International Journal of Mathematical, Engineering and Management Sciences
Vol. 11, No. 2, 991-1022, 2026
https://doi.org/10.33889/IJMEMS.2026.11.2.041

Unravelling the Blockades in Implementing Large Language Models in Construction Sector

Arpit Singh
Jindal Global Business School,
O.P. Jindal Global University, Sonipat, Haryana, India.
E-mail: asingh6@jgu.edu.in

Anchal Patil
Operations Management & Quantitative Techniques,
IMI Delhi, New Delhi, India.
Corresponding author: anchal.patil@imi.edu

Shri Krishna Pandey
Symbiosis International University Dubai, United Arab Emirates.
E-mail: skpandey@siu-dubai.ac.ae

(Received on October 4, 2025; Revised on December 23, 2025 & February 5, 2026; Accepted on February 12, 2026)

Abstract
The adoption of text-based Generative AI (GenAI), especially Large Language Models (LLMs), offers promising opportunities for improving documentation, coordination, compliance, and decision-making in construction Operations and Supply Chain Management (OSCM). Yet multiple constraints limit effective deployment in the Indian construction context. This study investigates the blockades hindering GenAI adoption and models their interrelationships using expert evaluations and a Grey-DEMATEL approach. Ten interconnected blockades are identified across technological, data-integration, and organizational–institutional domains. Real-time data processing, model accuracy and domain validity, and computational resource requirements emerge as the most influential cause blockades, shaping downstream challenges in collaboration, regulatory alignment, and workflow management. By revealing how these blockades interact, the study provides a structured framework for understanding GenAI adoption barriers and offers theoretically grounded implications for policymakers, contractors, SMEs, and technology providers. The findings deliver a focused evidence base to guide targeted interventions aimed at strengthening readiness for GenAI-enabled transformation in India’s construction supply chains.

Keywords- Generative artificial intelligence, Architecture engineering and construction, Blockades, Operations and supply chain management, Grey DEMATEL.

1. Introduction

In the last few decades, sophisticated intelligent techniques established a strong foothold in various industrial landscapes. Among such techniques, Artificial Intelligence (AI) in particular has become quite popular due to its human-like interpretations and faster solutions to complicated problems (Peres et al., 2020; Javaid et al., 2023). Within AI, Machine Learning (ML) techniques have found extensive application in addressing decision-making problems that require in-depth understanding (Islam et al., 2024). Recently, a sub-domain of ML, deep learning phenomenon based on Artificial Neural networks (ANNs) have gained momentum in solving varied kinds of problems in industrial setups (Jauhar et al., 2024). Generative AI (GenAI), an AI-based technology enabled by Large Language Models (LLMs), has witnessed rapid global adoption across industries (Feuerriegel et al., 2024). Notably, the launch of GenAI-powered ChatGPT in 2022 marked a historic milestone, as it became the fastest-growing internet service to reach one million users within five days (Kumar et al., 2024). GenAI has the ability to summarize content, extracting key facts, and creating new content and in this process mimicking the human behavior, tone, and output (Riemer

& Peter, 2024; Brin et al., 2025). Business leaders are expressing excitement about AI as their organizations discover valuable AI applications tailored to their industries. According to Autodesk's 2024 global research report, State of Design & Make, 78% of leaders and experts believe that AI will improve their sectors, with 66% predicting that AI will become "indispensable" in the next two to three years. In the Architecture, Engineering, and Construction (AEC) industry, a major portion of AI is employed to increase productivity which is used by approximately 44% of the AEC firms, followed closely by creating designs using the available data used by almost 36% of the firms, and finally detecting anomalies and errors in performance in buildings and assets that account for roughly 34% of the AEC firms (Autodesk, 2024).

For clarity, this study distinguishes between three terms that are often used interchangeably in industry discussions. "AI" is used here as a broad umbrella encompassing predictive analytics, machine learning, optimization algorithms, and rule-based systems. "GenAI" refers to models capable of producing new content based on learned patterns; this includes LLMs, diffusion models, GANs, and multimodal architectures. However, the empirical focus of this study is specifically on text-based GenAI—particularly LLMs—as these are the tools most relevant for documentation, decision-support, planning, and regulatory tasks in construction Operations and Supply Chain Management (OSCM). GenAI is more than just a tool that helps enhance productivity, especially for the construction sector. The construction industry is growing by leaps and bounds, spiking by more than US$4.2 trillion over the next 15 years, jumping from US$9.7 trillion in 2022 to US$11.9 trillion by 2037 (AON, 2024). This growth propels the construction sector to be more proactive in adopting emerging AI based technologies to attain competitive edge and stay relevant in the industrial landscape. The usage of AI in the construction sector is expected to grow at about 20% every year from 2023 to 2032 (Wadhwani & Ambekar, 2024).

