based decision-making framework (DMF) to enhance decision-making. This study uses a mixed-method approach to collect, analyze, synthesize, and validate contextual data. The findings were utilized to construct the DMF, which was validated in real life. The DMF may enhance project investment evaluation by bridging infrastructure assessment limits and epistemic environment knowledge. More educated decision-making may improve project investment success.
- Panagiotis K. Marhavilas et al. [20] proposed a new risk assessment and analysis (RAA) technique for sustainable engineering projects. This method combines multi-criteria decision-making (MCDM), deterministic (DET), and stochastic (STO) processes. The paper integrates the analytical hierarchy process (AHP) with the fuzzy-extended AHP (FEAHP) of the MCDM technique. The proportional risk assessment method (PRAT), time-series process analysis (TSP), and fault-tree analysis are all included.
- Ibrahim Mekawy [22] suggested Blockchain-Powered Wireless Sensor Networks to improve security and privacy in the IoT era. Because of their unique features necessitated by real-time collaboration among the Sensor Nodes (SNs), WSNs are widely used for tracking and surveillance applications because of their simplicity. Because WSNs use centralized server/client architectures, there are a lot of obstacles to overcome when putting them into practice, including storage and security. However, WSNs may provide several advantages and conveniences. This study delves into a comprehensive analysis of a blockchain-based method for detecting malicious nodes, a thorough review of blockchain integration with WSNs (BWSN), and insights into this new idea.
- Wencun Wang et al. [23] recommended the Fuzzy Cognitive Environment for Blockchain and Social Networks in Rural Management Systems. The article starts by highlighting the importance of rural culture diffusion and analyzing current problems in rural development processes, paying special attention to social networks' role in this process. Next, a thorough system for rural administration is created by merging blockchain technology with fuzzy set theory and using an improved consensus method for blockchain, the Byzantine Fault Tolerance (BFT) algorithm. Finally, an intelligent traffic management system is created to efficiently convey goods between metropolitan areas to handle distribution and logistical issues related to rural revival. As part of its distribution route planning process, the system incorporates a hybrid genetic algorithm and automatically calls the Matlab dynamic link library.
- Selvarajan Shitharth et al. [24] proposed the Federated learning optimization for the computational blockchain process with offloading analysis to enhance security. Integrating an offloading mechanism for data processing using blockchain technology, where total security is maintained for each data, is the primary relevance of the suggested method. A load-balancing strategy is integrated with data weights in a problem methodology created regarding clusters. Parametric assessments are done in real-time to evaluate the consistency of each data that is monitored with IoT. In a five-scenario research, the author found that offloading analysis via blockchain is safer, leading to an 89% improvement in data processing accuracy for all IoT applications.
- Hadi Faghihmaleki et al. [25] introduced Building Information Modeling (BIM) for Value Engineering and Its Impact on Construction Projects. Using BIM, the project team can virtually inspect the construction site. The use of BIM in areas such as time and money savings, quality improvement, control, monitoring, cost and time estimation, reporting, and comparing present circumstances to standards is explored in this paper. Both the BIM-based and the more conventional approaches were examined as well. Project execution is smooth and error-free thanks to BIM's ability to include value engineering.
- Sayyid Ali Banihashemi et al. [26] presented the Fuzzy best–worst method (BWM) for Identifying and Prioritizing the Challenges and Obstacles of Green Supply Chain Management in the Construction Industry. "Green Design," "Green Procurement," and "Green Production" were the five primary components, while "Green Management" and "Green Information" were the two supplementary components. Then, concerning each component, the sub-components were identified. Lastly, five experts with practical expertise were polled to establish the relevance weights of the discovered components and sub-components using the fuzzy best-worst method (BWM). The fuzzy BWM

method's results reveal that out of the three components, "Green Design," "Green Management," and "Green Implementation" are the most crucial. "Lack of designers, contractors and planners" was placed #1 among the identified sub-components.

- Ismail A. Mageed [27] discussed Ismail's Ratio Conquers New Horizons the Non-Stationary M/D/1 Queue's State Variable Closed Form Expression. A temporal first-order differential equation represents the number of consumers in a non-stationary or time-varying $M/D/1$ queueing system, and this study explores the search for an exact analytical solution to this equation. At this time, simulating the situation is our exclusive option for a solution. Research, however, suggests a constant ratio β (Ismail's ratio) that connects the time-dependent means of arrival and service rates, providing a precise analytical answer. Next, the numerical analysis is used for the time-varying $M/D/1$ queueing system to study its stability dynamics concerning β and the queueing parameters.
- Maria Lincy Jacquline and Natarajan Sudha [28] deliberated the Weighted Fuzzy C Means and Enhanced Adaptive NeuroFuzzy Inference Chronic Kidney Disease Classification. The Fruit Fly Optimization Algorithm (FFOA) and the efficient Multi-Kernel Support Vector Machine (MKSVM) for sickness classification have been introduced in this study. Typically, FFOA is used to find the greatest characteristics of a collection. Medical data may be classified using MKSVM by using predefined dataset criteria. Various modifications in the data acquired for this research will affect the classifier's accuracy. There has been an increase the number of misclassified results produced by MKSVM. To alleviate such difficulties, the input CKD data values scale is normalized using a preprocessing phase based on min-max normalization. Next, we will use Improved FFOA (IFFOA) to identify important characteristics. Weighted Fuzzy C Means clustering (WFCM) will be used to cluster the chosen characteristics to decrease misclassification outcomes and forecast the class label of the data sample. Lastly, the Enhanced Adaptive Neuro Fuzzy Inference System (EANFIS) will classify CKD as normal or abnormal. F-measure, recall, accuracy, and precision results show the proposed technique is effective.
- Robert S. Keyser and Parisa Pooyan [29] investigated the Process Failure Mode and Effects Analysis (PDMEA) for Home Projects. Two RCA approaches are investigated in this study as they pertain to DIY projects: 1) a novel Lean PFMEA to fix a John Deere riding mower that starts up, then stops, and 2) a case of a house AC unit that runs continually but fails to cool using the 5 Whys method. It was via using the 5 Whys approach that the mistake in the original AC unit's colour-coded wiring to the thermostat was uncovered. Through a Kaizen event and Lean PFMEA, the author determined that grass clippings in the gasoline line caused the mower's start/stop problem. To fix this, the author cleaned the fuel tank and replaced the fuel lines, filter, and carburettor.
- Payam Shafi Salimi and Seyyed Ahmad Edalatpanah [30] examined the Fuzzy AHP Method and D-numbers for Supplier Selection. Two library and field approaches were used to gather information for this investigation. This study's goals demand the use of two approaches to fuzzy hierarchical analysis including D-numbers in evaluating suppliers. This case study aims to shed light on the differences and similarities between the two approaches by ranking providers using both methodologies and comparing the outcomes. Companies in the manufacturing sector had their suppliers assessed and graded according to four distinct types of components. Hierarchical analysis using D and fuzzy approaches yields significantly different assessment and ranking results for suppliers of type A and B components; this begs whether specialists in these fields have reasonable expectations.

