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Fuzzy Integrated Delphi-ISM-MICMAC Hybrid Multi-Criteria Approach to Optimize the Artificial Intelligence (AI) Factors Influencing Cost Management in Civil Engineering

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Abstract: This research paper presents a comprehensive study on optimizing the critical artificial intelligence (AI) factors influencing cost management in civil engineering projects using a multi-criteria decision-making (MCDM) approach. The problem addressed revolves around the need to effectively manage costs in civil engineering endeavors amidst the growing complexity of projects and the increasing integration of AI technologies. The methodology employed involves the utilization of three MCDM tools, specifically Delphi, interpretive structural modeling (ISM), and Cross-Impact Matrix Multiplication Applied to Classification (MICMAC). A total of 17 AI factors, categorized into eight broad groups, were identified and analyzed. Through the application of different MCDM techniques, the relative importance and interrelationships among these factors were determined. The key findings reveal the critical role of certain AI factors, such as risk mitigation and cost components, in optimizing the cost management processes. Moreover, the hierarchical structure generated through ISM and the influential factors identified via MICMAC provide insights for prioritizing strategic interventions. The implications of this study extend to informing decision-makers in the civil engineering domain about effective strategies for leveraging AI in their cost management practices. By adopting a systematic MCDM approach, stakeholders can enhance project outcomes while optimizing resource allocation and mitigating financial risks.

Keywords: artificial intelligence; cost management; civil engineering projects; Delphi; interpretive structural modeling; MICMAC; multi-criteria decision-making

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1. Introduction

Effective cost management is a critical issue in civil engineering projects, especially given the increasing complexity and scale of construction activities. As economic conditions fluctuate, robust cost management strategies are essential to avoid cost overruns and delays, which can undermine project success and stakeholder satisfaction [1]. These issues often arise from inadequate cost management, and addressing them is crucial for ensuring the viability and sustainability of civil engineering projects. This research aims to optimize AI factors to improve cost efficiency, reduce financial risks, and ultimately enhance project outcomes. This aligns with the broader goal of ensuring that civil engineering projects are successful and sustainable. The need for innovative methodologies to boost cost management and reduce financial risks is more pressing than ever. With the rapid advancements in AI technologies, AI applications like predictive analytics, machine learning, and autonomous systems offer new ways to improve traditional cost management practices [2]. These AI tools can provide real-time monitoring, detect potential cost overruns early, and support proactive decision-making to mitigate risks. By leveraging these technologies, civil engineering projects can enhance their cost management strategies and improve their overall project performance.

Integrating AI factors into the cost management frameworks in civil engineering remains a complex and evolving challenge. This complexity arises from the multifaceted interactions among stakeholders, technical specifications, environmental considerations, and regulatory requirements [1,2]. Furthermore, uncertainty and ambiguity in project data, along with the dynamic nature of construction, complicate AI's implementation in cost management. To address these challenges, this research proposes a novel methodology: the fuzzy integrated Delphi-ISM-MICMAC hybrid multi-criteria approach [3]. This approach combines fuzzy sets, the Delphi method, ISM, and MICMAC to optimize the AI factors in civil engineering cost management. By incorporating this hybrid approach, this research aims to overcome the inherent complexities in and contribute valuable insights to the field.

Civil engineering projects are complex, involving various factors like material costs, labor, equipment rentals, and compliance with regulations. The addition of AI technologies introduces further intricacies. To effectively navigate these complexities, a systematic approach is needed to optimize AI's role in cost management. The rapid development of AI offers opportunities to improve cost estimation, budget allocation, and resource management through predictive analytics, machine learning, and autonomous systems. Given this potential, this research aims to develop methods that fully leverage AI in cost management. With growing competition and pressure to complete projects on time and within budget, there is a rising demand for innovative cost management strategies in civil engineering. This research seeks to meet those demands by providing practical tools and methodologies to optimize AI factors for better cost efficiency and project outcomes. In summary, the motivation of this research is the need to address civil engineering complexities, harness AI's potential, advance industry knowledge, and fulfill the demand for innovative cost management solutions.

Incorporating fuzzy sets into the Delphi-ISM-MICMAC framework allows for managing uncertainties and imprecise data in real-world decision-making. This combination of fuzzy logic with Delphi, ISM, and MICMAC analyses offers a novel way to optimize AI factors in cost management. This research aims to advance MCDM knowledge and create innovative methodologies to tackle the real-world challenges in civil engineering. By integrating these MCDM tools, this study provides a structured framework to identify, evaluate, and prioritize the AI factors relevant to cost management in civil engineering [3,4]. This research takes a holistic approach that considers the interdependencies and dynamic interactions between AI factors, aiming to offer insights into using AI technologies strategically for cost optimization in civil engineering projects. This hybrid methodology helps bridge the gap between theoretical AI advancements and practical cost management in civil engineering [4]. The findings of this study could guide decision-makers, practitioners, and researchers, contributing to the advancement of cost management practices in civil engineering.

This research is significant for its theoretical insights and practical applications, providing industry practitioners with a roadmap to manage the complexities of cost management in an AI-driven world [5]. By linking theory with practical application, it offers a transformative framework poised to redefine cost management in the civil engineering sector. This study represents a pioneering effort to revolutionize cost management practices through a fuzzy integrated Delphi-ISM-MICMAC hybrid multi-criteria approach [2,3]. The research addresses the urgent need for improved cost optimization strategies in civil engineering projects. By creating a structured approach to optimize the AI factors involved in cost management, this hybrid model not only advances theoretical knowledge but also delivers practical solutions to real-world industry challenges. This research is a significant step toward enhancing cost management efficiency, reducing financial risks, and promoting innovation within the civil engineering field, setting the stage for sustainable project success in the future [6]. Let us now explore the potential implications of this research across several key areas:

- This research presents a systematic approach to optimizing the AI factors in civil engineering cost management by combining fuzzy sets, the Delphi method, ISM, and a MICMAC analysis. This hybrid approach offers decision-makers a comprehensive framework to improve cost management's efficiency and effectiveness.
- By utilizing MCDM techniques, this research helps stakeholders make informed choices about selecting, prioritizing, and implementing AI technologies in cost management. The proposed approach takes into account the interdependencies among AI factors, aiding strategic decision-making.
- Optimizing key AI factors also contributes to reducing the financial risks of civil engineering projects. Effective cost management ensures project viability, profitability, and stakeholder satisfaction. The proposed method identifies cost-saving opportunities, predicts potential cost overruns, and proactively addresses financial risks, ultimately leading to better project outcomes.
- Integrating fuzzy sets, the Delphi method, ISM, and MICMAC represents a novel application of MCDM for optimizing the AI factors in civil engineering cost management. This research contributes to the field by showcasing the effectiveness of this hybrid approach in tackling complex decision-making challenges in real-world settings.
- The research findings have practical implications for industry practitioners, including project managers, engineers, and policymakers in civil engineering. By offering actionable insights and recommendations, this study provides stakeholders with tools and methodologies to effectively use AI for cost optimization in civil engineering projects.

Problem Statement

The key issue addressed by this research is the challenge of effectively managing costs in civil engineering projects, especially with their growing integration of AI technologies. These projects are complex, with many variables such as material costs, labor expenses, equipment rentals, and unforeseen circumstances like weather or regulatory changes. Traditional cost management relies on experience-based decisions, historical data, and standardized cost estimations. However, these methods often fall short due to the dynamic nature of construction, leading to cost overruns and delays [7]. The rapid advancement of AI technologies presents potential solutions through its predictive capabilities, data-driven insights, and automation of routine tasks. AI applications like machine learning, predictive analytics, and autonomous machinery can optimize cost management, improve project efficiency, and reduce financial risks. Despite these benefits, the effective integration of AI into cost management frameworks remains a challenge. Selecting, prioritizing, and implementing AI technologies in civil engineering requires careful consideration of their relevance, impact, and interdependencies. The problem statement, therefore, calls for a systematic methodology to optimize the AI factors involved in the cost management of civil engineering projects [8]. This approach must consider the complex interactions among AI factors, the uncertainties in project data, and the ever-changing construction environment. Additionally, it should offer decision-makers actionable insights for strategic interventions and resource allocation. To address these challenges, the proposed research introduces a fuzzy integrated Delphi-ISM-MICMAC hybrid multi-criteria approach, providing stakeholders with a comprehensive framework to improve cost management's efficiency and effectiveness in civil engineering projects [9]. This research aims to leverage AI technologies to optimize cost management practices and deliver practical solutions to industry stakeholders.

2. Literature Review

Effective cost management in civil engineering projects is crucial for project success, stakeholder satisfaction, and profitability. The recent spread of AI technologies across various sectors has fueled the interest in using AI to improve cost management in civil engineering [10]. This literature review explores key concepts, methodologies, and past studies that relate to optimizing AI factors for cost management in civil engineering, emphasizing the fuzzy integrated Delphi-ISM-MICMAC hybrid multi-criteria approach.

According to Song et al. [11], cost management is paramount in civil engineering projects to ensure that projects are completed within budget constraints and deliver value for stakeholders. Liao et al. [12] stated that effective cost management practices are crucial for achieving project objectives, meeting client expectations, and optimizing resource allocation. Studies by Qiang et al. [13] emphasized the significance of cost management in enhancing project efficiency and mitigating financial risks. Various cost estimation techniques are employed in civil engineering projects to forecast project expenses accurately. Zarei et al. [14] outlined a parametric estimation that utilizes mathematical models and historical data to estimate costs based on project parameters. Wakjira et al. [15] discussed analogous estimating that involves the use of past similar projects as benchmarks for cost estimations. These techniques are vital for providing early cost projections and guiding budgetary decisions. Budgeting and cost control are essential components of effective cost management in civil engineering projects. Ahsan [16] emphasized the importance of budgeting in allocating financial resources to project activities. Sahoo et al. [17] described cost control parameters, which involve monitoring project expenses, identifying variances, and implementing corrective actions to maintain adherence to the budget.

Civil engineering projects also face various challenges in cost management, including inaccurate cost estimations, scope changes, and material price fluctuations. Khazaelpour and Zolfani [18] highlighted the challenge of accurately estimating costs due to uncertainties and dynamic project conditions. Son and Khoi [19] discussed the complexities of managing costs in large-scale infrastructure projects, emphasizing the need for proactive risk management strategies. Technological advancements have transformed cost management practices in civil engineering. Abualigah et al. [20] studied the integrated project management systems that streamline the cost estimation and budgeting processes by centralizing project data and facilitating collaboration among stakeholders. Khademian [21] demonstrated Building Information Modeling (BIM), which enhances cost management by providing accurate 3D models for cost estimations and project visualization. Sustainability considerations and lifecycle costing have gained prominence in civil engineering projects as well. Song et al. [22] advocated for sustainable construction practices to minimize environmental impact and promote long-term economic viability. Khodabakhshian et al. [23] highlighted the importance of lifecycle costing in assessing the total cost of ownership over a project's lifecycle, including construction, operation, and maintenance costs.

In summary, cost management is a critical aspect of civil engineering projects, influencing project outcomes, stakeholder satisfaction, and project sustainability. Effective cost management practices rely on accurate cost estimation, proactive budgeting, and robust cost control measures. Technological advancements, sustainability considerations, and lifecycle costing have reshaped the cost management practices in civil engineering, offering new opportunities for improving project outcomes and stakeholder satisfaction.

2.1. The Role of Artificial Intelligence in Cost Optimization

AI has attracted considerable interest for its role in cost optimization across various industries, including civil engineering, where cost management is vital for project success and profitability. This literature review explores key concepts, methodologies, and prior studies on AI's impact on cost optimization. AI comprises a spectrum of technologies like machine learning, natural language processing, and predictive analytics, all of which can be used to optimize costs across multiple industries [12]. In civil engineering, AI offers the potential to transform cost optimization practices by delivering data-driven insights, predictive capabilities, and the automation of routine tasks [9,10]. AI algorithms can process large volumes of project data, detect patterns, and produce accurate cost estimates, allowing project managers to make more informed decisions and reduce financial risks [13].

Machine learning algorithms like regression analyses, decision trees, and neural networks are extensively used for cost estimation in civil engineering projects [21]. They analyze historical project data—such as project specifications, materials, labor costs, and project durations—to predict future costs [22]. These models learn from past data to identify cost drivers, estimate project budgets, and optimize resource allocation, thereby enhancing cost efficiency and project outcomes [9]. Predictive analytics techniques, including risk modeling and Monte Carlo simulation, are used to evaluate and mitigate the financial risks in civil engineering projects [7,8]. These techniques examine project variables and external factors, such as market conditions, regulatory changes, and weather patterns, to forecast potential cost overruns and schedule delays [21]. By identifying risks early in the project lifecycle, predictive analytics helps project managers develop risk mitigation strategies, allocate contingency funds, and improve project planning and execution [13].

AI technologies automate the routine tasks in cost optimization, including data collection, analysis, and reporting [15]. Natural language processing (NLP) can extract the relevant information from project documents, contracts, and reports, streamlining cost estimation and budgeting [16]. Robotic Process Automation (RPA) tools further enhance efficiency by automating repetitive tasks like invoice processing and payment tracking, reducing manual errors [17,18]. The integration of AI with Building Information Modeling (BIM) presents new avenues for cost optimization in civil engineering projects [13,14]. BIM models contain detailed information about project components, materials, and quantities, which AI algorithms can use for cost estimations, quantity takeoff, and value engineering [19]. This combination of BIM data with AI-driven analytics allows project stakeholders to optimize costs, improve decision-making, and enhance project collaboration and communication [20,21].