In this study, GenAI refers specifically to text-based models—particularly LLMs—as they are most relevant to documentation, planning, contract review, and compliance tasks in construction OSCM. While GenAI includes many architectures such as diffusion models and GANs, the empirical analysis in this paper focuses only on LLM-based applications (Akpan et al., 2024). Accordingly, the purpose of this study is not to assess current industry adoption levels or future benefits, but rather to identify the structural blockades that constrain GenAI readiness in India's construction supply chains.

Traditionally, AEC industry has been relatively slower in adopting innovative digital technologies. This industry is supposedly the largest contender to benefit from GenAI enabled technologies (Ghimire et al., 2024). Market analysts such as McKinsey postulate that certain contingencies like the demand for infrastructure, shortage of skilled workforce, and pressure from the stakeholders for data transparency can promulgate industries to adopt digital technologies faster than expected (Hovnanian et al., 2024). As a result of which the investment in the AEC technology has grown significantly. It is estimated that about US$50 million has been invested from 2020 to 2022; a whopping 85% spike from the previous three years (Brozovsky et al., 2024).

In this context, the Indian AEC industry is poised to make substantial investments in GenAI, as the country anticipates a significant boom in infrastructure projects. Infrastructure development is gaining momentum in India supported by various national initiatives. National Infrastructure Pipeline (NIP) has been instrumental in approving thousands of projects in energy, transport, urban development, and industry. In the similar vein, Smart Cities Mission has completed over 7,400 projects with a committed investment of ₹1.64 lakh crore as of 2025. These facts and figures are proof enough of how rapidly India's construction and infrastructure sector is expanding. The adoption of new technologies like GenAI is required to accelerate this growth. GenAI can transform various construction sector operations, such as procurement, design, planning, and compliance, by making them more efficient and organized. This is why the research on GenAI in the Indian AEC is crucial.

There are several features unique to the developing economies like India that provides essential platform for studying GenAI adoption. The Indian supply chain is highly fragmented as opposed to the developed countries with strong and robust digital systems. Contractors exhibit varying levels of capability, documentation practices remain inconsistent, and digital systems across organizations are often poorly coordinated. More specifically, limited access to real-time data remains a major challenge for the construction sector, compounded by fragmented digital infrastructure and often slow, paper-based regulatory processes. All the above factors pertinent to Indian construction sector makes it an important and a uniquely challenged environment to study the GenAI adoption.

Despite numerous potential advantages for improving the supply chain processes, the research on the topic is relatively scanty. Several recent studies indicate that GenAI can bring about significant changes in OSCM (Kshetri et al., 2024). Several industry reports highlighted the business values of these technologies, the skills needed to use them, risks involved (Rane, 2023; Rane et al., 2023), challenges in scaling them (Ghimire et al., 2024), and the ethical and governance issues linked to their use (Patil et al., 2024). The year 2023 is dubbed as the "breakout year" for GenAI in construction (Dahlen, 2023). All of the above culminate to indicate that more research is needed to understand the possibilities of adopting GenAI within the construction industry's OSCM.

This study attempts to investigate the blockades preventing companies from adopting LLM-based GenAI in OSCM activities in the Indian constructions sector. The blockades are investigated from the lens of organizational, technical, and data-related viewpoints that influence the adoption propensity of the Indian construction firms. While the authors present the various types of GenAI for contextual purposes, the actual data analysis and experts' inputs are restricted to only LLM-based applications. Although studies have examined digital technologies in construction, including BIM, Digital Twins, and AI-enabled analytics, very few have investigated the specific blockades that shape the adoption of LLMs in construction OSCM. Existing research does not model how these blockades interact, nor does it reveal their causal structure. This creates a gap in understanding the systemic constraints that determine GenAI readiness in construction supply chains. The present study addresses this gap by identifying the key blockades and analyzing their cause–effect relationships using a Grey-DEMATEL approach.

Specifically, this study seeks to address the following Research Questions (RQs):
RQ1: What are the key blockades hindering the adoption of LLMs in construction OSCM in India?
RQ2: How do these blockades interact within a cause–effect structure that shapes LLMs adoption outcomes?

Given the exploratory nature of GenAI adoption in construction OSCM and the limited availability of large-scale empirical data, this study focuses narrowly on modelling the structural blockades identified by experts rather than evaluating current use cases or forecasting benefits. In order to address the research questions mentioned above, data were gathered from a group of experts actively working in the domain of construction project management for more than 10 years. The study used an exploratory research approach and Grey-DEMATEL approach to model and describe the blockades of GenAI in construction OSCM (R2). The blockades identified were scrutinized by the experts and subsequently finalized. To understand how the blockades were related to and the influence they exercised on each other, semi-structured interviews were conducted using open-ended questions. Finally, the experts' responses were analyzed to extensively assess the challenges faced by the construction firms.

The rest of the study is arranged as follows. Section 2 discusses the key literature on blockades to implementing GenAI in the construction sector. Section 3 explains the methodology used in the study. Section 4 presents the results and discussion. Section 5 highlights the implications, and Section 6 concludes the study with suggestions for future research.