2 Proposed Method

The method for selecting interdisciplinary design teams to construct complicated technical systems. The onus for hiring multi-disciplinary designers falls squarely on the shoulders of the project manager when such projects call for the creation of intricate technological systems. The domain-specific project manager may direct, coordinate, and supervise the designers and planned activities. The number of designers required, the budget for hiring designers, and the specific technical and personal abilities required of each designer are all factors that project managers in charge of complex engineering system design projects must consider (Figure 1).

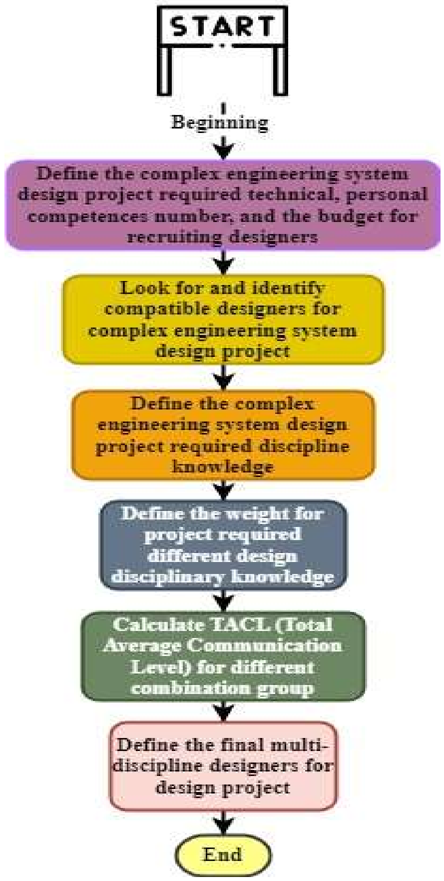

Figure 1. Multi-disciplinary designer selection process.

Beginning:
At the outset, an initiation phase marks the commencement of the design project. Everything is predicated on this.
The complex engineering system design project requirements:
The first and most important stage in creating a sophisticated technical system is recognizing the project's requirements. Here, the company will lay out the technical requirements, determine the number of designers it will need, assess their skills, and allocate funds to employ them. If these requirements are articulated in detail, assembling the appropriate project team will be feasible.
Identify compatible designers:
After defining project requirements, find relevant designers. Designer compatibility is meeting technical and human capabilities. This stage ensures the chosen team can handle the project's intricacies.

The required discipline knowledge:
After finding competent designers, determine the project's domain knowledge. This paper can ensure your design team has the broad skills to work together and the particular knowledge to solve the project's difficulties by completing this step.
The weight for required disciplinary knowledge:

Knowing what disciplines are needed for the project, this paper may order them by significance. This prioritizes the different categories of competence, making it more straightforward to pick the ideal team by emphasizing the most essential elements.

Calculate the Total Average Communication Level (TACL):

The TACL model may adapt to various engineering project types by adjusting to changes in the number of disciplines or the specialized skills needed. The model adapts in real-time by integrating interaction flows and patterns of communication across different teams as the complexity of a project grows and new disciplines or specialized knowledge are required. Blockchain guarantees exact tracking and transparent recording of all updates, choices, and changes, while AI algorithms constantly examine these interactions to find any communication gaps or inefficiencies. The model's versatility makes it scalable, so it can handle projects of any size or with a wide range of skills. This, in turn, improves coordination and decision-making throughout the project's lifetime. To proceed, the paper must determine the Total Average Communication Level (TACL) for various designer combinations. It's reasonable to assume that TACL evaluates the team's ability to work together effectively by considering each member's area of specialization. The optimal lineups can be better determined using this computation. The study's goal function (Equation (1)) and associated limitations (Equation (3)) may then be released. First and foremost, the target function (1) seeks to determine the TACL value. The steps in calculating TACL are detailed in Equations (1) through (3).

$$TACL = \frac{\sum_r^R ACL_r}{\frac{V.(V-1)}{2}} \tag{1}$$

$$ACL = \frac{\sum_b^O \sum_c^N \frac{\omega_b.EM_b.S_{bc} + \omega_c.EM_c.S_{cb}}{2}}{O.N} \tag{2}$$

$$\sum_{v=1}^{V} D_v \leq C \tag{3}$$

ACL = One-Pair Designer Average Level of Communication. Level of subject knowledge acquisition: DL. Discipline b ranks above discipline S_{bc}. The number of disciplines a collaborative designer has mastered is c. N *and* O is the number of design disciplines the team has mastered. $TACL$ is the average degree of whole-group communication in one design? For each group, the total number of designers is$V$. One group has a total of ten communication pairs. D_v is the cost of recruiting the vth interdisciplinary designer for a single combination group C is the budget for hiring a group of combined designers. One designer combination group may maximize their average knowledge communication level using the goal function (1).

The value of "V" in Equation (1) represents the sum of all designers belonging to a particular group. DL denotes the degree of disciplinary knowledge acquisition in Equation (2). S Stands for the relationship's rank in the discipline. When it comes to disciplinary knowledge, the weight is " ω ". A more excellent value of " ω " indicates that the discipline expertise is more critical to the project. Project managers may define the coefficient value " ω " using the AHP (Analytic Hierarchy Process) approach. There is a practical, straightforward, and adaptable multi-criteria decision-making technique called the AHP method for quantitatively examining qualitative issues. Parameters, like criteria or alternatives, are given weights in the AHP framework according to their relative relevance (weighting) using the pairwise comparison approach. Indeed, the AHP method's hierarchical structure allows for the measurement and synthesis of several elements of a complicated decision-making process in a hierarchical fashion, simplifying the integration of the respective components. Experts' subjective assessments of the qualitative and quantitative indicators of many fields of knowledge are necessary to define the weight value of that knowledge. So, the AHP technique may be used to determine the weights of design discipline knowledge, which is adaptive. Analytic Hierarchy Process (AHP) discipline knowledge weighting criteria relied heavily on domain-specific expertise and expert opinion rather than empirical facts.