In conclusion, AI is crucial for cost optimization in civil engineering projects, providing advanced analytics, predictive capabilities, and the automation of routine tasks. Machine learning algorithms, predictive analytics, and automation tools help project managers optimize costs, reduce risks, and improve project outcomes. Integrating AI with Building Information Modeling (BIM) enhances these practices, offering stakeholders actionable insights and enabling data-driven decision-making in civil engineering projects.

2.2. Previous Studies Involving the Fuzzy Integrated Delphi-ISM-MICMAC Hybrid MCDM Model

Previous studies involving the fuzzy integrated Delphi-ISM-MICMAC hybrid MCDM model have demonstrated its effectiveness in addressing complex decision-making problems across various domains. Fuzzy sets are a mathematical approach that the handles uncertainty and imprecision in decision-making processes by assigning degrees of membership to linguistic terms [23]. In the context of MCDM, fuzzy sets enable decision-makers to express subjective preferences and uncertainties in a quantitative manner, facilitating the integration of qualitative and quantitative criteria in decision-making models [24]. Studies by Zhan et al. [25] have highlighted the applicability of fuzzy sets in handling vagueness and ambiguity in decision-making problems. The first method, Delphi, is a structured communication technique used to gather and distill the knowledge and opinions of experts on a particular subject [17]. In the context of MCDM, the Delphi method is often employed to elicit expert judgments and preferences regarding decision criteria, weights, and alternatives [8]. Previous studies by Onyelowe et al. [2] demonstrated the effectiveness of the Delphi method in achieving consensus among experts in decision-making processes.

Yenugula et al. [2] applied the Delphi technique to elicit expert judgments on multi-criteria decision-making in the context of environmental management and discussed the integration of the Delphi method with an Analytic Hierarchy Process (AHP) for decision-making in complex systems. Wang et al. [4] utilized the Delphi method to determine the weights for criteria in a fuzzy AHP framework for supplier selection and also evaluated the effectiveness of the Delphi method in achieving consensus among experts during decision-making processes within healthcare management. Abbasnejad et al. [5] conducted a systematic review assessing the reliability and validity of the Delphi method in various fields, including business, healthcare, and education. They also discussed the application of the Delphi method in technology forecasting and innovation management, highlighting its utility in addressing uncertainties and eliciting expert opinions. Al Awadh and Mallick [6] explored the use of the Delphi method in healthcare research, emphasizing its role in synthesizing diverse perspectives and generating consensus among stakeholders. They examined the application of the Delphi method in urban planning, demonstrating its effectiveness in eliciting expert judgments for decision-making in complex urban environments. Ünal et al. [7] proposed modifications to the traditional Delphi method, including the use of online platforms and statistical convergence criteria, to enhance its efficiency and reliability. They introduced the Policy Delphi method, which incorporates structured feedback and iterative rounds of expert consultation to address complex policy issues and decision-making challenges.

The next method, ISM, is used to analyze complex systems and identify the hierarchical relationships among elements [13]. In the context of MCDM, ISM enables decision-makers to visualize and understand the interdependencies among criteria or factors influencing a decision problem [14,15]. Studies by Saglam [26] demonstrated the application of ISM in structuring decision problems and identifying driving and dependent factors. They applied ISM to analyze the factors influencing sustainable supply chain management practices, highlighting its utility in identifying key drivers and relationships. In subsequent research, Saglam [26] also utilized ISM to model the interrelationships among critical success factors for implementing Total Quality Management (TQM) in manufacturing organizations. Nalluri and Chen [27] employed ISM to understand the complex interactions among factors affecting sustainable business performance in the context of green supply chain management. The authors proposed an extension of ISM called fuzzy ISM, which incorporates fuzzy sets to handle the uncertainty and vagueness in the modeling process. Nalluri and Chen [27] also introduced an integrated approach, combining ISM with an Analytic Network Process (ANP) to analyze the interdependencies among critical success factors for sustainable supply chain management. Alshahrani et al. [24] conducted a comparative study of ISM and DEMATEL (Decision-Making Trial and Evaluation Laboratory) techniques for analyzing the factors influencing lean manufacturing implementation, highlighting the strengths and limitations of each approach. Mahdiraji et al. [28] proposed a hybrid approach, combining ISM with graph theory and entropy-based weight determination to prioritize the factors influencing sustainable manufacturing practices. They applied ISM to model the complex relationships among factors influencing the adoption of cloud computing technology in the manufacturing industry, providing insights for decision-makers to prioritize adoption strategies. Kumar et al. [29] presented a case study on the application of ISM to analyze the factors affecting employee engagement in the healthcare sector, demonstrating its effectiveness in identifying key drivers and formulating actionable strategies.

The third technique, MICMAC analysis, is a technique used to assess the relative influence and interactions among factors in a decision-making problem [8]. In the context of MCDM, a MICMAC analysis helps identify driving and dependent factors and their impact on the overall decision problem [8–10]. Previous studies by Zabihi et al. [1] demonstrated the application of a MICMAC analysis in understanding the dynamics of complex decision problems. They applied a MICMAC analysis to identify the key drivers and barriers influencing the adoption of renewable energy technologies in rural areas, highlighting its utility in understanding the dynamics of sustainable energy transitions. Sharma and Kumar [8] utilized a MICMAC analysis to explore the interrelationships among factors affecting innovation capabilities in small and medium enterprises (SMEs), providing insights for enhancing innovative management practices. They proposed an extension of the MICMAC analysis called fuzzy-MICMAC, which incorporates fuzzy sets to handle the uncertainty and imprecision in the assessment of factor interdependencies. Chen et al. [9] introduced a hybrid approach, combining MICMAC analysis with AHP for the prioritizing factors influencing sustainable supply chain management practices, enhancing the robustness of decision-making. Sahoo et al. [10] conducted a comparative study of MICMAC analyses and the DEMATEL (Decision-Making Trial and Evaluation Laboratory) technique for analyzing the factors influencing corporate social responsibility (CSR) performance, highlighting the strengths and limitations of each approach. They also proposed an integrated framework combining a MICMAC analysis with ISM for analyzing the interrelationships among the factors influencing sustainable manufacturing practices, providing a comprehensive understanding of the factor dynamics. Tushar et al. [30] presented a case study on the application of a MICMAC analysis to assess the factors influencing the adoption of green building technologies in the construction industry, facilitating informed decision-making for sustainable construction practices. Nalluri et al. [31] used a MICMAC analysis to understand the dynamics of the factors affecting the consumer adoption of electric vehicles, providing insights for policymakers and industry stakeholders to promote sustainable mobility solutions.

Overall, the fuzzy-enabled Delphi-ISM-MICMAC hybrid MCDM model combines fuzzy sets, the Delphi method, ISM, and a MICMAC analysis together to address complex decision-making problems [32]. This hybrid model combines the strengths of each methodology, enabling decision-makers to handle uncertainty, elicit expert opinions, analyze interdependencies, and assess relative influences effectively. Previous studies by Lianto [32] demonstrated the applicability and effectiveness of the hybrid model in various decision-making contexts, including supply chain management, environmental sustainability, and technology adoption. Zhao et al. [33] applied a fuzzy hybrid MCDM model to evaluate renewable energy technology adoption in the agricultural sector, demonstrating its effectiveness in addressing sustainability challenges. Jain et al. [34] utilized this hybrid concept to prioritize green manufacturing practices in the automotive industry, highlighting its utility in promoting environmental sustainability and competitiveness. Khan et al. [35] proposed an extension of the hybrid model through the integration of fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) for supplier selection in sustainable supply chain management, enhancing decision robustness and accuracy. Pekkaya et al. [36] introduced a novel variant of the hybrid model by incorporating Bayesian networks to analyze the uncertainties and dependencies among the factors influencing green product development decisions. Sahoo et al. [37] conducted a comparative study of the hybrid model and traditional decision-making approaches for evaluating eco-friendly packaging alternatives, demonstrating its superiority in handling complexity and uncertainty. Sánchez-Garrido et al. [38] proposed a hybrid approach integrating the hybrid model with multi-objective optimization techniques for sustainable land use planning, providing decision-makers with optimal solutions considering their economic, environmental, and social objectives. Gupta et al. [39] presented a case study on the application of the hybrid model to assess sustainable transportation alternatives in urban areas, facilitating informed decision-making for urban mobility planning. Khalilzadeh et al. [40] used the hybrid model to prioritize sustainable practices in the food processing industry, supporting stakeholders in identifying opportunities for improving their environmental performance and competitiveness.

2.3. Advantages and Drawbacks of the Adopted MCDM Tools

MCDM has been an effective tool for making precise decisions for decades. The hybrid MCDM concept, combining the Delphi method, ISM, and a MICMAC analysis, integrates diverse perspectives from experts, stakeholders, and decision-makers, ensuring a comprehensive approach to the various factors and relationships affecting the decision problem. The incorporation of fuzzy sets into the hybrid MCDM model addresses the uncertainties and ambiguities in decision-making [4], allowing for a qualitative assessment of the criteria and factors, even amid the imprecision in expert judgments and preferences. The Delphi method promotes consensus-building among experts through iterative feedback, enhancing the credibility of their decisions. ISM helps analyze the structural aspects of decision problems by identifying the hierarchical relationships among factors [41], providing insights into which factors drive or depend on others. This hierarchy aids decision-makers in prioritizing actions and allocating resources effectively. A MICMAC analysis examines the relative influence and interactions among factors, distinguishing between driving and dependent factors [5]. This analysis helps us understand the complexity of decision problems, allowing decision-makers to focus on the critical factors that significantly impact outcomes.

The hybrid MCDM concept is flexible and adaptable, suiting various decision contexts and problem domains. It accommodates a wide range of criteria, factors, and decision alternatives, making it useful across fields like civil engineering, environmental management, and healthcare. By integrating multiple decision-making methodologies, this hybrid concept leverages the strengths of each approach, resulting in more comprehensive and accurate decisions. This hybrid approach enhances decision quality by considering multiple perspectives, factors, and uncertainties [6]. It reduces the reliance on any single methodology, thereby increasing the robustness and reliability of the decision-making process. Combining different techniques mitigates the limitations and biases of individual methods, leading to more robust outcomes [42]. The flexibility of the hybrid approach allows decision-makers to customize the process to fit specific requirements, based on the problem's complexity, available data, and stakeholder preferences. The hybrid concept can address various aspects of decision-making, such as criteria selection, weighting, ranking, and sensitivity analyses. This comprehensive view helps decision-makers make well-rounded choices. Additionally, the hybrid approach exploits the synergy between different methodologies, yielding better insights, more accurate predictions, and improved decision recommendations. This flexibility and adaptability cater to diverse decision-making needs, boosting stakeholders' confidence in the process and the reliability of the results.

Given the stated benefits, the authors found it appropriate to use the Delphi, ISM, and MICMAC decision-making models for the current analysis. No other alternative MCDM tools can replace these models [5,6]. The hybrid approach built with these models enables consensus building through iterative feedback, establishes the hierarchical relationships among factors, identifies driving and driven factors, and effectively handles the imprecision and uncertainty in expert judgments.

Despite these advantages, the hybrid model has limitations. Combining multiple methodologies like Delphi, ISM, MICMAC, and fuzzy sets can be time-consuming and create a complex framework. Implementing this hybrid approach requires considerable expertise and resources, posing challenges for its users [4,5]. The reliance on expert judgments in Delphi and ISM can introduce subjectivity and bias into the decision-making process, leading to results influenced by individual opinions. The effectiveness of this hybrid approach depends on the availability of accurate and reliable data. Obtaining such data, especially for fuzzy set-based components, may be challenging and potentially affect decision accuracy. Analyzing the interrelationships among factors with ISM and MICMAC can be computationally complex, particularly with many factors, limiting the scalability of this hybrid concept to larger problems. Additionally, parameterizing fuzzy set-based components, like membership functions and fuzzy rules, requires careful calibration and validation, making it difficult to determine accurate parameter values [41,42]. Despite these drawbacks, the benefits are compelling, motivating the authors to adopt these tools for the ongoing analysis. Its advantages in consensus-building, structured analysis, and the handling of uncertainty make the hybrid concept a valuable approach, despite its complexities and challenges.

2.4. Research Gaps and the Novelty of the Research

The existing literature shows that fuzzy integrated hybrid MCDM models have been used in various domains like supply chain management, environmental sustainability, and technology adoption. However, there is a lack of research applying these models specifically to cost management in civil engineering projects. Additionally, no prior studies have combined the Delphi, ISM, and MICMAC methods to tackle a decision-making problem. Moreover, previous research has not extensively explored the integration of AI factors into decision-making processes, indicating that there is a gap in our understanding of how AI can optimize cost management in civil engineering. The proposed research aims to fill this gap by integrating AI factors into a fuzzy hybrid model designed specifically for the cost management of civil engineering projects. This approach acknowledges AI's growing role in construction and its potential to enhance cost optimization. The focus on civil engineering includes unique challenges such as project scope, resource allocation, and regulatory constraints. The research also explores innovative techniques to integrate AI into the decision-making framework, including new algorithms and models to analyze AI's impact on cost management decisions, enhancing accuracy and efficiency.