2. Literature Review

This section discusses various uses of GenAI in the construction OSCM and how it can be used to improve operations such as demand forecasting, resource planning, and decision-making. More important, this section enlists the main blockades that impede the adoption of LLMs. To complement the recent industry reports referenced above, prior scholarly work on digital construction technologies offers useful theoretical grounding for this study. Research on Building Information Modeling (BIM)–AI integration highlights long-standing interoperability and data-governance challenges that directly influence GenAI readiness (Heidari et al., 2024; Li et al., 2024). Studies on real-time decision analytics in construction emphasize the centrality of high-frequency data flows, sensor integration, and multi-source fusion—conditions that map onto the "real-time data processing" and "data integration" blockades identified in this paper (Omrany et al., 2023). In parallel, the AI trust literature, including explainability, reliability, and domain-specific validation frameworks (Bayer et al., 2022; Islam et al., 2022), provides conceptual foundations for interpreting model accuracy and domain validity concerns.

2.1 GenAI in Construction and OSCM

GenAI encompasses the branch of AI that models' scenarios generating new texts, designs, or structural variations by learning patterns from historical data (Ooi et al., 2023). This makes GenAI different and in many cases even superior to the older AI systems that followed fixed rules or just made predictions without any context (Liao et al., 2024). GenAI possesses the ability to understand and adapt to situations and even help with creative and technical decisions. It has been shown that some GenAI applications, especially deep learning techniques such as Generative Adversarial Networks (GANs) and LLMs can come up with totally original ideas to solve industrial problems (Lee, 2024; Yenduri et al., 2024).

Several industries have experienced the benefits provided by GenAI in terms of automating documents, information retrieval, summarizing texts, and decision making. However, there are two specific challenges that some industries including the construction sector are concerned about. First, GenAI performs reliably only when the input data is complete, connected, and relevant for the industry (Dahal, 2023). In other words, good quality data is crucial for GenAI based applications to work effectively. Second, many organizations do not understand how much infrastructure, governance, and workflow changes are needed to use GenAI properly (Gołąb-Andrzejak, 2023). The above-mentioned facts explain some of the blockades considered in this paper, such as real-time data processing (A3), model accuracy and domain validity (A2), and the need for strong computing resources (A7). GenAI comprises several techniques that offer unique advantages. GANs, for example, operate using two neural networks that work against each other to create realistic images that can be employed for architectural visuals and design ideas (Lin et al., 2023a; Liu et al., 2024). Variational autoencoders (VAEs) take a design, compress, and rebuild it. In this process it learns new designs, run material simulations, and generate early prototypes quickly (Vahdat & Kautz, 2020; Sharif et al., 2021). Autoregressive models generate outputs step by step, making them useful for design sequences, project scheduling, and cost estimation (Rombach et al., 2022; Moreno-Pino et al., 2023; Vajrobol et al., 2024).

GenAI phenomenon is gaining traction relatively quickly, but construction sector has its own specific characteristic set of challenges. Every construction project is operated differently with its own workforce, resources, and site conditions. The supply chain is often the most fragmented as opposed to other sectors that are expensive to manage, and easily affected by weather, regulations, and market conditions. GenAI may prove immensely useful with writing documents, planning schedules, procurement, checking regulations, risks detection, and swift decision making. It can also assist in improving schedules, summarize design files, choosing suppliers, and automating compliance work (Pan & Zhang, 2021). In order to use GenAI effectively, industries must have strong data systems, smooth information flow, and high-quality industry data, things many construction firms are still struggling to have. This combination of high potential and structural constraints underscores the need to examine the blockades to GenAI adoption specifically within construction OSCM. The subsequent sections review literature on current GenAI applications in construction, digitalization challenges, and established barriers from BIM, Digital Twin, blockchain, and Industry 4.0 studies, which helped identify the blockades in context of LLMs.

2.2 Current Utilization of GenAI in Construction OSCM

The existing literature suggests that research efforts are increasingly directed toward tailoring GenAI models for industry-specific and task-oriented applications. The five main categories of GenAI models vary from text and image generation to design and non-image output; the major types are: GANs to generate images that are realistic (Yi et al., 2019), VAEs to create grammatically correct text (Tu et al., 2023), Autoregressive models for generating sequential text (Miao et al., 2020), Diffusion models for generating images that are visually smooth, and Flow-based models for converting data to more creative formats (Li et al., 2022b). As these underlying models continue to evolve, researchers are actively exploring new architectures to enhance generative capabilities. In the construction domain, possible uses include generating design images, scheduling optimization, and documentation workflow enhancement. The other sub-sections provide a close look at these models and examine their construction applications.