This study surveyed subject-matter experts from across the board to determine how each engineering speciality stacked up against the project's unique objectives. Each discipline's importance to the project's outcome was evaluated, as was the degree of cooperation they needed and the possible consequences of setbacks or mistakes in each field. Following the organization of these expert opinions in a pairwise comparison matrix, the AHP determined the relative importance of each field. Expert judgment was crucial in determining the importance of disciplinary knowledge in dynamic, real-world project situations, even if empirical evidence might improve these weights even more. Afterwards, get the ACL value (Equation (2)) by dividing the total number of disciplinary knowledge communication pairings ($O \cdot N$ in (2)) by the sum of all disciplinary knowledge communication amongst designers. Next, this paper may get the TACL value by dividing the total number of communication pairs in the group by the ACL value for each pair of designers (1). This paper must consider how much it will cost to employ a team of designers from different fields (3). After that, the project manager may choose the most flexible designers based on their TACL rating, which will help them communicate and solve difficulties with complicated engineering system designs. A higher TACL number indicates improved communication efficiency. A single value produced from communication models is known as the Total Average Communication Level (TACL), and it is a quantifiable measure that assesses the efficacy of information flow in engineering projects. The TACL value offers a more complex examination of communication efficiency under different project circumstances by including fuzzy approaches, which deal with uncertainty and imprecision. This strategy guarantees that choices are based on trustworthy communication metrics, which is especially helpful in the context of approaches that aim to reduce costs, enhance decision-making, and implement predictive maintenance. Incorporating decision-making performance indicators and cost-reduction curves into the research adds weight and provides visual proof of the actual effects and advantages of the suggested framework in complicated engineering environments.

Define the Final Multi-Disciplinary Design Team:

Lastly, the multi-disciplinary design team should be defined according to the TACL and the weighted relevance of the necessary discipline expertise. This group has been hand-picked because of its demonstrated ability to work together productively and answer all of the project's requirements.

End:

The recruiting and selection phase of the complicated engineering system design project ends when the design team is finalized. This step-by-step approach ensures a systematic and thorough process for assembling a highly competent and compatible design team for complex engineering projects. First, the characterization of the projected effect; second, the construction of metrics; third, the impact model; and fourth, the knowledge bases comprise the projecting impacts of complex decisions (PICD) framework (Figure 2). Each module represents the intricate image of the decision's effect projection. Considering a project to make the framework adaptable in usage and development is vital to account for the complexity of the impact's projection. Therefore, ongoing updates and revisions to the knowledge bases are essential. Using a multi-layered analysis of interaction flows, the TACL computation guarantees the correct depiction of communication across disciplines, particularly important in big, heterogeneous teams. It considers the complexity of the communicated information and measures communication frequency, clarity, and efficacy across different disciplines. Artificial intelligence systems analyze data on communication patterns in real time, finding information transmission bottlenecks, misalignments, or gaps. By creating an unchangeable and visible record of all transactions, blockchain technology ensures that all trades are recorded accurately, adding an extra degree of precision. Improving multi-disciplinary cooperation and decision-making across complicated projects is made possible by TACL's regularly updated data and refined communication models, which provide an up-to-date, comprehensive perspective of how diverse teams communicate. The Projection Base, Information on the Decision Structure, and Contextual Data are all stored in the Knowledge Base, which acts as the base. The Decision Making Group receives input from all these sources to synthesize insights and direct choices. The three-tiered Impact Projection Characterization framework begins with Level 1, defining the context, moves on to Level 2, which is concerned with collaborative impact projection by linking particular impacts to collaboration, and finally, Level 3 is concerned with instantiation, which is responsible for turning abstract impacts into concrete examples. Impact Model Notation provides a formal framework for quantifying results by including visuals like charts and indicators in the Impact Metric module.

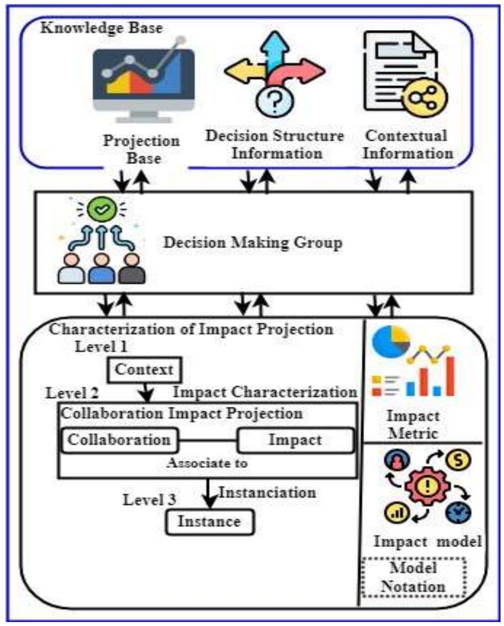

Figure 2. Projecting Impacts of Complex Decisions (PICD).

An effort that represents the requirements of this setting is the modularization of the ideas and connections intrinsic to this projection; this will make it easier to act on complicated judgments when taking their features, particularly their interdependence, into account. This technique allows for more conceptual structural flexibility and growth by layering the pieces and defining their interactions. The literature on difficult choices in naturalistic decision-making provided the basis for proposing the four fundamental modules. The paper advocates for the decision-making team, decision-making knowledge bases, knowledge organization (mental models as a technique), and decision rate to facilitate complicated decision-making. This research takes an impact projection perspective on these four PICD modules. Creating settings that aid decision-makers in their work is the goal of the knowledge base module.

The projection basis, data about the decision structure, and data about the context make up the whole. The primary goal of the first foundation is to facilitate impact reuse and manage the effect projection generated to back its application in various contexts. The decision data is based on the decision structure information concerned with the decision question's details and aims. The third foundation, devoted to contextual information, manages all potential internal and external factors that could influence a decision. The decision-maker's background, intuition, experience, and available funds might play a role. Any implicit or explicit knowledge relevant to a choice is considered contextual information. At three levels, as described in the knowledge structures, the impact projection module's characterization organizes the knowledge involved in the effect projection. The context level places the semantic burden on the decision-making environment by providing a generic presentation of the ideas and connections inherent to this medium. At the level of collaborative impact projection, agents' points of view are considered while characterizing the effect projection. Elevation three is the manifestation of the impact projection defining features. It is in the application of these aspects that the impact model deals with their externalization.