To address the noted gaps and improve the cost management practices in civil engineering, the authors formulated research questions, guiding this investigation into developing and applying this hybrid model. This article aims to answer these questions and contribute to advancing cost management within the field.

Q1: What are the key AI factors that influence cost management in civil engineering projects?
Q2: How can expert opinions and consensus be elicited to determine the significance of AI factors in cost management within the civil engineering domain using the fuzzy integrated Delphi method?
Q3: What are the interrelationships among the AI factors relevant to cost management in civil engineering, and how can ISM be employed to analyze these interdependencies?
Q4: Which AI factors are identified as driving forces and which ones are dependent factors influencing cost management, and how can a MICMAC analysis facilitate their identification?

Apart from the above research questions, the following research also intended to elucidate the practical implications of the proposed approach to enhancing cost management efficiency and mitigating financial risks in civil engineering projects. Furthermore, the following study also delves into the potential challenges and limitations associated with the implementation of the proposed approach, and also ensures its successful adoption in practice.

2.5. Objectives of the Study

Following the four research questions discussed previously, the authors have anticipated fulfilling the following set of objectives:

1. To identify and analyze the key AI factors relevant to cost management in civil engineering projects.
2. To utilize the fuzzy integrated Delphi method to solicit expert opinions and consensus on the significance of AI factors in cost management within the civil engineering domain.
3. To analyze the interrelationships among the AI factors relevant to cost management in civil engineering projects using ISM.
4. To employ a MICMAC analysis to identify the driving forces and dependent factors among the AI factors influencing cost management in civil engineering projects.

By achieving these objectives, this research aims to contribute to the advancement of cost management practices in civil engineering projects by offering a systematic and holistic approach to integrating AI factors into decision-making processes.

3. Materials and Methods

In this section, the systematic approach adopted to optimize the AI factors influencing cost management in civil engineering is described. All the computational steps are elaborately described to ensure the clarity, transparency, and reproducibility of this study's findings. The first step is to form a panel of experts and conduct a brainstorming session to identify potential factors. Following several meetings with the experts, the chosen parameters are refined through a Delphi managerial session followed by an ISM analysis, to establish the hierarchical relationship among the factors, and a MICMAC analysis, to identify the driving and dependent nature of the aspects related to cost optimization in civil engineering projects [43,44]. Let us start with a step-by-step analysis of each model in the subsequent section, one by one.

3.1. Brainstorming Session with the Experts

The brainstorming session marked the beginning of the study, bringing together industry experts and researchers to discuss the AI applications affecting cost management in civil engineering projects. This in-person session fostered dynamic discussions and idea exchanges. Cost management in civil engineering involves planning, estimating, budgeting, and controlling financial resources throughout a project's lifecycle. Despite its importance, the industry often faces cost overruns and budget deviations, leading to delays, disputes, and poor project outcomes. Recently, AI's integration has emerged as a promising way to improve cost management in civil engineering. AI technologies, including machine learning, predictive analytics, and data-driven decision-making, offer opportunities to optimize cost-related processes. Optimizing AI factors for the cost management of civil engineering involves identifying the key AI applications and strategies used to tackle cost-related challenges. This requires multidisciplinary collaboration, with teams of civil engineers, data scientists, project managers, and domain experts. A team of 10 highly qualified experts was formed to identify the potential AI factors influencing cost management in civil engineering. These experts, associated with various respected government and private organizations, have years of practical experience in their respective fields. Identifying the right team for the brainstorming session involves selecting individuals with diverse expertise to ensure a comprehensive evaluation of multiple criteria. Our step-by-step guide explains how this expert team was assembled for the current analysis:

Step 1 (define the scope and objectives): Begin by establishing the goals and scope of the MCDM analysis. Conduct a needs assessment to define the problem and understand the project's objectives and requirements.

Step 2 (identify relevant disciplines): identify the key disciplines relevant to the decision. This study focuses on civil engineering projects in the construction sector.

Step 3 (identify key stakeholders): Determine the stakeholders who have a vested interest in the decision, such as subject matter experts, decision-makers, end-users, customers, and affected communities. Stakeholder mapping helps ensure all relevant participants are included.

Step 4 (assess expertise and experience): Evaluate the stakeholders' expertise, qualifications, and experience. Consider their educational background, professional history, specialized skills, and track record in the relevant fields.

Step 5 (criteria alignment): match the expertise of the team with specific decision criteria to ensure the group collectively addresses each factor effectively.

Step 6 (ensure diversity): aim for diversity in expertise, perspectives, and backgrounds within the team to foster robust discussions and innovative solutions.

Step 7 (consider interdisciplinary collaboration): MCDM benefits from interdisciplinary collaboration, allowing for a broader analysis of complex decision problems. Seek experts from various disciplines to offer unique insights.

Step 8 (engage decision-makers and end-users): involve both decision-makers and end-users in the brainstorming session to ensure that practical considerations and preferences are addressed.

Step 9 (facilitate communication and collaboration): encourage open communication and collaboration among team members during the brainstorming process, promoting active participation and constructive feedback.

Step 10 (select facilitators and moderators): appoint facilitators or moderators to guide the brainstorming session, keeping discussions focused and inclusive.

Step 11 (review and refine team composition): periodically reassess and adjust the team composition as needed, being open to adding or replacing members to meet evolving needs or address new challenges.

To create a well-equipped team for a successful MCDM brainstorming session, the authors conducted interviews and verbal communication with several experts, ultimately selecting 10 individuals with diverse backgrounds in construction and civil engineering. The team demographics are detailed in Table 1. These experts used the Scopus and WOS databases to access relevant research articles in the field, allowing them to identify the most pertinent studies. After several in-person meetings, the team identified 17 key factors likely to impact cost management optimization in civil engineering, which are listed in Table 2 and depicted in Figure 1. Following the brainstorming session, the authors developed a structured questionnaire based on the insights gathered, aiming to evaluate the importance of each identified AI application area. This questionnaire used a Likert scale, allowing participants to rate each factor's significance from "not important" to "extremely important". The factors included areas like algorithm selection, risk analysis, resource optimization, and compliance monitoring. This structured approach ensured consistent data collection and enabled a quantitative analysis of the responses, facilitating a comprehensive assessment of AI's role in the cost management of civil engineering projects.

Table 1. Demographic details of the brainstorming session experts.

Designation	Company	Experience (In Years)	Number of Experts
General manager	Reliance Infrastructure Ltd.	21	1
Site in-charge	Larsen & Toubro Ltd.	14	1
Professor	IIT Kharagpur	23	2
Project manager	Macrotech Developers Pvt. Ltd.	17	1
Architect	Dilip Buildcon Ltd.	12	1
Civil engineer	Hindustan Construction Co. Ltd.	13	2
Construction engineer	Shapoorji Pallonji & Co. Ltd.	15	2

(Source: author's own elaboration).

Table 2. List of factors identified by the panel of experts.

Symbol	Factors	Internal Factors	Designation
F1	AI Algorithms and Models	Algorithm Selection Model Development	F11 F12
F2	Cost Estimation and Prediction	Cost Components Temporal Considerations	F21 F22
F3	Risk Management	Risk Identification Risk Analysis Risk Mitigation	F31 F32 F33
F4	Resource Allocation	Resource Optimization Resource Constraints	F41 F42
F5	Sustainability Considerations	Environmental Impact Social Impact	F51 F52
F6	Regulatory Compliance	Regulatory Requirements Compliance Monitoring	F61 F62
F7	Integration with Existing Systems	System Compatibility User Interface	F71 F72
F8	Ethical and Social Implications	Equity and Fairness Privacy and Data Security	F81 F82

(Source: expert panel members).

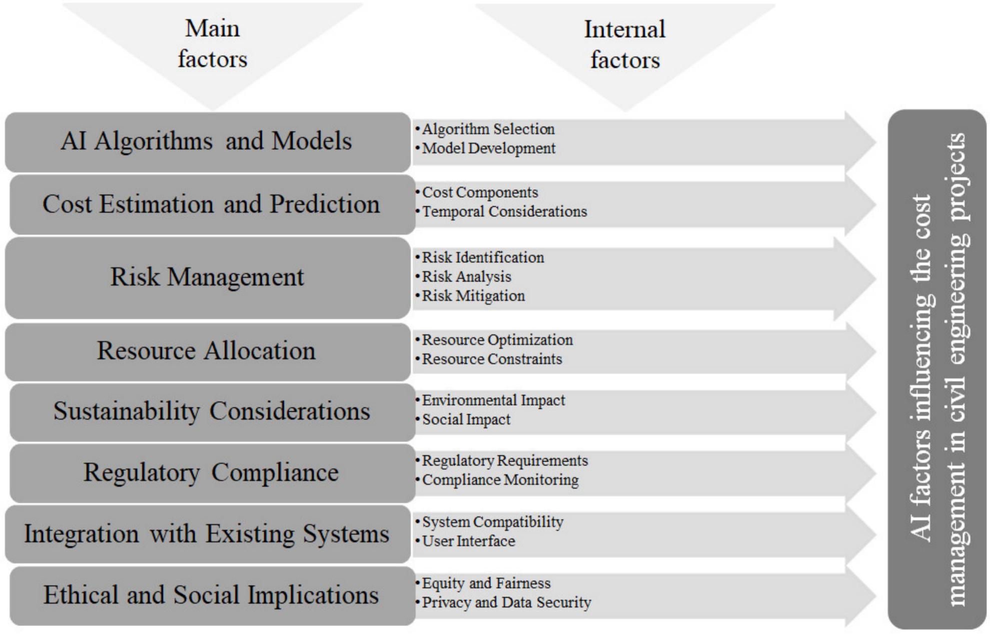

Figure 1. Categorization of AI factors into different groups (source: author's own elaboration).

3.2. The Critical AI Factors Identified by the Experts

Several factors are crucial in managing cost-related issues in civil engineering projects. In this study, "AI factors" refer to various aspects of AI technology that can influence the cost management practices in these projects. These factors encompass different AI technologies, methodologies, strategies, or considerations that affect how cost management is conducted, optimized, and improved. The importance of these critical AI parameters in cost management lies in their ability to enhance decision-making, optimize resource allocation, and increase project efficiency [41,45]. After several in-person meetings, the panel identified 17 AI factors that significantly influence cost management in civil engineering, which were further categorized into eight groups, as shown in Figure 1. Understanding these factors is essential because they guide the optimization of cost management practices in civil engineering. Here is the list of the selected factors and their relevance to cost management in civil engineering projects:

1. AI algorithms and models (F1): AI algorithms and models are crucial for accurate cost estimations, real-time budget monitoring, optimized resource allocation, and effective risk assessment, leading to better budget adherence and financial efficiency in civil engineering projects [20–22,33,34,42].
    - Algorithm selection (F11): Selecting the right algorithm is key to accurate cost estimation and resource allocation. Proper algorithm choices ensure an efficient use of project resources, reduce financial risks, and enhance the likelihood of project success within budget constraints [21,22,46].
    - Model development (F12): Developing robust models creates frameworks that accurately reflect project dynamics, facilitating precise cost estimation and resource allocation. Well-constructed models improve project planning, reduce financial risks, and contribute to the successful completion of civil engineering projects within budgetary limits [33,34,42,47].
2. Cost estimation and prediction (F2): Cost estimation is key for budget planning, resource allocation, and project decision-making. Accurate estimates enable proactive budget control, reduce the risk of cost overruns, and ensure financial feasibility, leading to successful project delivery within budgetary constraints. AI enhances cost estimation by using historical data, project parameters, and other factors to produce accurate cost forecasts. AI techniques like regression analysis, time series analysis, and

machine learning can analyze large datasets and identify patterns that human experts might miss, increasing the accuracy and reliability of cost predictions. AI-driven systems can adapt and improve over time [5,6,8,9].

- Cost components (F21): Understanding the cost components allows for the allocation of resources to specific project elements, aiding in accurate budgeting and cost control. Analyzing these components helps optimize resource utilization, reduce financial risks, and improve the efficiency and profitability of civil engineering projects [5,6,48].
- Temporal considerations (F22): Temporal considerations address the fluctuating nature of costs over time, facilitating effective planning and budget allocation. By accounting for these fluctuations, project managers can anticipate cost variations, manage financial risks, and maintain budget compliance throughout the project's lifecycle [6,8,9,49].