2.2.1 Generative Adversarial Networks (GANs)

GAN has two neural networks: a generator and a discriminator. The purpose of such networks is to train them to outsmart each other and hence develop the generator which can produce very realistic data, for example, images (Lin et al., 2023a). The discriminator is the logical one in this play which receives fake data from the generator and checks whether it is truthful or not (Caporusso et al., 2020). This mechanism allows the model to become smarter in data generation with time. GANs have several applications in the construction industry, primarily in architecture and the design of buildings (Ikeno et al., 2021). GANs are used to design realistic concepts of buildings and several building designs out of basic ideas or sketches (Wu et al., 2022). These models enable architects to explore a wider range of design possibilities more efficiently than traditional design approaches. An example is that GANs could be the means of generating the floor plans and architectural structures, thus making the process more repeated and hence short in time (Liu et al., 2024). To model buildings using GANs is one of the most successful strategies for rapidly generating high-quality and detailed 3D models from 2D blueprints or photographs (Parente et al., 2023). Such 3D visualizations give the possibility for architects, engineers, and clients to see how the project will look like in reality before starting the construction (Aalaei et al., 2023). GANs can simulate the texture, color, and pattern of different materials, thus enabling architects to see how different materials will look like using a range of environmental conditions such as the lighting effect.

2.2.2 Variational Auto Encoders (VAEs)

VAEs are types of GenAI models that intend to learn the data patterns and create new instances resembling those it has learned (Akkem et al., 2024). VAEs act as data encoders and transformers, compressing information into a lower-dimensional latent space before decoding it back to its original form (Yan et al., 2023). They are particularly beneficial for users, serving as data compressors and generators of possibilities for input designs.

VAEs may have several applications that can improve AEC sector. In the field of architectural design, VAEs technology can generate several possible designs that are variations of the same basic plan or layout (Vahdat and Kautz, 2020). By manipulating latent vectors, architects can explore the underlying design space, enabling VAEs to generate a wide variety of design alternatives, making them effective tools for the rapid production of design variants (Lew and Buehler, 2021). Thus, the company can benefit from the speedy availability of design versions with the primary structure intact. They demonstrate their exceptional benefit in material simulations (Sharif et al., 2021). Such models produce virtual material mixtures and predict their behavior under particular stress circumstances. According to this application, it is possible to discover some new and interesting ways of combining materials, which would be beneficial in the design and construction of energy-saving and eco-friendly buildings (Suphavarophas et al., 2024). VAEs can automatically produce BIM variations with a minimal number of changes in the specifications of spaces, layers, materials, and energy. VAEs can gain experience from the BIM datasets that already contain the information and thus propose the most suitable solution to the problem with fewer human efforts and a shorter time span (Sharif et al., 2021). For the purpose of project cost estimation, VAEs can mine historical data of past projects to identify trends and generate forecasts of costs and resources for new projects (Velykorusova et al., 2023). Both construction managers and power plants can enjoy the advantages of smart technologies over pure algorithms by placing such technologies as, yet high-level tools on which smartness rests.

2.2.3 Autoregressive Models

Autoregressive modeling is a GenAI type that predicts data incrementally, relying on previous data to create the next segment of the sequence (Kaur et al., 2023). This approach is especially strong in the area of generating sequences, for example, text or time-series data, by means of the analysis of former patterns and the construction of new data.

The autoregressive models in the building sector can have various applications. In architecture, the step-by-step design generation based on past design sequences can be helped by such models, in turn, layout creation becomes more efficient and manual design efforts are lessened (Moreno-Pino et al., 2023). These models can suggest better and efficient solutions after learning the structure or layout of designs (Kauss et al., 2024). These models can prove instrumental in predicting the project timelines and update schedules as new data comes in, thus making them a powerful tool for project management. Also, autoregressive models can be used in cost estimation. In this way, autoregressive models are able to forecast future expenses using historical spending patterns as a basis.

2.2.4 Diffusion and Flow-Based Models

Diffusion models are a class of AI that can start with noise and end up with a meaningful output, making them well suited to high-quality image generation and design (Rombach et al., 2022). In a design-based setting, such models can assist in the creation of the visual renderings of buildings or materials that look very real by converting the rough drafts submitted to the agency into the required detailed pictures. Moreover, they are functioning in the realm of urban planning as they emulate environmental impacts (like lighting or weather) on building sites, demonstrating how seasoned architects can get insights into how designs will appear in different weather conditions. Flow-Based Models learn reversible transformations to reduce the dimensionality of the data (Tu et al., 2022). In construction, architectural design is made through such models by performing different kinds of modifications on the input idea thus letting designers come up with different design options. They are a smart choice for material selection since they permit an accurate modeling of textures and colors, as a result, clients may choose from a variety of options. Flow-based models can also be a reliable choice when it comes to quality control by the structural comparison of the digital design to the actual construction outcome to get the exact deviations (Fernandez-Solis, 2013).

While recent GenAI studies have demonstrated value in automating text-intensive tasks such as summarization, document generation, contract analysis, and risk identification, their connection to OSCM within construction has received limited scholarly attention. Prior OSCM research in construction highlights recurring challenges—such as fragmented information flow, coordination delays, procurement inefficiencies, and documentation bottlenecks—that map directly onto the types of tasks LLM-based GenAI systems can support (e.g., specification extraction, design–procurement alignment, and real-time reporting). However, existing GenAI studies rarely position these capabilities within a construction OSCM framework, nor do they examine the structural barriers that influence whether such tools can be operationalized. This gap strengthens the need for a focused examination of GenAI adoption blockades specifically through an OSCM lens.