The impact metrics module evaluates all decision-analyzed outcomes' environmental, action-related, and individual-level effects. Another component of the system is the impact model. Considerations for the impact model's framework are based on the knowledge organization suggested in the effect projection module's characterization. This study will not investigate the optimal impact representation, even though all models need a notation for their portrayal. Proposing a means to make explicit the interest knowledge is our primary emphasis. The purpose of the knowledge base module is to keep track of the structural and contextual information and the current decision effect estimations. Besides technical competence and project schedules, the TACL model incorporates communication efficiency, which is critical for multi-disciplinary teams. The approach is structured to ensure that the emphasis on communication does not overshadow technical competence and timely project completion. This is remedied by the model's overarching communication structure, which considers weighted evaluations of the technical competence needed for each subject. By monitoring project milestones and timeframes, AI-driven predictive analytics ensure that effective communication helps, not hinders, development. The TACL model keeps everything in check by coordinating planning for communication with skills in technical areas and goals for the project's completion date.

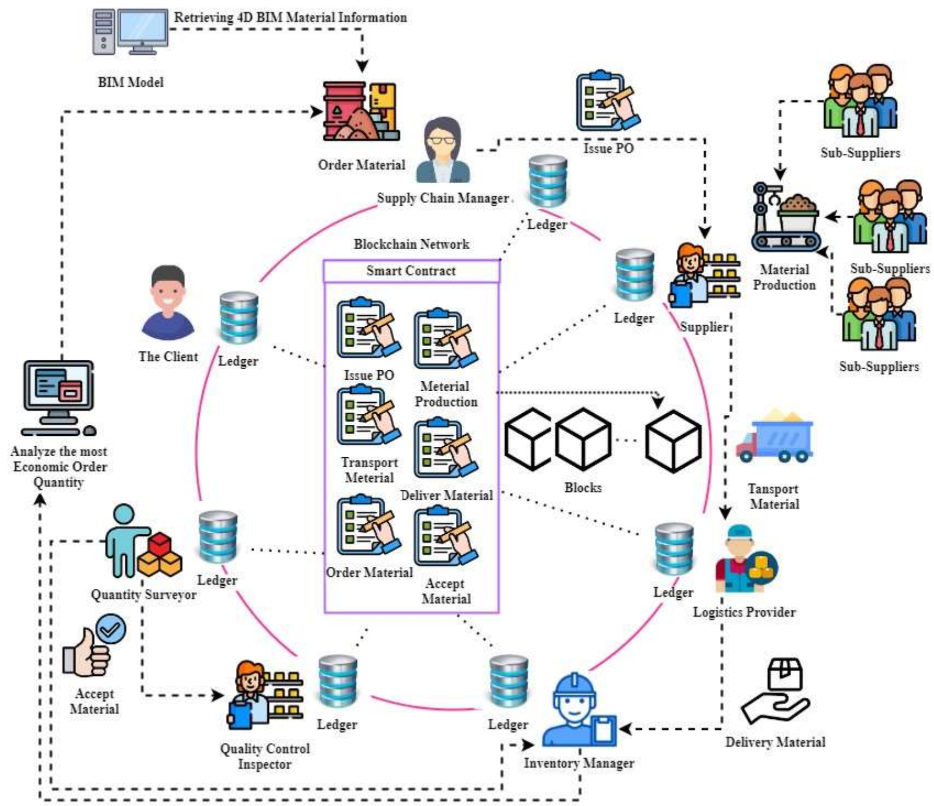

Figure 3. Blockchain-based Construction Material Information Management.

All parties involved in the project will have access to up-to-the-minute material information under the proposed solution to track any changes to the status of materials and compare them to the original data included in the Purchase Order. Five prominent permanent members of the supporting supply chain network will be the client, the supply chain manager, the inventory manager, the inspector of quality control, and the quantity surveyor. Furthermore, as shown in Figure 2, a separate channel allows the smooth addition of pre-approved vendors and logistical providers to the network. As seen in Figure 3 above, every network member has a copy of the ledger, which gives them access to essential details about current and previous purchase orders.

The ordered material is the principal asset inside this pre-existing network, and transactions represent different processes about the item. These processes include handling purchase orders, acquiring materials, transporting them, delivering them, accepting them, and processing payments. The associated client peer must initiate each operation, and for a particular transaction to be processed, agreement among the endorsing peers is essential. This rigorous architecture guarantees the trustworthiness and authenticity of the supply chain network's material transactions. In the organizational framework for chain code operations in material management, as mentioned earlier in the literature study, the various transactions within the framework would be executed in a Hyperledger Fabric context. One advantage of consortium networks is the ease with which new "suppliers and logistic companies" may be added, together with the ability to specify their functions and the means of communication they would use. The suggested chain code is laid forth in the article. It consists of three main categories that branch into eight functions. The three main areas are managing inventories, accessing purchase order information, and issuing and monitoring purchase orders. Blockchain technology has transformed building supply chain management; the consumer orders supply are recorded in a secure ledger.

BIM gives the supply chain manager specific material information, which he sends to the supplier. A blockchain network employs smart contracts to automate and preserve transparency in all transactions, from purchase orders to material fabrication, transit, and delivery. The supplier and logistics provider make supplies and may cooperate with sub-suppliers to deliver them to the construction site. After receiving the materials, a quality control inspector verifies them, and the inventory manager updates the ledger. Quantity surveyors optimize order processes by studying economic order quantities. The blockchain ledger securely records every change and transaction across the supply chain, making it immutable and transparent.

Blockchain Integration:

- Transparency and Trust: Blockchain ensures that every transaction is transparent and trustworthy.
- Automation: Smart contracts automate the process, reducing the need for manual intervention.
- Security: The decentralized nature of blockchain provides a secure environment where data tampering is nearly impossible.

This system highlights the efficiency, security, and transparency that Blockchain technology can bring to supply chain management, particularly in the construction industry. Hyper ledger Fabric intelligent contract formulation for transaction-based use case when implementing blockchain technology into materials supply management, it is necessary to study current practices closely and improve them by adding logical statements and optimizing mathematical equations. It adds beginning and ending dates to all model components in 4D BIM models. As a result, it is possible to derive material take-off schedules for each model element associated with its installation date. Predominantly, these timetables will address permanent content. The following may be used to create material planning schedules after exporting the schedules to XLS format and taking each material lead time into account it can be expressed as equation (4),

$$Order\ date\ = Installation\ date\ - Material\ lead\ time\ (days) \tag{4}$$

The term "Material lead time" refers to the time it takes for the material to be transported, delivered, accepted, and handled until it reaches the point of installation. In engineering design, the decision-making process typically has four phases: defining potential solutions, assessing performance, interpreting performance, and synthesizing. As seen in Figure 4, the connection of uncertainties in each of these four processes leads to a misguided conclusion. Correctly addressing the problem of decision-making assistance requires understanding these phases and any uncertainty associated with them. Prioritizing and quantifying the value of different discipline inputs is done using the AHP. Criteria such as expertise needs, project phase significance, and communication dependencies are employed for this purpose.