3. Risk management (F3): Risk management involves identifying, assessing, and mitigating potential threats to project budgets and timelines. Effective risk management strategies address risks like unexpected weather, supply chain disruptions, or regulatory changes, reducing cost overruns and ensuring project stability, ultimately leading to project success and stakeholder satisfaction. AI improves risk management by identifying, assessing, and mitigating risks more effectively. AI algorithms can analyze various datasets to detect potential risks, predict future events, and recommend mitigation strategies. Machine learning techniques enable risk models to adapt to changing conditions, enhancing their predictive accuracy and responsiveness. AI-driven risk management systems can detect anomalies, anticipate threats, and support informed decisions to minimize risks and maximize project success [20–24,38–40,43].
   - Risk identification (F31): Risk identification allows for the early recognition of financial uncertainties, enabling proactive mitigation strategies to ensure budget adherence. It helps minimize cost overruns, optimize resource allocation, and improve the overall financial performance of civil engineering projects [20–23,43,48].
   - Risk analysis (F32): Risk analysis assesses potential uncertainties and quantifies their impact on project finances, aiding informed decision-making. This process identifies cost drivers, helps mitigate financial risks, and ensures project success within budgetary limits [24,38].
   - Risk mitigation (F33): Risk mitigation involves implementing strategies to minimize the impact of identified uncertainties on project finances, ensuring budget compliance and project success. Effective risk mitigation helps control costs, optimize resource allocation, and safeguard the financial viability of civil engineering projects [39,40,43].
4. Resource allocation (F4): Resource allocation is key to civil engineering cost management, and it involves the effective distribution of labor, materials, and equipment to optimize project outcomes within budget. Proper resource allocation reduces waste; enhances productivity; and contributes to cost savings, timely project delivery, and an improved overall performance in civil engineering. AI helps optimize resource allocation by analyzing project requirements, constraints, and objectives to allocate resources efficiently. AI-based optimization algorithms consider multiple factors—cost, time, availability, and utilization rates—to create optimal resource plans. Machine learning can learn from historical data to predict resource demands and dynamically adjust allocation strategies. AI-driven systems can maximize productivity, minimize waste, and improve outcomes with limited resources [12,17–21,44,47].
   - Resource optimization (F41): Resource optimization focuses on allocating materials, labor, and equipment efficiently to minimize costs and maximize project outcomes. This leads to effective budget utilization, reduced waste, and improved project efficiency and profitability [12,18,44].

- Resource constraints (F42): Resource constraints involve planning and allocating limited resources to meet project objectives within budget limits. Understanding resource constraints helps identify potential bottlenecks, optimize resource use, and ensure project success while maintaining financial stability [19,20,44,49].

5. Sustainability considerations (F5): Sustainability in civil engineering cost management promotes environmentally responsible practices, minimizes long-term operational costs, and enhances project resilience. By incorporating sustainable design principles and materials, projects can reduce their lifecycle costs, mitigate their environmental impact, and meet regulatory requirements, leading to improved financial viability, stakeholder satisfaction, and long-term value in civil engineering. AI aids in sustainability by enabling data-driven decision-making and optimization strategies. AI algorithms can analyze environmental data, energy consumption, and resource usage to identify sustainability opportunities. Machine learning models can optimize energy usage, reduce waste, and lower environmental impact, leading to more sustainable civil engineering practices. AI-driven sustainability efforts allow organizations to meet environmental goals while maintaining their project's cost-effectiveness and efficiency [36–39,45,46].
   - Environmental impact (F51): Considering environmental impact in civil engineering cost management is crucial for compliance, minimizing ecological harm, and avoiding costly penalties. Addressing environmental impact fosters long-term project viability, community goodwill, and reduces the financial risks associated with environmental liabilities [36,37,45].
   - Social impact (F52): Social impact focuses on community engagement, stakeholder satisfaction, and reduced project disruptions, ultimately contributing to project success. Considering social impact supports sustainable development, mitigates reputational risks, and ensures positive outcomes for both the project and surrounding communities [39,41,42,46].
6. Regulatory compliance (F6): Regulatory compliance is crucial in civil engineering cost management as it ensures that projects meet legal requirements, permits, and standards. Non-compliance can lead to costly fines, delays, and legal disputes, affecting budgets and timelines. By prioritizing regulatory compliance, projects avoid unnecessary expenses, maintain stakeholder trust, and reduce the risk of costly setbacks, contributing to successful project delivery within budget. AI assists in compliance by automating monitoring, reporting, and documentation. AI algorithms can analyze regulatory requirements, legal documents, and industry standards to ensure adherence to laws and regulations. Natural language processing (NLP) can extract and interpret regulatory information, allowing organizations to proactively identify compliance gaps and take corrective action. AI-based compliance management systems enhance transparency, accountability, and regulatory oversight in civil engineering projects [3,5,9,23,24].
   - Regulatory requirements (F61): Adhering to regulatory requirements avoids costly fines, legal disputes, and delays, ensuring that projects remain within budget. Understanding these requirements enables proper planning, risk mitigation, and efficient resource allocation, contributing to the success and financial viability of civil engineering projects [9,23,24].
   - Compliance monitoring (F62): Compliance monitoring ensures adherence to regulatory standards, reducing legal risks and preventing penalties, thereby maintaining budget integrity. It allows for the timely identification and resolution of non-compliance issues, promoting project success while upholding legal and ethical standards [3,24,48,49].
7. Integration with existing systems (F7): Integration with existing systems is crucial in civil engineering cost management, as it allows seamless collaboration and data exchange among various project phases and stakeholders. By integrating cost man-

agement systems with existing project management, accounting, and procurement systems, organizations can streamline their workflows, improve data accuracy, and enhance their decision-making processes. This integration facilitates efficient resource allocation, accurate cost-tracking, and timely budget adjustments, leading to better project cost control and outcomes in the civil engineering sector. AI supports this integration by providing interoperability, scalability, and compatibility with diverse technologies and platforms. AI-driven integration solutions can connect disparate systems, databases, and applications, promoting smooth data exchange, communication, and collaboration among project stakeholders. AI algorithms can handle data from multiple sources, enabling their seamless integration with existing workflows. This AI-based approach enhances efficiency, interoperability, and data-driven decision-making in civil engineering projects [33,34,47,48].

- System compatibility (F71): System compatibility ensures the seamless integration of software tools and data platforms, improving project efficiency and reducing operational costs. It facilitates smooth data exchange and communication, fostering collaboration among project stakeholders and ultimately optimizing cost management within budget constraints [33,47].
- User interface (F72): A user-friendly interface promotes ease of use, reduces training time, and encourages the effective utilization of cost management software among stakeholders. An intuitive interface streamlines data entry, analysis, and reporting, leading to informed decision-making and optimal cost management practices within the project's budget [41–44,48,49].

8. Ethical and social implications (F8): The ethical and social considerations in civil engineering cost management ensure responsible decision-making and sustainable practices. Issues like fair labor practices, community engagement, and environmental impact assessments are critical to maintaining ethical standards and fostering positive social outcomes. Prioritizing these considerations helps projects mitigate reputational risks, build stakeholder trust, and achieve cost management objectives while contributing to societal well-being. AI introduces ethical and social challenges that require attention to ensure the responsible and equitable use of AI technologies. Ethical concerns include fairness, transparency, accountability, privacy, bias, and discrimination in AI-driven decisions. The social implications cover broader issues like job displacement, inequality, and autonomy concerns due to AI's adoption. Ethical AI frameworks, guidelines, and governance mechanisms are crucial for managing risks, fostering trust, and promoting ethical practices in civil engineering projects [43,45,47,49].

- Equity and fairness (F81): Equity and fairness ensure transparent decision-making, foster stakeholder trust, and reduce potential conflicts. Emphasizing these values in cost management encourages accountability and stakeholder participation and supports the social responsibility of civil engineering projects [45,46,49].
- Privacy and data security (F82): Privacy and data security protect sensitive project information, reduce the risk of data breaches, and maintain stakeholder trust. Ensuring privacy and data security prevents unauthorized access, preserves confidentiality, and supports compliance with legal and regulatory requirements, enhancing the integrity of cost management in civil engineering [33,40,45,46,49].

3.3. Fuzzy-Delphi Analysis

Fuzzy-Delphi analysis combines the principles of the Delphi method with fuzzy sets to address the uncertainty and ambiguity in decision-making processes. Originating from the Delphi method as indicated in the flow diagram shown in Figure 2, it gathers expert opinions through iterative rounds of feedback, fuzzy-Delphi extends this approach by incorporating fuzzy sets into the method to quantify subjective judgments and handle imprecision [31,32,50]. By integrating these methodologies, fuzzy-Delphi analysis provides a systematic framework for eliciting and aggregating expert opinions in situations where traditional Delphi methods may encounter challenges due to vagueness or uncertainty.

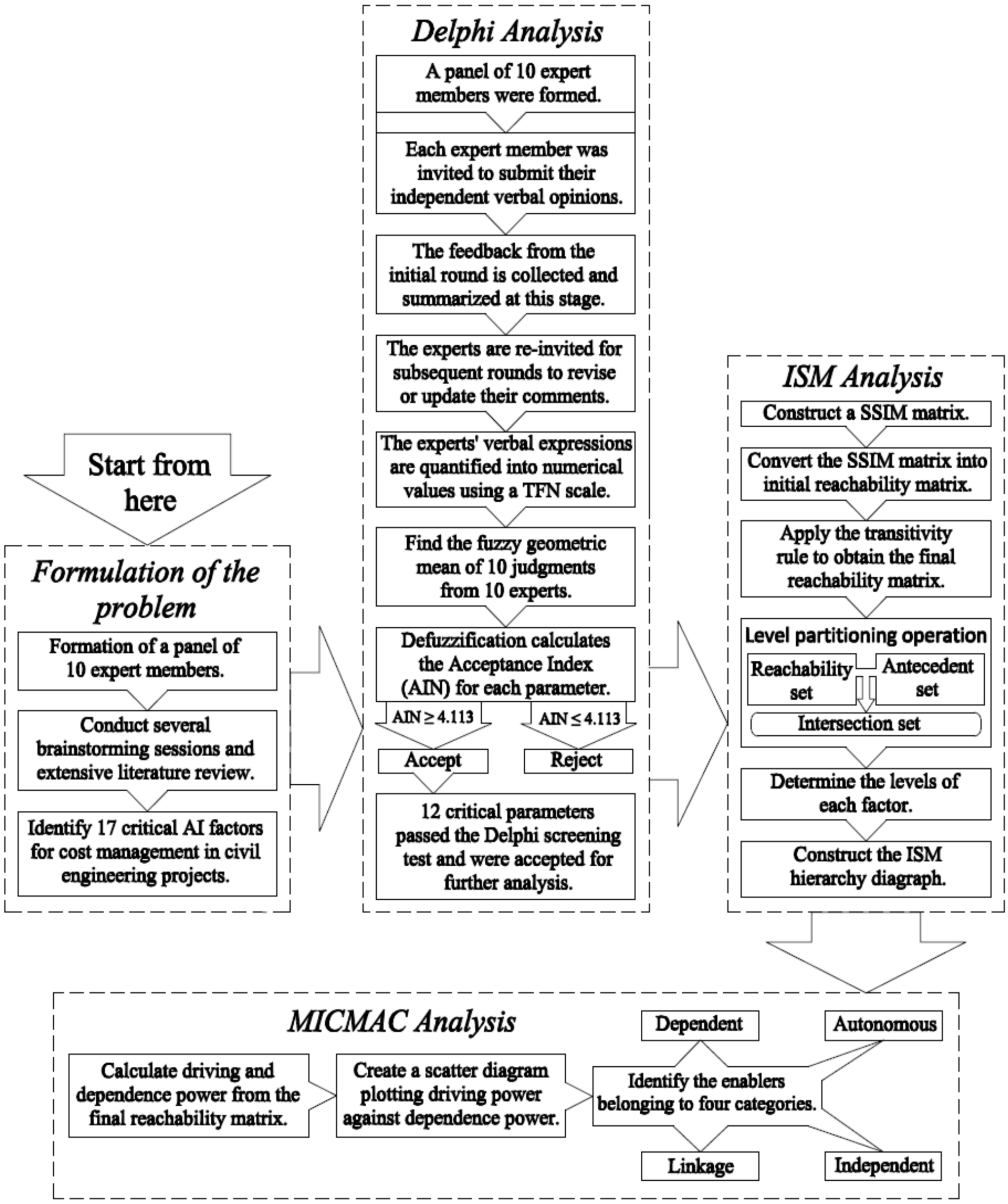

Figure 2. Flow diagram of Delphi-ISM-MICMAC hybrid model (source: author's own elaboration).

As is evident from Table 3, each of the ten expert panel members provided their judgements regarding the relevancy of the seventeen parameters shown in Figure 1 to the ongoing problem in linguistic terms. This was followed by their quantification into numeric values and finally into Triangular Fuzzy Numbers (TFNs); this conversion was performed according to the scale given in Table 4 [24,25,51]. The conversion scale presented in Table 4 has been decided on by the expert team from their years of experience. The value 4.113 calculated in Table 4, following the Fuzzy Geometric Mean Value (FGMV) and defuzzification operation using Equations (1) and (2), which is meant to serve as an acceptance degree level, means that all the chosen parameters have to achieve a minimum score of 4.113 to qualify for the next stage of analysis.