The selection of blockades in this study is grounded in established innovation-adoption frameworks that explain how technological change unfolds within complex organizational environments. The Technology–Organization–Environment (TOE) framework (Awa et al., 2017) suggests that adoption barriers typically arise from technological characteristics, organizational capabilities, and external environmental conditions. Similarly, socio-technical systems theory argues that successful technology use depends on the alignment of technical subsystems with human, organizational, and workflow elements (Sony & Naik, 2020). These perspectives provide a theoretical rationale for organizing the ten identified blockades across technological, data-integration, and organizational–institutional domains and justify their relevance to GenAI adoption in construction OSCM. Thus, the blockades examined in this study are not arbitrary but reflect categories consistently emphasized in foundational innovation-adoption scholarship. Accordingly, throughout the remainder of the paper, the term “GenAI” refers specifically to LLM-based text generation and reasoning systems, unless explicitly stated otherwise.

2.3 Blockades in the Implementation of GenAI in Construction OSCM

2.3.1 BIM and Systems Integration

Construction sector relies heavily on BIM systems for creating designs, coordinating work, and managing buildings throughout their life cycle. It becomes challenging for organizations to connect BIM with GenAI because technically BIM requires different software platforms to smoothly work together. Adding to this issue is the fact that stakeholders use different BIM tools with different data formats and structures (Le et al., 2022). Studies show that established regulations and shared data frameworks are required for a strong GenAI-BIM integration, as the existing BIM systems often struggle with data compatibility and consistency (Rane et al., 2023). Several other studies postulated that new API standards and data exchange methods are needed so that BIM systems can send out real-time updates and work seamlessly with GenAI algorithms (Onatayo et al., 2024). Some scholars opined that Industry Foundation Classes (IFC) can be used to create a common data structure for GenAI in BIM (Gerbino et al., 2021; Díaz-Rodríguez et al., 2023).

Cloud-based BIM integrated with GenAI is observed theoretically to facilitate centralized data processing framework that can assist smooth operations especially in situations involving large teams. However, this is still to be operationalized in real time (Li et al., 2022a). Though there has been significant progress in the field, still some real-world problems persist, such as data security and processing delays that must be tackled before GenAI can be used confidently in real construction projects (Mukherjee et al., 2022).

2.3.2 Model Accuracy and Domain Validity

Model Accuracy and Domain Validity of GenAI in the construction OSCM context refer to the degree of certainty and dependability in AI-produced results, for example, design predictions, structural simulations, and scheduling forecasts (Karami et al., 2024). AI-generated schemes should be error-free and show no variation in functionality under different construction conditions and project types (Rafsanjani &

Nabizadeh, 2023). Such factors are sure to be the most important, if not, the involvement of inaccuracies can cause the biggest safety problems and even lead to the failure of projects, time loss in doing rework, and mismanagement of resources (Memon et al., 2023). During recent years, investigations have been conducted on the problems of accuracy and reliability in GenAI for construction. For example, Waqar et al. (2023) note that even minor errors in AI-generated structural models can pose significant safety risks, necessitating more rigorous project verification processes and potentially increasing project costs. Marquis et al. (2024) examined the issue of reliability for AI tools by suggesting the use of implementation and approval as testing and validation measures. The implementation of GenAI models with quality control regulations allows for increased reliability through compliance with engineering standards and safety regulations, thus building up the trust level of management in AI-generated outputs in construction SCM (Lu et al., 2023; Saihi et al., 2023).

2.3.3 Real Time Data Processing

In construction, real-time data processing means the fast handling and analyzing of non-stop data streams from sources, such as sensors, drones, and IoT devices, that are monitoring different sections of a construction site, from equipment status to environmental conditions (Yenugula et al., 2023). Good real-time data processing is the prerequisite of GenAI for making timely, informed decisions that will optimize site safety, efficiency, and resource allocation (Jackson et al., 2024). However, managing the endless stream of fast paced data is a major technical blockade. It requires strong data integration, low delays, and high computing power (Patil & Desai, 2023). Many studies have proved that these challenges can affect GenAI significantly. For example, it was shown that huge volumes of data in the construction sites can slow down systems and create delays in important AI-based decisions (Kumar & Agarwal, 2023). Malacaria et al. (2023) emphasizes the significance of solid data architecture to tie diverse data sources together to guarantee smooth transition for GenAI models. Previous literature highlights the computational demands associated with processing high-frequency data, noting that while scalable cloud-based solutions facilitate data management, they may not adequately mitigate on-site latency issues (Patil & Desai, 2023), particularly in scenarios involving complex, multi-source data integration (Latha et al., 2023; Sathupadi, 2023; Gutta, 2024).