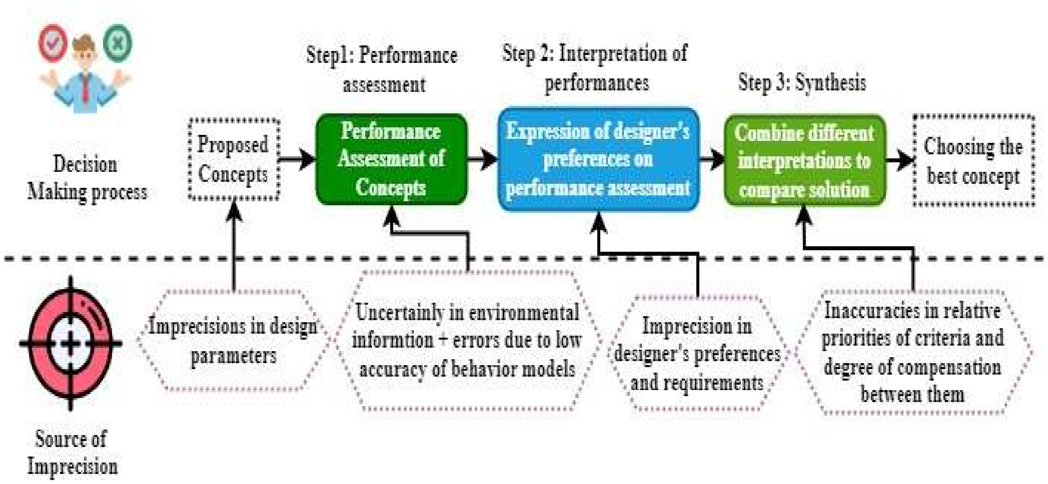

Figure 4. Decision-making process in engineering design.

Step 0:
Potential answers are outlined. Potential answers are below, which are ideas for new designs. Development engineers make do with an inaccurate depiction of the design (imprecise specification of design parameters) while an idea is still in its early stages of development since they lack the expertise to provide a more detailed description. Although there are a variety of possible values for a design parameter, engineers may have preferences for one of those values over another. Their understanding of the topic and their own experiences may inform this. It is challenging to compare ideas when design parameters are described in a blockchain way.
Step 1: Performance assessment
To ensure that the original requirements are met, it is necessary to evaluate the performance of each idea in terms of mass, maximum stress, carbon footprint, and so on. Various types of behaviour models (such as mechanical testing, expert opinions, and finite element models) are used to evaluate these performances, and these models have the potential to be mistaken. Performance evaluations also need data about the outside world, which only sometimes ensures that the original requirements are met; each idea's performance in terms of mass, maximum stress, carbon footprint, and so on must be evaluated reliably. Due to its flexibility, the model's performance changes depending on the project's complexity, size, and needs. The approach is very efficient for smaller projects with fewer disciplines because it streamlines decision-making and communication routes due to the decreased scope. This speeds up the Total Average Communication Level (TACL) optimization. The model's capacity to handle big datasets, different fields of study, and complex decision-making hierarchies determines how well it performs on bigger and more complicated tasks. Incorporating AI-driven algorithms guarantees scalability via the dynamic allocation of resources and the identification of crucial decision nodes, even if this raises computing demands. The model uses the Analytic Hierarchy Process (AHP) to change its weighting criteria and prioritize critical disciplines in complicated circumstances to keep costs down, communication up, and project results high. The validation findings show that the model maintains its strong accuracy and decision-making efficiency across different project sizes, while complexity makes processing time a little longer.
Step 2: Interpretation of performances
The decision-makers rank the performance evaluations in order of preference, considering their needs and goals. When it comes to engineering design, design-making may be more challenging. Designers' preferences and criteria could be more precise, clearer, and more manageable at the early stages of the design process. The term "acceptance threshold" will be used throughout this article to describe the minimum performance requirements a notion must meet to be acceptable. On the other hand, it can be verified.
Step 3: Synthesis
Combining interpretations of the many performances gives the decision-maker a holistic opinion. This global assessment is essential when comparing several ideas. At this stage, imprecision might influence the weighting of criteria and the extent to which they are compensated for.

- **Risk criticality index (RCI)**

Determining the danger of utilizing this data follows establishing the precision of the input data. They are worried that this paper won't be able to meet all of the design criteria in time and with our resources. Consequently, it is essential to draw a diagram that links the characterization of input data imprecision to the risk of failing to satisfy design criteria. Failure mode effects analysis (FMEA) is the basis for the methodology used to achieve this goal. Decision-makers and design engineers frequently use this method because it is straightforward to comprehend and implement.
Let RCI_j^Y represent the risk evaluation associated with the non-fulfilment of criteria j for a specific idea Y. The three primary aspects of this risk that have been identified and assessed are the probability of occurrence P_j^Y, the likelihood of detection E_j^Y, and the severity of failing to meet the criteria T_j. This paper can get RCI_j^Y by multiplying these three variables (Equation 5). Finally, by adding all RCI_j^Y (Equation 6), this paper gets the global risk criticality index RCI^Y associated with idea Y. RCI^Y design criteria are there. The next part presents the three components, $P_j^Y . E_j^Y$ and T_j and explains how to calculate them in equation (5) and equation (6),

$$RCI_j^Y = P_j^Y . E_j^Y . T_j \quad (5)$$

$$RCI^Y = \sum_{j=1}^{n} RCI_j^Y \tag{6}$$

The probability of something happening to the concept's performances cannot be established adequately because of the imprecision in describing the design and environmental conditions. This makes it hard for the design engineer to know whether a notion can meet a need. The probability of a design requirement being unsatisfied can be a better alternative to consider. After an idea Y has been evaluated, the performance value is Q_j^Y. This number may represent everything from mass to maximum tension displacement to speed. This determination is necessary to confirm compliance with criteria j. Concerning criteria j, let g_j^Y represent the function that evaluates performance Q_j^Y(Equation 7) concerning design parameters $\vec{e}^Y = (EQ_1^Y, \dots, EQ_o^Y)$and development parameters $FQ_1, .., FQ_o$ in such a way that expressed as equation (7),

$$Q_j^Y = g_j^Y(EQ_1^Y, \dots, EQ_o^Y, FQ_1, .., FQ_o) \tag{7}$$

Methods g_j^Ymay examine performanceQ_j^Y, including formulas, heuristics, expert opinions, physical prototype testing, or finite element analysis. In performanceQ_j^Y, the Vertex approach transfers the imprecision in the input parameters from the function g_j^Y. This approach is seen in Figure 4. The result is a distributed ledger entry for the numberQ_j^Y. The probability of meeting criterion j is calculated as the ratio of all possible values to the overlap surface, which is the intersection of the allowable and potential values ofQ_j^Y. Equations detail the process for calculating this value using the α-cut approach. Numbers eight through ten. T_j is the cut-off for accepted criteria j.