The FGMV of 'k' fuzzy numbers, such that $\{\widetilde{Z}_1 = (l_1, m_1, u_1), \widetilde{Z}_2 = (l_2, m_2, u_2) \ldots \ldots \widetilde{Z}_k = (l_k, m_k, u_k)\}$, can be computed as

$$\widetilde{GM}\ (\widetilde{Z}_1,\ \widetilde{Z}_2\ldots.\widetilde{Z}_k) = (\ (\prod_{i=1}^{k} l_i\Big)^{\frac{1}{k}},\ (\prod_{i=1}^{k} m_i)^{\frac{1}{k}},\ (\prod_{i=1}^{k} u_i)^{\frac{1}{k}}\ ) \tag{1}$$

The defuzzification of a fuzzy number $\widetilde{Z} = (l,\ m,\ u)$

$$Defuzzify\ (\mathrm{Z}) = \frac{\mathrm{l} + \mathrm{m} + \mathrm{u}}{3} \tag{2}$$

Table 3. Expert's judgements from Delphi analysis.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	FGMV	Score	Status	Anno-tation
F11	MHI (5,6,7)	HI (6,7,8)	VHI (7,8,9)	MHI (5,6,7)	VHI (7,8,9)	HI (6,7,8)	EHI (9,9,9)	MLI (3,4,5)	VHI (7,8,9)	HI (6,7,8)	(5.887, 6.850, 7.790)	6.843	Accept	A1
F12	MLI (3,4,5)	MLI (3,4,5)	LI (2,3,4)	VLI (1,2,3)	VLI (1,2,3)	MI (4,5,6)	ELI (1,1,1)	VLI (1,2,3)	LI (2,3,4)	LI (2,3,4)	(1.762, 2.653, 3.478)	2.631	Reject	-
F21	HI (6,7,8)	EHI (9,9,9)	EHI (9,9,9)	VHI (7,8,9)	VHI (7,8,9)	VHI (7,8,9)	VHI (7,8,9)	HI (6,7,8)	EHI (9,9,9)	HI (6,7,8)	(7.207, 7.962, 8.688)	7.952	Accept	A2
F22	ELI (1,1,1)	MI (4,5,6)	ELI (1,1,1)	LI (2,3,4)	ELI (1,1,1)	MLI (3,4,5)	VLI (1,2,3)	MI (4,5,6)	LI (2,3,4)	MLI (3,4,5)	(1.888, 2.431, 2.908)	2.409	Reject	-
F31	VHI 7,8,9)	EHI (9,9,9)	MI (4,5,6)	EHI (9,9,9)	VHI (7,8,9)	VHI (7,8,9)	VHI (7,8,9)	VHI (7,8,9)	MI (4,5,6)	EHI (9,9,9)	(6.749, 7.544, 8.299)	7.531	Accept	A3
F32	MLI (3,4,5)	HI (6,7,8)	VHI (7,8,9)	MHI (5,6,7)	HI (6,7,8)	HI (6,7,8)	EHI (9,9,9)	MHI (5,6,7)	EHI (9,9,9)	HI (6,7,8)	(5.945, 6.840, 7.699)	6.828	Accept	A4
F33	MHI (5,6,7)	VHI (7,8,9)	EHI (9,9,9)	EHI (9,9,9)	MI (4,5,6)	EHI (9,9,9)	VHI (7,8,9)	VHI (7,8,9)	VHI (7,8,9)	MHI (5,6,7)	(6.673, 7.465, 8.219)	7.452	Accept	A5
F41	HI (6,7,8)	HI (6,7,8)	MLI (3,4,5)	MHI (5,6,7)	MHI (5,6,7)	EHI (9,9,9)	EHI (9,9,9)	MLI (3,4,5)	EHI (9,9,9)	VHI (7,8,9)	(5.776, 6.632, 7.432)	6.613	Accept	A6
F42	MHI (5,6,7)	VHI (7,8,9)	HI (6,7,8)	HI (6,7,8)	EHI (9,9,9)	HI (6,7,8)	HI (6,7,8)	HI (6,7,8)	MI (4,5,6)	EHI (9,9,9)	(6.231, 7.103, 7.946)	7.093	Accept	A7
F51	EHI (9,9,9)	VHI (7,8,9)	HI (6,7,8)	VHI (7,8,9)	HI (6,7,8)	HI (6,7,8)	EHI (9,9,9)	MHI (5,6,7)	EHI (9,9,9)	HI (6,7,8)	(6.862, 7.634, 8.373)	7.623	Accept	A8
F52	MLI (3,4,5)	VLI (1,2,3)	MI (4,5,6)	LI (2,3,4)	LI (2,3,4)	VLI (1,2,3)	MI (4,5,6)	MLI (3,4,5)	LI (2,3,4)	ELI (1,1,1)	(2.024, 2.908, 3.728)	2.886	Reject	-
F61	MLI (3,4,5)	LI (2,3,4)	VLI (1,2,3)	MLI (3,4,5)	ELI (1,1,1)	VLI (1,2,3)	ELI (1,1,1)	VLI (1,2,3)	LI (2,3,4)	ELI (1,1,1)	(1.431, 2.024, 2.531)	1.995	Reject	-
F62	EHI (9,9,9)	EHI (9,9,9)	VHI (7,8,9)	VHI (7,8,9)	VHI (7,8,9)	VHI (7,8,9)	VHI (7,8,9)	VHI (7,8,9)	EHI (9,9,9)	EHI (9,9,9)	(7.740, 8.386, 9.000)	8.375	Accept	A9
F71	MHI (5,6,7)	MHI (5,6,7)	EHI (9,9,9)	MI (4,5,6)	MHI (5,6,7)	EHI (9,9,9)	MLI (3,4,5)	HI (6,7,8)	MHI (5,6,7)	MHI (5,6,7)	(5.322, 6.231, 7.103)	6.218	Accept	A10
F72	HI (6,7,8)	EHI (9,9,9)	HI (6,7,8)	VHI (7,8,9)	EHI (9,9,9)	HI (6,7,8)	EHI (9,9,9)	VHI (7,8,9)	HI (6,7,8)	EHI (9,9,9)	(7.277, 7.950, 8.586)	7.938	Accept	A11
F81	LI (2,3,4)	VLI (1,2,3)	MI (4,5,6)	ELI (1,1,1)	LI (2,3,4)	MI (4,5,6)	LI (2,3,4)	LI (2,3,4)	MLI (3,4,5)	MLI (3,4,5)	(2.169, 3.028, 3.837)	3.011	Reject	-
F82	VHI (7,8,9)	MLI (3,4,5)	HI (6,7,8)	VHI (7,8,9)	EHI (9,9,9)	MHI (5,6,7)	HI (6,7,8)	MI (4,5,6)	VHI (7,8,9)	VHI (7,8,9)	(5.847, 6.817, 7.762)	6.809	Accept	A12

(Source: expert panel members).

Table 4. Linguistic scale for conversion.

Qualitative Measures	Notations	Quantitative Measures	TFN Values
Extreme low importance	ELI	1	(1,1,1)
Very low importance	VLI	2	(1,2,3)
Low importance	LI	3	(2,3,4)
Medium low importance	MLI	4	(3,4,5)
Moderate importance	MI	5	(4,5,6)
Medium high importance	MHI	6	(5,6,7)
High importance	HI	7	(6,7,8)
Very high importance	VHI	8	(7,8,9)
Extreme high importance	EHI	9	(9,9,9)
Fuzzy geometric mean value		(3.292, 4.147, 4.901)	
Acceptance degree		4.113	

(Source: author's own elaboration).

FGMVs have been calculated for each of the chosen factors using Equation (1), followed by their defuzzification using Equation (2) in Table 3 to check which factors are able to pass the Delphi screening test. In Table 3, the factors achieving a value more than 4.113 are selected for further analysis, whereas the factors with scores below 4.113 are rejected. It is clearly evident from Table 3 that, in the end, 12 parameters out of 17 qualified for the next stage of analysis, ISM, while 5 parameters were rejected, since these were considered to be inferior to the others.

3.4. Interpretive Structural Modeling (ISM)

Following the flow diagram in Figure 2, next method is ISM, which is used to analyze and understand the complex interrelationships among factors or variables within a system. Originating from operations research and systems theory, ISM provides a structured approach to model and visualize the hierarchical relationships among factors, allowing decision-makers to gain insights into the system's structure, dynamics, and key drivers [28,30–32]. By identifying and interpreting hierarchical relationships, ISM enables effective decision-making, strategic planning, and problem-solving in diverse domains such as engineering, management, and policy analysis. ISM uses several steps to analyze and understand the hierarchical relationships among the factors influencing a complex system [42]. Below are the typical steps involved in ISM.

It begins by identifying and listing all the factors or elements relevant to the problem or system under study. These factors could include variables, components, activities, or concepts that contribute to the overall system.

Step 1—defining relationships: Determine the relationship among the identified factors to construct a Structural Self-Interaction Matrix (SSIM), as prescribed by the board members in Table 5. The SSIM is used to assess how each factor influences or is influenced by other factors in the system [52]. These relationships can be based on expert judgment or empirical data obtained by studying past research and brainstorming sessions. Table 5 shows the SSIM matrix and the letters V, A, X, and O represent the nature of the influences shown in Table 6. In Table 5, the evaluations provided by the board members were aggregated using a systematic approach to build consensus. The consensus-building process involved multiple rounds of discussion, deliberation, and refinement to reach agreement on their evaluations. In this process, the experts iteratively reviewed and revised their judgments based on feedback from other members until a consensus was reached. However, to build the SSIM matrix, input from each decision-maker regarding their perceptions of the relationships among the identified factors has been gathered. The relationships denoted by the letter in each cell are finalized according to the majority of the votes provided by the 10 experts.

For example, 'A' has been allotted to $cell_{12}$ (i.e., A1-A2) due to the fact that six experts have recommended 'A', three experts have recommended 'V', and only one expert has recommended 'O' for $cell_{12}$. In this case, since the majority of expert members voted for letter 'A' in $cell_{12}$, 'A' has been allotted in cell A1-A2. Likewise, depending on the expert recommendations, the relationships of all other cells have been established as depicted in Table 5.

Table 5. SSIM matrix.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
A1	1	A	A	V	A	A	A	A	X	A	X	X
A2		1	V	V	A	X	V	V	O	A	O	O
A3			1	V	A	V	V	A	V	O	A	A
A4				1	A	A	A	A	X	A	A	X
A5					1	V	V	V	V	A	V	X
A6						1	V	A	O	X	O	O
A7							1	A	X	A	A	A
A8								1	X	X	V	V
A9									1	O	A	A
A10										1	O	X
A11											1	A
A12												1

(Source: expert panel members).

Table 6. Significance of the letters used in the ISM analysis.

Symbol	Significance	Explanation
V	'i' leads to the achievement of 'j'	If cell r_{ij} = V, then r_{ij} = 1 and r_{ji} = 0
A	'j' leads to the achievement of 'i'	If cell r_{ij} = A, then r_{ij} = 0 and r_{ji} = 1
X	'i' and 'j' both will help to achieve each other	If cell r_{ij} = X, then r_{ij} = 1 and r_{ji} = 1
O	'i' and 'j' do not have any relation with each other	If cell r_{ij} = O, then r_{ij} = 0 and r_{ji} = 0

(Source: author's own elaboration).

Step 2—constructing an initial reachability matrix: Create a reachability matrix based on the relationships identified in the previous step, as shown in Table 7. Replace the letters V, A, X, and O with '1' or '0', accordingly, from Table 6 to create the initial reachability matrix according to Equation (3). The reachability matrix is a binary matrix that indicates whether there is a direct or indirect relationship between pairs of factors.

$$\mathrm{R_i}\ (\mathrm{n_i} \times \mathrm{n_j}) = \begin{bmatrix} 1 & r_{12} & \cdots & r_{1j} \\ r_{21} & 1 & \cdots & r_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ r_{i1} & r_{i2} & \cdots & 1 \end{bmatrix} \quad (3)$$

Step 3—deriving a Digraph: Use the reachability matrix to construct a directed graph (digraph) representing the relationships between factors. In the digraph, each factor is represented as a node, and the relationships between factors are represented as directed edges or arrows, as shown in Figure 3.

Step 4—identifying strongly connected components: Analyze the digraph to identify strongly connected components (SCCs). SCCs help to identify clusters of factors that are mutually influential or interdependent within the system. In an ISM analysis, SCCs are essential because they help reveal the interdependencies and relationships among the factors being studied within a complex system. SCCs represent subsets of factors where every factor within the subset is connected to every other factor through direct or indirect relationships. These components represent clusters of factors that are closely interconnected. SCCs are indispensable in ISM analyses as they offer a systematic way to uncover core relationships, understand system dynamics, prioritize interventions, simplify complexity, and facilitate decision-making within complex systems. By identifying and analyzing these components, ISM analyses provide valuable insights into the underlying structure and behavior of the systems under study, enabling informed decision-making and effective intervention strategies.

Table 7. Initial reachability matrix.

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**	**A11**	**A12**
A1	1	0	0	1	0	0	0	0	1	0	1	1
A2	1	1	1	1	0	1	1	1	0	0	0	0
A3	1	0	1	1	0	1	1	0	1	0	0	0
A4	0	0	0	1	0	0	0	0	1	0	0	1
A5	1	1	1	1	1	1	1	1	1	0	1	1
A6	1	1	0	1	0	1	1	0	0	1	0	0
A7	1	0	0	1	0	0	1	0	1	0	0	0
A8	1	0	1	1	0	1	1	1	1	1	1	1
A9	1	0	0	1	0	0	1	1	1	0	0	0
A10	1	1	0	1	1	1	1	1	0	1	0	1
A11	1	0	1	1	0	0	1	0	1	0	1	0
A12	1	0	1	1	1	0	1	0	1	1	1	1

(Source: author's own elaboration).