2.3.4 Structural Behavior Simulation Challenges

The structural behavior simulation in the construction field is the usage of models to anticipate the way the materials and structures will change under different conditions, e.g. load, temperature extremes, and environmental stressors being some of the issues. Generative AI, in such a scenario, must possess the ability to film physical properties and recognize the interrelationship of various materials to present an artificial environment that is true to nature. Developing such models is arduous work, since besides using vast information on the engineering sector, advanced algorithms are needed to ensure predictions that will fit real-world behavior. Kim et al. (2025) emphasize that GenAI models should be aware of the exact material features so that they could, in turn, help improve the accuracy of making predictions if needed. Furthermore, Vamvakas et al. (2025) asserts that the implementation of physics-based neural networks in GenAI is a vital step towards the enhancement of its understanding of structural dynamics, thereby making simulations more practical. Wang et al. (2026) came up with another study, which underlined the importance of domain-specific dataset training in GenAI models, as the general-purpose data do not contain the necessary information suitable for construction use.

2.3.5 Customizability for Project-specific Designs

Designing customizable structures is a very important part of construction work since many a time, clients' requirements, local regulations, and regional building codes demand extremely tailored solutions (Gil Pérez & Knippers, 2023). Delivering the required designs, GenAI models in construction sectors must be able to invent novel designs that satisfy the existing local standards. An important concern is that AI tools must adhere to regulatory requirements while preserving flexibility in the design process (Schuett, 2023). The studies have been conducted on the difficulties associated with the potential AI-generated designs of clients' satisfaction, which nevertheless remain compliance-approved. Kibriya et al. (2024) stress that implementation of rules pertaining to the regulations of the generative models allows region-specific variations and makes it simpler for them to be gotten through. Besides, Liao et al. (2024) propose smart algorithms that enable AI systems to add, remove or change the blueprint for the design. Sometimes, the purpose of algorithms may be to supply the customer with accurate outputs – which may not break the norms.

2.3.6 Regulatory Validation and Code Compliance

It is very necessary that the AI-generated designs in the construction industry conform to the standards when the construction industry abides by the rules (Lu et al., 2023). Safety, quality, and legal compliance in this manner are due to the safe and quality designs as well as the fact that the designers are able to come up with meticulously safe and quality designs (Calver et al., 2024). This validation process involves measurement in a detailed way of the connection between AI-generated designs and the firm needs on the industry of quality standards. New studies are pointing at the fact that there have been difficulties in ensuring that GenAI outputs are generated according to the construction norms (Saka et al., 2023; Na et al., 2023). As pointed out by Diaz-Rodriguez et al. (2023), the purpose of AI is also to build a tool that can evaluate designs based on specific regulations in real-time, thus saving the trouble of compliance audits. Likewise, the development of AI models is so hard because of the location-based rules that are different, and we need to collect the data of the regions with the same rules (Wang et al., 2015; Sauvola et al., 2024). Also, Mylrea & Robinson (2023) emphasize the development of highly interpretable AI models, therefore the interpretability in AI models is the key as, with this clearer output, assessing compliance will be easier for human experts.

2.3.7 Computational Resource Requirements

The implementation and training of high-level GenAI algorithms indeed require super computing power (Tourassi, 2024), however, it might become a problem for the small construction enterprises that often have poor IT infrastructures and lack the necessary financial means (Waqar et al., 2023). The costly investments in hardware and the significant energy consumption that occurs in processing intricate models can furthermore instigate basic construction firms to shy away from such costly ventures (Yilmaz et al., 2023; Sharma & Yadav, 2022). Kissi et al. (2023) argue in their study that the high cost and technical complexity of sophisticated AI tools are the major issues that are slowing down the smaller construction firms from adopting new technologies. Likewise, Sharma et al. (2023) proposes that cloud-based platforms could make this process easier for smaller businesses by offering more flexible, cheaper computational resources for AI model training. Hua et al. (2023) investigate AI designs that significantly reduce the computing resources needed which allows companies to adopt them even if they have limited technological capabilities.

2.3.8 Cross Disciplinary Collaboration Challenges

Construction projects are founded on the strategy of teaming up of architects, engineers, and contractors with the profoundly insightful vision represented by each one of them (Lin et al., 2023b). Humanization of GenAI tools thereby enhancing inter-team communication can be very difficult especially when every team uses different software and does not follow common data protocols (Gao et al., 2024). Effective integration of GenAI can not only streamline processes and address industry-specific needs but also foster a shared platform for dialogue and knowledge exchange among stakeholders. The report, however, indicated that the tools provided by the cloud-based GenAI platforms have served as the common ground whereby communication among the different departments is improved and misunderstandings if any occurred over the situations have been minimized (Nah et al., 2023).