$$BTS_k = 1 - \frac{1}{O}\sum_{j=1}^{O} D^j \tag{8}$$

With:

$$D^j = \begin{cases} 0 & if\ T_j < G_h^j \\ \dfrac{T_j - G_h^j}{G_e^j - G_h^j} & if\ G_h^j < T_j \leq G_e^j \\ 1 & if\ T_j \geq G_h^j \end{cases} \tag{9}$$

And:

$$\begin{cases} G_h^j = b + \dfrac{j}{O} \times (c - b) \\ G_e^j = d + \dfrac{j}{O} \times (e - d) \end{cases} \tag{10}$$

The ability to remove imprecision in evaluating performances $Q_j^Y$is just as significant for decision-makers as the chance of occurrence in (Equation (8)). Therefore, our method considers detectability to determine the probability that performance measures Q_j^Ywill be evaluated accurately within the given time constraints (deadline consideration) and organizational resources (Equation (9)). To find out the chance of detecting criteria j for a particular idea Y, you need to know two things about the input parameters (design or environmental factors): the variation indicesw_j (Equation (10)), which are found using and how these indices affect the performance of the output. d_{kj}^Y represents the impact of input parameter Y on criteria k. Using impact measures j, a design engineer may learn more about the relationship between the inputs and outputs of design calculations when he employs blockchain to describe the input parameters and output performances. Using these metrics, the design engineer may also find out which input factors have the most negligible impact on performance and which have the most effect on output performance. The design engineer may simplify the challenge by fixing the least influential parameters to the most desirable value. A γ-level metric for determining how different input factors affect the final product. This study uses the d_{kj}^{Y} level measure to choose (Equation (11)) E_j^Y. Equation (5) is used to determine the probability of detecting criteria j for a given notion Y.

$$E_j^Y = \sum_{k=1}^{o_Y} d_{kj}^Y w_k^Y + \sum_{k=1}^{o_f} d_{kj}^Y w_k^f \; with \begin{cases} 0 \leq d_{kj} \leq 1 \\ \sum_{k=1}^{o_f+o_Y} d_{kj} = 1 \end{cases} \tag{11}$$

Final detectability E_j^Y is maintained since d_{kj}^Y are normalized. The assessment procedure heavily relied on interpersonal abilities, such as communicating and working together. The abilities in question were evaluated using several tests, including surveys, peer evaluations, and behavioural interviews. We measured people's communication efficacy by looking at their ability to express themselves clearly, listen attentively, and tailor their messages to different audiences. Examining prior team experiences allowed for the evaluation of collaboration abilities, with an emphasis on cooperation, conflict resolution, and the capacity to make meaningful contributions in interdisciplinary contexts. Social network analysis and AI-powered personality assessment techniques were also used to determine team compatibility and the possibility of encouraging fruitful connections. This technique optimized technical and interpersonal dynamics for project success by including these soft skills in the evaluation. It guaranteed a well-rounded assessment. Besides technical abilities, qualitative and quantitative methods were used to evaluate designer compatibility. Interpersonal characteristics, including communication style, flexibility, and collaborative inclinations, were assessed using behavioural profiling instruments and team dynamics analysis. Network analysis, which looked at previous project interactions to find designers with similar work styles and records of productive cooperation, further improved compatibility criteria. Surveys and expert assessments further illuminated designers' capacity to mesh with team culture and project objectives.

The teams were selected using a multi-dimensional strategy considering technical competence while encouraging a cohesive work atmosphere to improve project efficiency and results. The AI-BC-CEP method streamlines complicated engineering project management, decision-making, and communication by combining blockchain technology with AI-driven decision-making models. Artificial intelligence (AI) can now anticipate hazards, provide real-time decision assistance, and guarantee effective cross-disciplinary resource allocation using the AI-BC-CEP technique, which improves existing approaches that depend on separate tools or systems. On the other hand, blockchain technology guarantees that all project data is authentic, allowing for secure and transparent communication amongst all parties involved and making every decision throughout the project traceable and auditable. Differentiating this strategy from previous ways is its capacity to dynamically adjust to changes in the project, deal with unexpected obstacles, and improve real-time multidisciplinary collaboration. Engineering projects are notoriously difficult and time-sensitive to manage, yet AI-BC-CEP provides a complete solution by integrating AI's predictive capabilities with blockchain's data security and transparency features. Prioritizing and quantifying the value of different discipline inputs is done using the AHP. Criteria such as expertise needs, project phase significance, and communication dependencies are employed for this purpose.

3 Result and Discussion

Using the blockchain's immutable record with AI algorithms allows for a trustworthy data flow and quicker and better decision-making. This synergy reduces the risk of biases and mistakes by using reliable facts to inform judgments. The blockchain promotes confidence and cooperation by ensuring everyone involved in a project can see the same information. Project results may be optimized using AI's predictive skills, which can improve risk management and resource allocation. To wrap things up, this paper has covered how AI and blockchain may work together to build a robust system that enhances engineering project management efficiency and decision-making in complicated settings. The performance of the proposed AI-BC-CEP model has been analyzed based on metrics such as cost reduction ratio, predictive maintenance ratio, decision-making ratio, and demand forecast compared to other existing models such as IF-ANP [16] and DAI-DSS [17].

Dataset: This research uses discursive psychology (DP) to examine how sustainable design conversations generate and regulate three psychological concepts: personal values, responsibility, and decision-making. Video recordings of design conference panel discussions and semi-structured interviews with sustainable product designers were used for this study. Jefferson's notations indicate loudness, pauses, pace changes, and laughter in the data. This clarifies conversational language and behaviours. Excerpts focus on designers' discourse on design choices and other decision-making processes, how personal ideals affect their work, and how they build sustainability-related responsibilities. Analyzing interactional speech sequences illuminates designers' self-presentation [21]. By splitting the data into training and testing subsets, cross-validation assesses the generalizability of the machine learning models used in the framework to predict outcomes. In scenario-based testing, the framework's adaptability and accuracy in impact forecasts are examined by simulating different project circumstances and decision-making situations.

3.1 Cost Reduction

Multiple case studies or simulated settings were used to analyze project results, cost savings, and efficiency gains to determine the long-term effect of combining AI and blockchain technology in decision-making. This study measured efficiency by looking at how quickly projects were completed, how much money was saved, and how long it took to make decisions. Cost savings were evaluated by comparing the AI-Blockchain integrated method to conventional decision-making procedures, emphasizing reducing mistakes, downtime, and duplicate work. Quality standards, timeliness, and stakeholder satisfaction were additional metrics used to assess project results, with blockchain technology facilitating transparency and responsibility in decision-making processes.