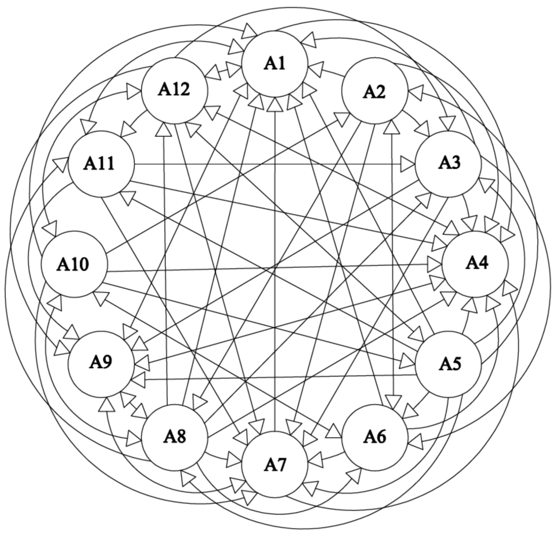

Figure 3. ISM directed graph (source: author's own elaboration).

Step 5—constructing a final reachability matrix $\{R_f = (n_i \times n_j)\}$: In this step, the transitivity has to be checked to identify that a direct or indirect relationship exists among the chosen factors. The '0' has been replaced by '1*' in some cells to represent the indirect relationship that exists between the factors. The final reachability matrix is depicted in Table 8, using to Equation (4).

$$R_f\ (n_i \times n_j) = \begin{bmatrix} 1 & r^f_{12} & \cdots & r^f_{1j} \\ r^f_{21} & 1 & \cdots & r^f_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ r^f_{i1} & r^f_{i2} & \cdots & 1 \end{bmatrix} \quad (4)$$

Table 8. Final reachability matrix.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	DrR_i	Rank
A1	1	0	1 *	1	1 *	0	1 *	1 *	1	1 *	1	1	10	8
A2	1	1	1	1	0	1	1	1	1 *	1 *	1 *	1 *	11	6
A3	1	1 *	1	1	0	1	1	1 *	1	1 *	1 *	1 *	11	6
A4	1 *	0	1 *	1	1 *	0	1 *	1 *	1	1 *	1 *	1	10	8
A5	1	1	1	1	1	1	1	1	1	1 *	1	1	12	1
A6	1	1	1 *	1	1 *	1	1	1 *	1 *	1	1 *	1 *	12	1
A7	1	0	0	1	0	0	1	1 *	1	0	1 *	1 *	7	12
A8	1	1 *	1	1	1 *	1	1	1	1	1	1	1	12	1
A9	1	0	1 *	1	0	1 *	1	1	1	1 *	1 *	1 *	10	8
A10	1	1	1 *	1	1	1	1	1	1 *	1	1 *	1	12	1
A11	1	0	1	1	0	1 *	1	1 *	1	0	1	1 *	9	11
A12	1	1 *	1	1	1	1 *	1	1 *	1	1	1	1	12	1
DpP_j	12	7	11	12	7	9	12	12	12	10	12	12		
Rank	1	11	8	1	11	10	1	1	1	9	1	1		

(Source: author's own elaboration).

Step 6: A level partitioning operation has been carried out to define the levels of each factor. The iteration process computed in Table 9 is carried out until all the parameters have been allotted certain levels. The reachability set identified during the iteration process in Table 9 represents all the factors which may influence other factors, whereas the antecedent set contains all the factors being influenced by other factors. Moreover, the intersection set are the common set of factors that are present both in the reachability and the antecedent set. When the factors in the reachability set and the intersection set exactly match with each other, their level has been allotted. If we consider the first row, A1, in Table 9, the 10 factors under the reachability set represent the fact that A1 influences all 10 of these factors; similarly, A1 is also influenced by all the 12 factors under the antecedent set. This also represents that the driving power (reachability) of A1 is 10 and the dependence power (antecedent) of A1 is 12, as can be seen from Table 8. Removing the common factors from these two reachability and antecedent sets leaves the intersection set, as presented in Table 9. It is evident from Table 9 that, in the first round of the iteration process, the intersection set exactly matches the reachability set for A1; hence level 1 has been allotted. Likewise, for all the other factors, the reachability and antecedent sets have been determined from Table 8 and their levels have been allotted upon determining their condition. The factors whose level has been determined are eliminated from the next round of iteration. This iteration process continues until and unless all the factors have been assigned to hierarchical levels.

Step 7—building the ISM hierarchy: This involves arranging the factors into the hierarchical structure depicted in Figure 4 based on the relationships identified in the digraph and the SCCs. Factors with higher levels of influence or control are placed at higher levels in the hierarchy, while factors with lower levels of influence are placed at lower levels. In ISM, both SCCs and hierarchical levels contribute to the understanding of the interrelationships among factors within a complex system. Both of them also provide insights into the structure of the relationships among factors within the system. SCCs reveal clusters of factors that are tightly interconnected, while hierarchical levels depict the influence hierarchy among factors. In ISM analyses, SCCs are often integrated into hierarchical levels to create a comprehensive understanding of the system's structure. Factors within the same SCC may be grouped together at the same hierarchical level if they exhibit similar levels of influence and dependency. The relationship between SCCs and hierarchical levels helps analysts interpret the complexity of the system. SCCs highlight clusters of factors that exhibit mutual influences, while hierarchical levels provide a structured framework for understanding the flow of influence and dependency among factors. Integrating SCCs and hierarchical levels enables better decision-making by providing a holistic view of the system's structure and dynamics. Decision-makers can use this information to prioritize actions, allocate resources, and develop intervention strategies that address the underlying relationships and dependencies identified through the ISM analysis.

Table 9. Determination of levels in ISM hierarchy.

		1st iteration		
Factors	**Reachability**	**Antecedent**	**Intersection**	**Levels**
A1	1,3,4,5,7,8,9,10,11,12	1,2,3,4,5,6,7,8,9,10,11,12	1,3,4,5,7,8,9,10,11,12	Level 1
A2	1,2,3,4,6,7,8,9,10,11,12	2,3,5,6,8,10,12	2,3,6,8,10,12	
A3	1,2,3,4,6,7,8,9,10,11,12	1,2,3,4,5,6,8,9,10,11,12	1,2,3,4,6,8,9,10,11,12	
A4	1,3,4,5,7,8,9,10,11,12	1,2,3,4,5,6,7,8,9,10,11,12	1,3,4,5,7,8,9,10,11,12	Level 1
A5	1,2,3,4,5,6,7,8,9,10,11,12	1,4,5,6,8,10,12	1,4,5,6,8,10,12	
A6	1,2,3,4,5,6,7,8,9,10,11,12	2,3,5,6,8,9,10,11,12	2,3,5,6,8,9,10,11,12	
A7	1,4,7,8,9,11,12	1,2,3,4,5,6,7,8,9,10,11,12	1,4,7,8,9,11,12	Level 1
A8	1,2,3,4,5,6,7,8,9,10,11,12	1,2,3,4,5,6,7,8,9,10,11,12	1,2,3,4,5,6,7,8,9,10,11,12	Level 1
A9	1,3,4,6,7,8,9,10,11,12	1,2,3,4,5,6,7,8,9,10,11,12	1,3,4,6,7,8,9,10,11,12	
A10	1,2,3,4,5,6,7,8,9,10,11,12	1,2,3,4,5,6,8,9,10,12	1,2,3,4,5,6,8,9,10,12	
A11	1,3,4,6,7,8,9,11,12	1,2,3,4,5,6,7,8,9,10,11,12	1,3,4,6,7,8,9,11,12	Level 1
A12	1,2,3,4,5,6,7,8,9,10,11,12	1,2,3,4,5,6,7,8,9,10,11,12	1,2,3,4,5,6,7,8,9,10,11,12	Level 1
		2nd iteration		
Factors	**Reachability**	**Antecedent**	**Intersection**	**Levels**
A2	2,3,6,9,10	2,3,5,6,10	2,3,6,10	
A3	2,3,6,9,10	2,3,5,6,9,10	2,3,6,9,10	Level 2
A5	2,3,5,6,9,10	5,6,10	5,6,10	
A6	2,3,5,6,9,10	2,3,5,6,9,10	2,3,5,6,9,10	Level 2
A9	3,6,9,10	2,3,5,6,9,10	3,6,9,10	Level 2
A10	2,3,5,6,9,10	2,3,5,6,9,10	2,3,5,6,9,10	Level 2
		3rd iteration		
Factors	**Reachability**	**Antecedent**	**Intersection**	**Levels**
A2	2	2,5	2	Level 3
A5	2,5	5	5	
		4th iteration		
Factors	**Reachability**	**Antecedent**	**Intersection**	**Levels**
A5	5	5	5	Level 4

(Source: author's own elaboration).

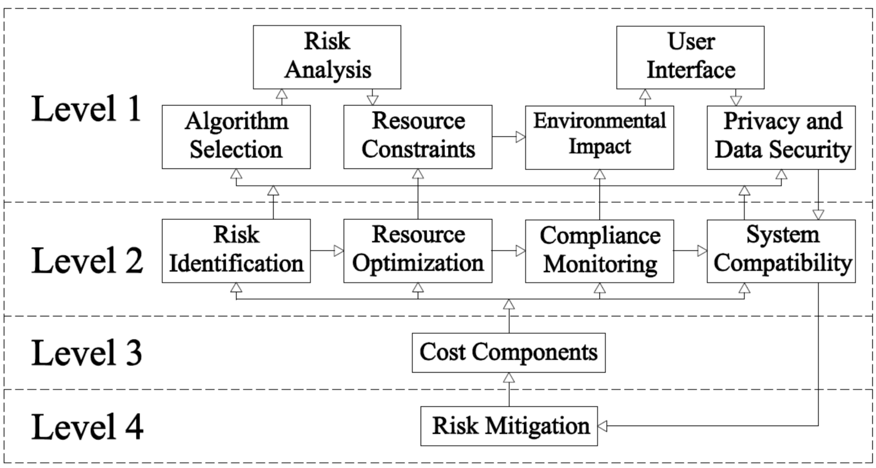

Figure 4. ISM hierarchy (source: author's own elaboration).

Step 8—interpreting the ISM hierarchy: We interpret the ISM hierarchy to understand the hierarchical relationships among factors and analyze how factors at different levels of the hierarchy influence each other and the overall system [50–52]. We identify key driving factors and dependent factors that play critical roles in shaping the system.

3.5. Cross-Impact Matrix Multiplication Applied to Classification (MICMAC)

MICMAC analysis is a method used in decision-making and strategic planning to assess the relative influence and interactions among factors within a complex system. Originating from operations research and systems theory, MICMAC analysis helps identify driving factors that have a high impact on the system and dependent factors that are influenced by others [8,23,28,29]. By analyzing the interactions among factors, a MICMAC analysis provides insights into the structure and dynamics of the system, aiding in prioritizing actions and resources for effective decision-making and problem-solving. A MICMAC analysis consists of the following steps:

Step 1: Calculate the driving (DrR_i) and the dependent power (DpP_j) of each alternative using Equation (5), as shown in Table 8, to determine the driving ability as well as the dependence tendency of the parameters considered in this ongoing analysis.

$$\begin{cases} DrR_i = \sum_{j=1}^{n} r_{ij}^{f} \\ DpP_j = \sum_{i=1}^{n} r_{ij}^{f} \end{cases} \tag{5}$$

Step 2: Prepare a scatter diagram by plotting the driving power against the dependence power of the factors shown in Figure 5. In a MICMAC analysis, the scatter plot diagram is divided into four quadrants, each representing different characteristics of the factors within the system. The coordinates of the horizontal and vertical error lines separating the four quadrants can be established in various ways depending on the nature of the problem and the current situation. In this specific instance, the decision-makers decided to position both lines precisely at the midpoint between the highest driving and dependence powers, which is 6 for each line, since the maximum value in both scenarios is 12. However, it is also true that, in some instances, previous researchers have decided the coordinates of the horizontal and vertical error lines by finding the average of the driving power and dependence power. This method may not be suitable in this case, as the coordinates of the error lines were found to be 10.667 based on the averages of the driving and dependence powers of the factors. Now, if the error lines are set at 10.667, then the scenario of Figure 5 will be that A2, A5, A6, and A10 will belong to independent quadrant-IV; A3, A8, and A12 will belong to linkage quadrant-III; A1, A4, A7, A9, and A11 will belong to dependent quadrant-II; and autonomous quadrant-I will remain empty as usual. Such situations are completely unjustified within Figure 4, where it can be clearly seen that all twelve factors act completely as linkage factors and none of the factors behave like dependent or independent factors. Therefore, placing the error lines exactly at the mid-points of the maximum values perfectly aligns with the present condition.