2.3.9 Data Quality and Fragmentation

In construction OSCM, data quality and fragmentation involve aggregating data from different systems and devices such as IoT sensors, structural analysis programs, and project management tools, into a format that is appropriate for GenAI applications (Chen et al., 2021; Meriton et al., 2021). With these connections GenAI can make better decisions by creating and analyzing data pertaining to data fields like traffic, temperature, and schedules, etc. (Hendriksen, 2023). But the major hindrance with the data mentioned above is that they come in multiple formats and structures, making it difficult to be operated using GenAI effectively (Feuerriegel et al., 2024). Prior studies highlight that consistent data frameworks constitute a key requirement for achieving interoperability and advocate consolidating dispersed data within centralized AI platforms through standardized data structures and interoperable interfaces (Bandi et al., 2023; Madaan et al., 2024). This will potentially help AI systems with accurate predictions within construction workflows.

2.3.10 Change Detection and Workflow Management Constraints

In organizations, change detection and workflow management indicates tracking the changes in the designs, schedules, and resources as they occur and taking remedial actions to manage the unanticipated consequences ensuing. This is crucial to ensure the projects are functioning as per the schedule and avoid expensive mistakes or rework (Weiner, 2020). GenAI-enabled technologies can facilitate rapid detection of changes in incoming data, support timely updates to project models, and help maintain consistency across design and construction processes (Agrawal, 2024). Involvement of advanced technologies such as GenAI, through its impeccable change detection mechanism, helps organizations to react quickly, maintain project quality, avert mishaps, and stay on schedule (Sun et al., 2022; Wamba et al., 2024).

Recent research examines the possibility of AI's utility in change management. Specifically, it has been noticed that GenAI, coupled with data analytics and machine learning, can monitor design changes (Ploennigs & Berger, 2024), detect mismatches or errors (Combs et al., 2024), and suggest updates in real time – some factors that can accelerate the progress of fast-moving construction projects.

2.4 Defining and Justifying the Blockades

To circumvent any possibility of confusion and ensure that the blockades are meaningful and are able to explain the inherent issues deeply, extensive literature review was conducted on BIM, Digital twins, AI in construction, Industry 4.0, and digitalization in construction supply chains. **Table 1** provides definitions, rationales, and supporting literature for each blockade. After brainstorming and discussions, the expert panel zeroed in on the ten important blockades that they envisage as the most influential ones in the adoption of GenAI in the construction supply chains in India. There were several other broader organizational issues that were excluded from the study because they were seen as background blockades rather than the direct blockades to GenAI's day-to-day functioning. The final set of blockades, therefore, represent the most severe barriers that influence the technical and operational viability of GenAI in construction OSCM.

The ten blockades form a coherent structure rather than a disconnected list. They can be grouped into three mutually reinforcing thematic domains as explained below.

- *Technological capabilities*: These include model accuracy and domain validity, structural behavior simulation, and computational capacity. They describe the intrinsic performance limitations of current GenAI systems when applied to construction tasks.

- *Data and systems integration*: This domain encompasses blockades such as BIM and system integration, real-time data processing, data fragmentation, and change detection. Collectively, it represents the technical setup and data ecosystem that is required for the GenAI to function effectively in OSCM.
- *Organizational and Institutional Readiness*: Blockades pertaining to cross-industry collaboration, regulatory validation, and project-level customization reflect on how the construction industry operates and institutional regulations that influence the adoption of GenAI.

This framework illustrates how technical, data-related, and organizational–institutional issues mutually reinforce each other, providing a structured foundation for the causal analysis conducted in subsequent sections.

Table 1. Mapping prior digital technology barriers to the ten GenAI blockades.

Existing literature theme	What is already known	Gap in literature	Corresponding blockades in this study
BIM adoption challenges	Interoperability issues, inconsistent data schemas, limited integration with other systems	Limited insights on how these issues translate to GenAI–BIM integration	A1, A9
Digital Twin barriers	Need for real-time data, high model accuracy, skilled workforce requirements	Lack of research connecting DT challenges with LLM performance constraints	A2, A3, A4
Blockchain in construction	High computational load, low digital maturity, interoperability issues	Missing connection to GenAI compute and data-governance challenges	A7, A9
Industry 4.0 / IoT implementation	Poor sensor integration, fragmented data ecosystems, weak digital infrastructure	Unclear how these infrastructure gaps hinder GenAI deployment	A3, A9, A6
Organizational readiness & collaboration	Resistance to change; siloed teams; low cross-disciplinary collaboration	Insufficient attention to collaboration as a blockade for AI scaling	A8
Regulatory compliance & documentation	Compliance processes complex and manual	Lack of clarity on GenAI's role in compliance and the risks of inaccurate outputs	A6, A5
General AI adoption studies	Trust, transparency, reliability concerns	Missing systematic characterization of causes vs. effects in construction	A2, A10