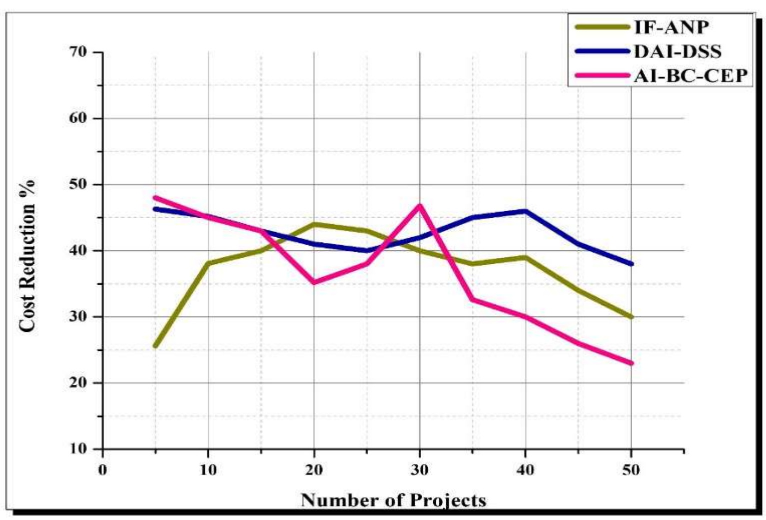

Figure 5. Cost Reduction.

Figure 5 displays the Cost Reduction curves of the refined AI-BC-CEP composites, as determined by Equations 1 to 3. The graph shows the cost reduction percentages for three approaches—IF-ANP, DAI-DSS, and AI-BC-CEP—over various projects. At first glance, the AI-BC-CEP method seems somewhat effective, with savings beginning at around 50%. By the 50th project, however, its efficacy had dropped to about 20%, and it had fallen precipitously with increasing project counts. The IF-ANP method, on the other hand, starts with a smaller decrease in costs but stays very consistent, varying by around 40% across projects. The DAI-DSS method also maintains initial cost reductions of 45–50%, but after the 50th project, the process starts to decline and ends up with savings of just over 30%. Compared to the more consistent patterns shown in IF-ANP and DAI-DSS, AI-BC-CEP delivers a considerable decrease in costs at the outset but sees a sharp decline in performance as the number of projects increases. AI algorithms analyze dynamic inputs from Internet of Things (IoT) sensors, project tools, and external sources to provide ongoing, data-driven updates to decision-making processes. For example, predictive models may spot possible hazards, and real-time resource availability or building progress data might guide scheduling or resource allocation modifications. By digitally recording changes and decisions, blockchain technology creates an immutable audit trail, guaranteeing transparency and traceability.

3.2 Predictive Maintenance

To evaluate time-series equipment data to forecast failures, the model used AI-driven algorithms such as Gradient Boosting Machines (GBMs) and Long Short-Term Memory (LSTM) networks, which are predictive maintenance models. Models like ARIMA and Prophet were able to capture patterns and seasonality in demand forecasting, while Random Forests and ensemble learning enhanced accuracy under variable circumstances. Reward systems and trial-and-error learning were the backbone of reinforcement learning (RL) frameworks, which improved decision-making. A combination of historical datasets, cross-validation methods, and real test scenarios was used to validate. Model performance under changing project circumstances was assessed using real-world pilot testing and reliability metrics such as precision/recall scores, Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE).

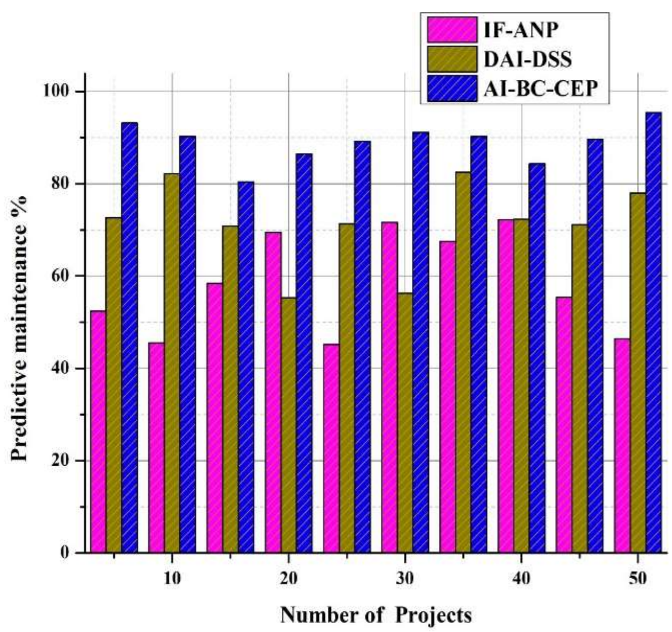

Figure 6. Predictive Maintenance.

Figure 6 displays the Predictive Maintenance curves of the refined AI-BC-CEP composites as determined by Equations 5 to 7. Over a range of project counts, the bar chart compares the predictive maintenance efficacy of three methods: IF-ANP, DAI-DSS, and AI-BC-CEP. The AI-BC-CEP method, which is representative of, typically achieves 80% or higher predictive maintenance percentages across all projects. The results show that although not as effective as AI-BC-CEP, the DAI-DSS method consistently achieves respectable results (often in the 70-80% range). The usual range for the predicted maintenance percentages shown by the IF-ANP method is between fifty and seventy per cent. According to the general trend, AI-BC-CEP has a better capacity to keep predictive maintenance levels high across many projects, which might be crucial in complicated engineering settings.

3.3 Decision Making

By enhancing decision-making, guaranteeing transparency, and decreasing operating costs, these technologies highlight the practical benefits of AI-driven blockchain solutions within the context of complicated engineering projects. Predictive maintenance is improved by AI's capacity to collect and interpret real-time data, which reduces downtime and increases equipment life. Important for reducing risks and increasing accountability, blockchain's decentralized and unchangeable nature guarantees data integrity by creating a safe and visible record of project decisions, contracts, and transactions. When used in tandem, these technologies provide a solid foundation that engineering projects may use to save money, operate more efficiently, and produce better results by responding fast to changes, accurately predicting future needs, and allocating resources to their full potential.