- Autonomous Factors (Quadrant I): Factors located in Quadrant I have low driving power (Y-axis) and low dependence (X-axis). These factors are considered independent factors as they have minimal influence on the other factors in the system and are not significantly influenced by external factors. They may represent peripheral or less critical aspects of the system that have limited impact on overall system dynamics.
- Dependent Factors (Quadrant II): Factors located in Quadrant II have low driving power (Y-axis) and high dependence (X-axis). These factors are considered dependent factors as they are strongly influenced by other factors in the system but have minimal influence on other factors themselves. They represent the outcomes, consequences, or dependent variables of the system and are influenced by the interactions among higher-level factors.
- Linkage Factors (Quadrant III): Factors located in Quadrant III have both high driving power (Y-axis) and high dependence (X-axis). These factors are considered linkage factors as they have a strong influence on other factors in the system and are also

influenced by external factors. They serve as mediators or connectors between different parts of the system and play a critical role in facilitating interactions among factors.

- Independent Factors (Quadrant IV): Factors located in Quadrant IV have high driving power (Y-axis) and low dependence (X-axis). These factors are considered autonomous as they have a significant influence on other factors in the system but are not significantly influenced by external factors. They are key drivers that play a central role in shaping the system's dynamics and outcomes.

By categorizing factors into these four quadrants based on their driving power and dependence, the scatter plot diagram in the MICMAC analysis provides insights into the relative influence and interactions among the factors within the system, aiding in prioritizing actions and resources for effective decision-making and problem-solving.

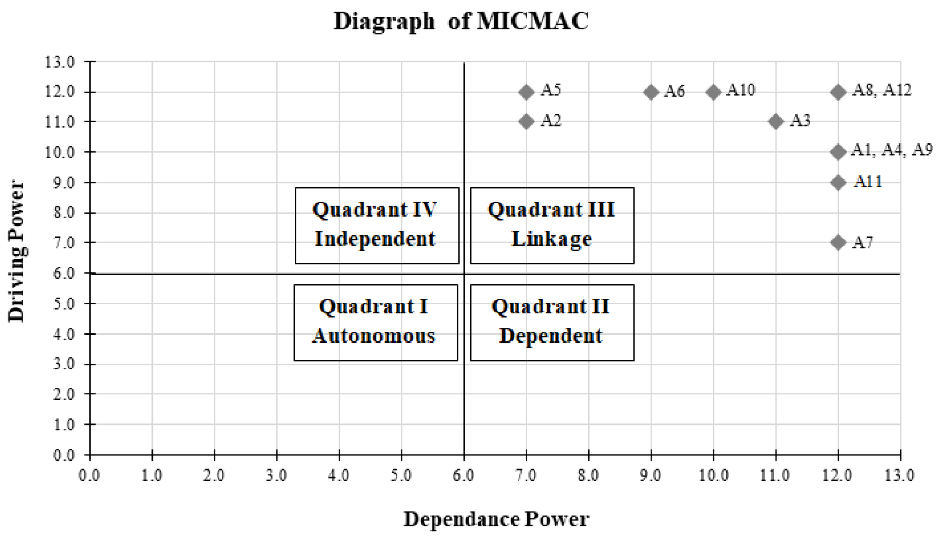

Figure 5. Diagraph of MICMAC analysis (source: author's own elaboration).

4. Results

The fuzzy integrated Delphi-ISM-MICMAC hybrid multi-criteria approach facilitated the identification of seventeen AI factors influencing cost management in civil engineering projects. These factors were categorized into the eight broad groups listed in Table 2. Initially, these seventeen chosen factors were processed through a Delphi screening test to check their relevancy to the ongoing decision-making problem, and the qualifying factors finally entered into the ISM and MICMAC analyses. The ISM analysis unveiled the intricate relationships and dependencies among the core aspects of the system under scrutiny. This section delves into the findings derived from the ISM hierarchy, elucidating the hierarchical structure, its interconnections, and the implications for decision-making.

4.1. Core Outcomes from the Delphi Technique

The Delphi method was used to collect and synthesize expert opinions to reach a consensus on the importance and relevance of AI factors in cost management. This iterative process helped refine the initial list and assign weights based on expert judgments, ensuring that the selected factors were comprehensive and aligned with domain requirements. The Delphi technique was also employed to further refine the selected parameters and remove irrelevant ones. Only factors that passed the Delphi screening would advance to the next stage of ISM and MICMAC analyses. As shown in Table 3, five factors—model development, temporal considerations, social impact, regulatory requirements, and equity and fairness—scored lower than 4.113 and were thus excluded from further analyses. After multiple sessions, the experts agreed that these five factors had minimal impacts on cost-related civil project issues and could be eliminated without affecting the ongoing study. Consequently, twelve factors successfully passed the Delphi screening test and moved on to the ISM and MICMAC analysis stages. The authors aim to explore these factors to understand why the excluded ones had little impact on cost-related civil project issues.

Model development (F12), temporal considerations (F22), social impact (F52), regulatory requirements (F61), and equity and fairness (F81) are essential aspects of civil engineering projects, but their direct impact on project costs can vary. Model development often uses pre-existing standardized tools and methodologies, reducing the need for extensive new development, especially in established industries. Temporal considerations, crucial for scheduling and project planning, may not significantly impact costs, particularly with flexible timelines and advanced project management techniques like CPM scheduling. Social impact, while important for community engagement and sustainability, generally incurs lower costs than other project expenses. Proactively addressing social concerns can even lead to cost savings by avoiding delays and disputes. Similarly, regulatory requirements, though vital for compliance and risk management, may not substantially affect costs in well-established regulatory frameworks where compliance costs are predictable. Equity and fairness, which promote social cohesion and public trust, typically have a limited direct impact on project costs, as they are often part of broader governance frameworks rather than direct financial considerations. However, emphasizing equity and fairness can enhance project success by fostering stakeholder engagement and reducing conflicts. In summary, while these five factors are crucial for responsible and sustainable project management, their direct influence on project costs is generally lower compared to factors like resource constraints or risk analysis.

Although the mentioned factors—model development, temporal considerations, social impact, regulatory requirements, and equity and fairness—are important in civil engineering projects, their direct impact on project costs can vary depending on the project context, regulatory environment, and stakeholder priorities. Thus, excluding these factors from the cost management analysis can be justified, as their influence on project costs may be lower than other factors. The Delphi method, a common research tool for building consensus among experts on complex issues, has proven effective in refining opinions and establishing agreement through iterative feedback and weighted judgments. It is known for synthesizing diverse expert opinions into a cohesive set of priorities or factors. Studies show that the iterative nature of Delphi, with multiple rounds of questions and feedback, ensures a comprehensive set of factors that meets specific field requirements. The Delphi method's ability to filter out irrelevant factors and focus on those with significant impact aligns with its documented use in research across various domains, including technology and project management. The excluded factors mentioned above support previous studies suggesting that some factors, while important for broader themes, may have a limited influence on project costs. Research also indicates that social impact and regulatory requirements, though essential for community engagement and compliance, typically incur relatively minor costs, emphasizing the varying impact of these factors based on context and implementation.

4.2. Core Outcomes from the ISM Analysis

The ISM analysis examined the complex interdependencies among factors to create a hierarchical structure. This section discusses the ISM analysis results, focusing on key factors of cost management for civil engineering projects. The aim was to identify fundamental, intermediate, and dependent factors to improve cost management practices. The analysis revealed intricate relationships among these factors. Figure 3 shows the ISM hierarchy, with the top level (Level 1) comprising six subordinate factors: algorithm selection, risk analysis, resource constraints, environmental impact, user interface, and privacy and data security. These factors are foundational and heavily rely on those at lower levels. They establish the base for the entire system, guiding further analysis and helping stakeholders understand key themes and interconnections. The ISM analysis helps clarify specific dependencies, providing a framework for understanding the system's dynamics and informing decision-making in the cost management of civil engineering projects.

The Level 2 factors in the ISM hierarchy are the dependent factors: risk identification, resource optimization, compliance monitoring, and system compatibility. These factors are influenced by those at lower levels but also impact the subordinate factors at Level 1. Although they derive their characteristics from the intermediate and fundamental factors at lower levels, they also affect the top-level factors, playing a dual role in the hierarchy. In ISM analyses, dependent factors represent specific elements within a system and often interact with intermediate factors, indicating complex interdependencies and hierarchical relationships. These dependent factors are critical for understanding the system's intricacies, serving as bridges between subordinate and intermediate factors. Analyzing these dependent factors helps stakeholders identify key pathways, bottlenecks, or leverage points, facilitating informed decision-making and strategic planning. Level 2 dependent factors are intermediate elements that contribute to the system's structure and dynamics. While more specific than the subordinate factors at Level 1, they are influenced by intermediate factors at Level 3 and connect to broader themes. This unique position allows them to shed light on specific processes and attributes affecting system performance. Understanding their role helps stakeholders develop targeted strategies to improve system resilience, performance, and sustainability.

Level 3 in the ISM hierarchy consists of the intermediate factor "cost components". These intermediate factors serve as bridges between the higher-level subordinate factors and the lower-level fundamental factors, creating a level of abstraction that connects broader themes with more specific elements. Cost components act as mediators, grouping related dependent factors under common themes. This structure helps explore complex interactions within the system, including specific processes, strategies, and attributes that contribute to the system's overall functioning. Intermediate factors are derived from dependent factors but are influenced by broader fundamental factors. While they share some characteristics with dependent factors, intermediate factors have more driving power, whereas dependent factors are more reliant on others. Understanding intermediate factors is crucial for gaining insights into the system's dynamics and supporting strategic planning and decision-making. By identifying and analyzing these elements, stakeholders can better understand how different components interact and influence each other, leading to more informed decisions.

Cost components, positioned at Level 3 in the ISM hierarchy, serve as the intermediate factors defining specific elements of the system's cost structure. They are closely connected to resource constraints, a Level 1 subordinate factor representing financial and other resource limitations that shape the overall cost framework. Understanding these cost components provides insight into how resource constraints impact the system's financial aspects. Cost components also relate to risk mitigation, a Level 4 fundamental factor, which involves the strategies used to manage risks and allocate resources to address vulnerabilities. By examining cost components, managers can assess the cost-effectiveness of risk mitigation measures and determine the best resource allocation strategies to minimize risks. Positioning cost components at Level 3 reflects their role as connectors, bridging broader themes from Levels 1 and 4 while providing a detailed view of the cost structure. Although influenced by risk mitigation, these components also impact resource constraints, helping stakeholders understand the system's cost-related dynamics. As intermediate factors, cost components support a deeper exploration of cost issues and their interactions with other system elements.

Risk mitigation, located at Level 4, is the root of the ISM hierarchy and serves as the fundamental factor upon which the entire structure is based. As the only independent factor in this analysis, risk mitigation directly or indirectly affects all other factors at higher levels. Fundamental factors like risk mitigation are crucial because they are the basic building blocks determining the system's behavior and outcomes. These fundamental factors consist of specific actions or conditions that impact system performance and are more granular than subordinate factors, which cover broader themes. They are generally identified through the analysis of dependent factors and their relationships. Risk mitigation, as a fundamental factor, helps us understand the mechanisms that drive system dynamics. Identifying fundamental factors is essential for implementing effective interventions, policies, and strategies to improve system performance, resilience, and sustainability. Fundamental factors like risk mitigation guide decision-making, offering insights into key drivers of system performance. By focusing on these core elements, stakeholders can identify actionable steps to address challenges, seize opportunities, and manage risks. This emphasis on fundamental factors enables targeted changes and strategic planning to enhance system functionality.

Risk mitigation is crucial for system resilience and sustainability, as it focuses on strategies to reduce the impact of identified risks. It is central to risk management and aligns with the broader themes of risk analysis seen at Level 1, which involve identifying and prioritizing risks. Risk mitigation turns this analysis into practical strategies to protect the system and influences strategic decisions regarding resource allocation, process optimization, and contingency planning. Positioning risk mitigation at Level 4 highlights its foundational role in enhancing system robustness. It is a continuous process requiring ongoing monitoring, evaluation, and adaptation. This emphasis on risk mitigation points to the need to integrate risk management into system governance and operations, fostering a culture of continuous improvement and resilience. Proactively addressing risks strengthens the system's adaptive capacity and builds stakeholder trust. Effective risk mitigation aligns with organizational objectives related to compliance, performance, and strategic goals. Ultimately, it contributes to system success and sustainability by protecting assets, improving stakeholder confidence, and supporting broader organizational strategies.

The ISM analysis reveals complex relationships and dependencies among the factors influencing system performance. It identifies algorithm selection, risk analysis, and resource constraints as key top-level factors, indicating their central role in system dynamics. The dependent factors—risk identification, resource optimization, compliance monitoring, and system compatibility—are critical for implementing strategies within the system. The intermediate factor, cost components, highlights the importance of considering economic viability and resource allocation during decision-making. Balancing costs with performance goals and risk management is essential for sustainable operations and optimal resource use. Overall, the ISM analysis provides valuable insights into the system's internal relationships and dependencies, supporting informed decision-making and strategic planning. This understanding contributes to enhanced performance, resilience, and sustainability.

ISM is valued for its ability to map complex interdependencies and establish clear factor hierarchies. Studies often use ISM to structure complex issues, providing guidance for decision-making. This aligns with research examining the factors that affect project costs in civil engineering, such as resource constraints, risk analysis, and algorithm selection. The focus on fundamental, intermediate, and dependent factors in cost management reflects common practices in engineering cost optimization research. Risk mitigation, positioned at the base of the ISM hierarchy, underscores its fundamental role in maintaining system resilience, a concept supported by the literature on risk management, which emphasizes the effective strategies to protect project integrity and reduce negative outcomes. The emphasis on continuous risk monitoring and adaptation resonates with studies that advocate for ongoing risk assessments in dynamic environments. Intermediate factors like cost components, which bridge the higher and lower levels of the ISM hierarchy, are viewed as crucial for connecting broader themes to specific elements, aiding strategic planning and decision-making. This discussion on how an ISM analysis supports informed decision-making, with a focus on performance, resilience, and sustainability, reflects earlier studies that use ISM for the structured analysis of complex systems, enabling stakeholders to make better decisions. In conclusion, the ISM analysis described for civil engineering projects is consistent with the key themes in the academic literature, focusing on hierarchical structuring, cost management, risk mitigation, and strategic planning—common themes in studies addressing complex systems and effective management.

4.3. Core Outcomes from the MICMAC Analysis

The MICMAC analysis has provided crucial insights into the interrelationships and influences among the twelve factors considered. The MICMAC diagram shown in Figure 5 categorizes these factors based on their driving power (the extent to which a factor influences others) and dependence power (the degree to which a factor is influenced by others). All twelve factors fall within the linkage quadrant, indicating their high driving power and high dependence, which underscores their significant interconnectedness. This section details the key outcomes from the MICMAC analysis and discusses their implications for decision-making and strategic planning. The high driving power and dependence among these factors suggest complex interdependencies, emphasizing the importance of a holistic and integrated approach to system management. The results highlight the need for strategies that consider these interconnected dynamics to effectively manage and make informed decisions within the system. The key takeaways from this analysis guide stakeholders in understanding these intricate relationships and planning strategic interventions accordingly.

- Integrated planning: Decision-makers should adopt integrated planning approaches that consider the interconnectedness of factors such as algorithm selection, risk analysis, resource constraints, and user interfaces. This entails identifying synergies and trade-offs to optimize system performance and resilience.
- Risk-informed strategies: Given the central role of risk analysis, decision-makers should prioritize risk-informed strategies that proactively identify and address potential threats and vulnerabilities. This involves continuous monitoring, evaluation, and adaptation to evolving risk landscapes.
- Resource optimization: Addressing resource constraints requires strategic resource optimization strategies that balance competing demands and priorities. Decision-makers should explore innovative approaches to resource allocation, utilization, and management to maximize efficiency and effectiveness.
- User-centric design: The significance of user interfaces underscores the importance of adopting user-centric design principles in system development. Decision-makers should prioritize usability, accessibility, and user satisfaction to enhance system adoption and acceptance.
- Data protection measures: Privacy and data security considerations should be integrated into all aspects of systems' design and operation. Decision-makers should implement robust data protection measures, compliance monitoring mechanisms, and user education programs to mitigate risks and safeguard sensitive information.

MICMAC analysis is a well-regarded method for understanding the interrelationships and influences among factors in complex systems. It categorizes factors based on their driving power (how much they influence others) and dependence power (how much they are influenced by others). The referral of our factors to the linkage quadrant, indicating high driving power and high dependence, aligns with studies that use MICMAC to identify highly interconnected factors, emphasizing their significant interdependencies. Research on MICMAC has shown its utility in strategic planning and decision-making through offering a structured view of system dynamics. The highlighted complex interdependencies suggest the need for integrated system management, resonating with the literature that advocates for holistic approaches to complex systems. The integrated planning approach mentioned in this research aligns with studies focusing on interconnected factors like algorithm selection, risk analysis, and resource constraints. These studies often examine how to balance synergies and trade-offs to enhance system performance and resilience.

Risk-informed strategies, we also noted, reflect the central role of risk analysis in managing complex systems. Research supports the idea of continuous monitoring, evaluation, and adaptation to evolving risk environments, consistent with its emphasis on proactive risk management. Resource optimization strategies are discussed in the literature as a way to address resource constraints by balancing competing demands and finding innovative approaches to resource allocation. This aligns with the need for effective resource use in complex projects. User-centric design and data protection measures have gained prominence in studies on system design and security. The literature emphasizes usability, accessibility, and user satisfaction, in line with the present recommendations for enhancing the system adoption. The research on data protection underscores the importance of privacy and compliance monitoring, echoing the call for robust data protection. Hence, the ongoing discussion of the MICMAC analysis and its focus on integrated planning, risk-informed strategies, resource optimization, user-centric design, and data protection reflects the common themes found in studies on complex systems and effective management.

5. Discussions

In this section, the study findings and the implications have been explored within the broader context of cost management in the civil engineering domain. This research aimed to optimize the cost associated with civil projects by identifying the potential AI factors that influence it. Through the in-depth analysis of the Delphi-ISM-MICMAC hybrid model and an examination of the AI factors, the authors tried to align the valuable insights gained from the present analysis with the research objectives in this section, as follows. First of all, the study identified and analyzed seventeen key AI factors relevant to cost management in civil engineering. These factors, categorized into eight groups (as shown in Table 2), were gathered through a comprehensive literature review and expert consultations. Secondly, the fuzzy integrated Delphi method helped us gather expert opinions on the relevance of these AI factors in cost management. This process, through structured questionnaires and iterative feedback, narrowed down the seventeen factors to twelve significant ones, eliminating five factors (model development, temporal considerations, social impact, regulatory requirements, and equity and fairness) from further analysis, as they were less relevant to cost-related civil project issues. Moving towards the third objective, the ISM analysis examined the interrelationships among the twelve significant AI factors in cost management. This method established a hierarchical structure (see Table 9 and Figure 4) that reflected their dependencies and interactions, providing a clear framework for their impact on cost management practices. Finally, the MICMAC analysis identified the driving and dependent forces among the twelve AI factors, placing them in the linkage quadrant (Figure 5). This indicated that all factors had both driving and dependent characteristics, with none being purely driving or dependent. This analysis helped classify these factors based on their influence and importance in decision-making.

This research addressed four objectives by offering insights into key AI factors and employing methodologies like the fuzzy integrated Delphi method, ISM, and MICMAC analyses. It successfully addressed several critical gaps in the literature, contributing to advancements in civil engineering cost management. Previous studies have used fuzzy integrated hybrid MCDM models in various domains, but their application to cost management in civil engineering projects was lacking. By integrating AI factors into this hybrid model, this research filled this gap, presenting a tailored approach to optimizing cost management in the construction sector. In addition, this study uniquely combined the Delphi, ISM, and MICMAC methods to create a cohesive framework for analyzing the decision-making problems in cost management. This integration enhanced the comprehensiveness and effectiveness of the decision-making process in civil engineering. Moreover, previous research had not extensively explored integrating AI factors into decision-making processes. The proposed research focused on incorporating AI factors specifically to improve cost management in civil engineering projects, addressing the increasing role of AI in the construction industry. This approach acknowledged AI's potential to improve cost optimization practices. Although the hybrid model used various methodologies, there was scope for further methodological enhancements. The study contributed to this by exploring innovative techniques to incorporate AI factors, including using algorithms and models to analyze AI's impact on cost management decisions, thereby enhancing the accuracy and efficiency of the decision-making process.

In conclusion, the proposed research successfully addressed existing research gaps by offering a novel approach to integrating AI factors into the fuzzy integrated hybrid MCDM model for civil engineering cost management. Through these methodological advancements and tailored solutions, this research contributed to addressing flaws in the literature and paved the way for more effective cost management practices in the construction industry.

Managerial Implications

This research work offers several key managerial implications for the stakeholders involved in civil engineering projects. These implications are derived from the insights and recommendations provided by the study and are aimed at enhancing cost management practices through the integration of AI factors. Here are some of the managerial implications:

- Managers should adopt an integrated strategic planning approach that considers the multifaceted relationships among the AI factors identified in the study. This involves developing comprehensive strategies that leverage AI technologies to optimize cost management practices while aligning with organizational goals and project objectives.
- Decision-makers should prioritize risk-informed decision-making processes, leveraging insights from the risk analyses and mitigation strategies identified in this study. By proactively identifying and addressing potential risks, managers can minimize uncertainties and mitigate adverse impacts on cost management in civil engineering projects.
- Organizations should focus on optimizing resource allocation and utilization by leveraging AI-driven approaches such as resource optimization and demand forecasting. This involves identifying opportunities for efficiency improvement, minimizing waste, and maximizing the value of the available resources to enhance cost-effectiveness and project outcomes.
- Managers should prioritize user-centric design principles in the development of civil engineering projects, with a particular focus on the user interface. By enhancing the usability, accessibility, and user experience of project interfaces, organizations can improve stakeholder engagement, satisfaction, and overall project success.
- Organizations must prioritize data security and compliance with regulatory requirements, particularly concerning privacy and data protection. Managers should implement robust data security measures, compliance monitoring mechanisms, and user education programs to mitigate risks and safeguard sensitive information.
- Managers should foster a culture of continuous improvement by encouraging feedback, learning, and adaptation throughout the project lifecycle. By leveraging insights from the study, organizations can identify areas for optimization, address emerging challenges, and capitalize on opportunities for innovation and growth.
- Organizations should invest in training and skill development programs to enhance the AI literacy and proficiency of project stakeholders. This involves equipping team members with the necessary knowledge, skills, and tools to effectively leverage AI technologies in cost management practices.
- Managers should promote collaboration and knowledge sharing among project stakeholders, both within the organization and across industry sectors. By fostering an environment of collaboration and information exchange, organizations can leverage their collective expertise, insights, and best practices to drive continuous improvement in cost management practices.

This research work offers valuable managerial insights for enhancing the cost management practices in civil engineering projects through the integration of AI factors. By adopting these recommendations, organizations can optimize project outcomes, minimize risks, and drive sustainable growth and success in the increasingly complex and dynamic field of civil engineering.

6. Conclusions

The ongoing research has yielded significant insights into the complex dynamics of cost management in civil engineering projects. By integrating various methodologies and techniques, including fuzzy-Delphi, ISM, and MICMAC, this study has provided a comprehensive framework for understanding and optimizing the role of AI factors in cost management within this domain. Through a systematic analysis, this study has identified the critical AI factors that exert a substantial influence on cost management in civil engineering projects. These factors encompass algorithm selection, cost estimation, risk management, resource allocation, sustainability, regulatory compliance, system integration, and social implications. Understanding the interconnectedness and dependencies of these factors is vital for devising effective strategies to optimize cost management practices. The hierarchical structure revealed by the ISM analysis illustrates the relationships and dependencies of these identified factors. This hierarchical perspective provides valuable insights into the systemic dynamics shaping cost management in civil engineering projects. Furthermore, the MICMAC analysis highlights the interconnected nature of the identified factors, with all factors falling within the linkage quadrant. This underscores the need for holistic and integrated approaches to optimize cost management practices. By considering the multifaceted relationships and influences among AI factors, shareholders can develop proactive strategies to address challenges, leverage opportunities, and enhance project outcomes.

Our research findings have significant implications for decision-makers and practitioners involved in cost management in civil engineering projects. By prioritizing risk-informed strategies, resource optimization, user-centric design principles, and data protection measures, organizations can enhance their competitiveness, efficiency, and sustainability. Integrated planning approaches that leverage synergies and address trade-offs effectively are essential for achieving optimal outcomes in this complex and dynamic environment. There are several avenues for future research, including the refinement of AI models and methodologies, the exploration of emerging technologies, and the evaluation of the best practices in cost management. Continued research and innovation will be critical to addressing the evolving challenges and opportunities in the field and driving sustainable growth in the civil engineering industry. In conclusion, this research provides a robust framework for enhancing cost management practices through AI integration. By leveraging the insights and recommendations offered by this study, stakeholders can navigate the complexities of cost management more effectively and achieve their project objectives with greater efficiency and success.

Limitations and Future Work

The research may have a limited scope, focusing primarily on cost management in civil engineering projects. Other aspects of project management or specific industry contexts may not have been adequately addressed. The availability and quality of the data used in the analysis may act as a barrier. Limited access to relevant data or reliance on secondary sources could impact the accuracy and robustness of these findings. Moreover, the complexity and novelty of the hybrid approach may introduce methodological challenges, such as subjective judgments in the fuzzy-Delphi analysis or assumptions made in the ISM and MICMAC analyses. These constraints could affect the validity and reliability of the results. Additionally, the findings of the research may not be readily generalizable to all civil engineering projects or organizational contexts. Factors such as project size, complexity, and geographic location could influence the applicability of the proposed approach. Lastly, the effectiveness of AI factors in cost management may be contingent upon the availability and reliability of AI technologies. Rapid advancements in AI and changing market dynamics may render certain findings obsolete over time.

Researchers may work on the above-stated limitations to extend the present research in the future. Addressing the above limitations may be intriguing and validations of the findings should be accomplished through empirical testing in real-world civil engineering projects. The research could also be expanded to explore the applicability of the hybrid approach to cost management in other industries beyond civil engineering. This would involve adapting the methodology to address industry-specific challenges and opportunities. Furthermore, this research could inform the development of decision support systems or software tools that integrate AI factors to facilitate cost management decision-making in civil engineering projects. These tools could offer practical guidance and insights to project managers. Collaboration with experts from related disciplines, such as computer science, economics, and business management, could also enrich this research domain and provide interdisciplinary insights into the optimization of AI factors in cost management.

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