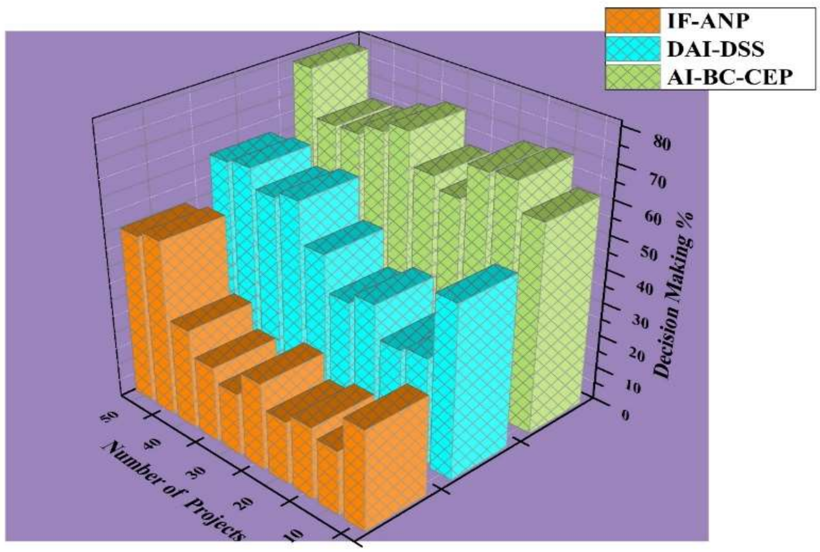

Figure 7. Decision Making.

Figure 7 displays the refined AI-BC-CEP composites' decision-making curves, as determined by Equations 8 to 10. With percentages typically reaching or above 70%, the AI-BC-CEP strategy regularly demonstrates the best decision-making efficacy. While the DAI-DSS method also delivers respectable results, its efficacy is usually between 50% and 70% lower. The IF-ANP method is perpetually behind the other two approaches; its decision-making efficacy is often below 50%. According to this investigation, AI-BC-CEP is the best method for making decisions in complicated engineering projects, and its performance stays high even as the number of projects grows. Projects necessitating very precise and consistent decision-making may not be well-suited to DAI-DSS since, while effective, it falls short of AI-BC-CEP, and IF-ANP demonstrates the lowest overall decision-making efficacy.

3.4 Demand Forecasting

The model incorporates adaptive decision-making algorithms and real-time data analysis to adjust for unexpected problems or changes in project needs. To detect new problems or changes in the project's scope, AI constantly processes data from various multi-disciplinary sources, including engineering, finance, and logistics. Maintaining openness and offering a clear audit trail, blockchain guarantees that all updates and changes are securely recorded. The technique uses predictive analytics to identify impediments or breakdowns in multi-disciplinary communication and then makes proactive modifications to overcome them. By being agile and responsive, the project team can meet changing demands, keep everyone in the loop, and lessen the blow of any unexpected that may develop.

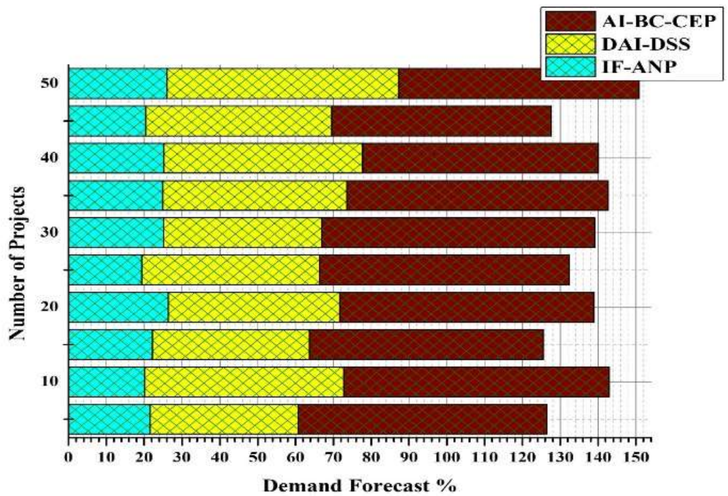

Figure 8. Demand Forecasting.

Figure 8 displays the Demand Forecast curves of the refined AI-BC-CEP composites, as determined by Equations 11. With demand projections that often surpass 100% and reach up to 150% as the number of projects rises, the AI-BC-CEP strategy regularly surpasses the others. It seems that the demand predictions are quite accurate and dependable. Alternatively, the DAI-DSS method still gets the job done but only gets somewhat accurate demand projections (between 50% and 90%). Regarding reliably estimating demand, the IF-ANP technique falls far behind, with projections often remaining below 50%. Regarding complicated project contexts, AI-BC-CEP is the best demand forecasting method. Different discipline responsibilities are given weights according to their significance and contribution to the project's goals using the Analytic Hierarchy Process (AHP). This will prioritize important skills while reducing unnecessary or ineffective positions. Furthermore, the technique incorporates cost-benefit analysis to assess the potential financial impact of employment selections concerning the anticipated enhancements in communication efficiency and project results. The system finds the most economical team configurations that get a TACL score high enough to improve teamwork and decision-making using AI-driven optimization algorithms.

4 Conclusion

In conclusion, using artificial intelligence-powered blockchain technologies is a revolutionary way to enhance decision-making in challenging engineering projects. The present study proposes a solution for assisting decision-makers before executing the choice. This solution involves projecting the influence of complicated decisions while the decision is still in the planning phase of the decision-making process. According to what was described, this solution is an example of a collaborative method. It enables decision-makers to communicate their experiences and knowledge to find common ground for their chosen duties. This helps evaluate and predict complex choices. These technologies improve project performance by combining artificial intelligence in data analysis and prediction with blockchain technology's openness and security. The comparative study shows that AI-BC-CEP beats traditional systems in cost, predictive maintenance, and demand prediction. This indicates that blockchain systems backed by artificial intelligence may enhance decision-making and manage complicated engineering projects efficiently, accurately, and reliably.

These new technologies must be adopted to be competitive and succeed because engineering projects will get more complex and extensive. After considering these data, longitudinal studies should be investigated to evaluate the long-term benefits of blockchain-based material management systems throughout a project. Additionally, new digital technologies should be considered for construction material management. IoT sensors, RFID, and blockchain technologies might automate inventory management and purchase order distribution to prospective suppliers. The experimental results demonstrate that the proposed AI-BC-CEP model increases the cost reduction ratio by 21.2%, predictive maintenance ratio by 95.6%, decision-making ratio by 85.3%, and demand forecast by 97.4% compared to other existing models. Future research might combine blockchain technology with digital twins to give project stakeholders comprehensive and transparent materials. These promising operations boost construction material chain efficiency and effectiveness.

Acknowledgement

Conflicts of interest

The authors declare no conflict of interest.

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