3. Methodology

The present study employed Grey-DEMATEL technique to analyze the intricate relationships among the blockades and their influence in the adoption of LLMs in the construction sector. The set of blockades was put through scrutiny by a group of experts (details are presented in **Table 2**) who thoroughly weighed the appropriateness of the blockades affecting the construction sector. All the experts considered for the study had at least 10 years of experience and therefore their assessments were crucial in building the initial matrix required for the Grey-DEMATEL analysis. Experts were recruited using purposive sampling to ensure informed judgment on LLM adoption in construction OSCM. Inclusion criteria required participants to have: (i) a minimum of 10 years of professional or research experience in the construction sector, (ii) direct involvement in digital systems such as BIM, ERP, project controls, or supply chain coordination, and (iii) familiarity with AI-enabled or data-driven decision support tools. All the experts were based out of North India and had varied experience in construction sector. The final panel comprised six experts representing Engineer, project manager, professor and consultant. A panel size of six experts is considered appropriate for Grey-DEMATEL studies, as the method emphasizes depth of expertise rather than statistical representativeness. Prior MCDM and DEMATEL research demonstrates that stable causal structures can be obtained with small expert panels when participants possess strong domain knowledge and judgments are aggregated using grey numbers to capture uncertainty (Dwivedi et al., 2022).

The data collection process was also facilitated by the experts. Data was collected under the framework of grey-DEMATEL methodology using a semi-structured interview. Each interview lasted approximately 90 minutes. The experts were presented with an interview guide that contained open-ended questions on how the blockades influenced one another. The responses were recorded and transcribed. The semi-structured interviews were guided by open-ended questions focusing on practical difficulties encountered when attempting to introduce LLM into construction-related workflows. Questions explored the sources of implementation difficulty, interactions among technical and organizational constraints, and factors that tend to trigger secondary challenges during adoption. Interview transcripts were reviewed manually and analysed using an iterative coding process. In the first stage, recurring issues were noted directly from the interview narratives. These issues were then compared across experts and consolidated into a smaller set of conceptually distinct blockades. The preliminary coding was reviewed by the authors independently, and differences in interpretation were resolved through discussion to improve analytical consistency. To reduce the risk of construct omission or misclassification, the resulting blockade set was cross-checked against findings reported in prior peer-reviewed studies on AI and digital technology adoption. Conventional reliability testing (e.g., internal consistency of multi-item scales) was not applied because the Grey-DEMATEL procedure is based on experts' pairwise influence assessments and matrix operations, rather than on scale-based latent constructs that require psychometric reliability analysis (Sheng-Li et al. 2018).

Table 2. Profile of experts.

S. No.	Profile	Experience	Sector
1.	Professor civil	20	Academic
2.	Project manager	18	Construction
3.	Project manager	20	Construction
4.	Executive engineer	16	Construction
5.	Assistant engineer	13	Construction
6.	Architect	11	Construction

Grey set theory is helpful for analyzing data that is unclear, uncertain, or incomplete. Also, it is one of the most accurate tools for analyzing qualitative inputs (Patil et al., 2023). On the other hand, DEMATEL is a useful multi-criteria technique to unearth the cause-and-effect relationships among factors and rank ordering them on the basis of their influence (Si et al., 2018; Sheng-Li et al., 2018). Therefore, integrating the grey set theory with DEMATEL can prove immensely useful in dealing with fuzziness or ambiguity in the qualitative data (Raj et al., 2020). This strategy is particularly useful for the current study which rely heavily on expert judgment and subjective interpretation. This combination of grey set theory and DEMATEL has been employed several times in the past to model the relationships among factors and extracting useful information from ambiguous qualitative data (Xia et al., 2015; Yang & Wang, 2024). The steps followed for the analysis are described below:

Identifying blockades: A comprehensive literature review and consultations with experts helped finalize ten key blockades influencing GenAI adoption in construction industry, as discussed in Section 2.

Developing the initial matrix: Expert panel assessed the direct influence of each blockade on every other blockade. A five-point grey linguistic scale ranging from "No Influence" to "Very High Influence" was utilized to collect the experts feedback regarding blockades influence. The process begins by having each expert independently evaluate the directional influence of each blockade i on every other blockade j, where i and j range from 1 to n (n = 10). This results in an n x n matrix for each expert, capturing their individual perspectives on the interrelationships among the blockades. The linguistic scale is provided in the Appendix A, **Table A1**. These individual assessments were then aggregated to form initial matrixes for each expert.

Conversion to grey relation matrix: These initial matrices are used to construct grey relation matrices based on pairwise comparisons. For instance, if expert k indicates a "Low influence" of blockade *i* on blockade *j*, the corresponding grey number is represented as [0.25, 0.5], where 0.25 is the lower limit and 0.5 is the upper limit of the grey number. The grey relations matrix for an expert is shown in Appendix A, **Table A2**. These grey numbers are formally defined as:

$$\otimes a_{ij}{}^{k} = \left(\underline{\otimes}\, a_{ij}{}^{k}, \overline{\otimes}\, a_{ij}{}^{k}\right) \tag{1}$$

In Equation (1), $1 \le k \le e; 1 \le i \le n; 1 \le j \le n;$ $\underline{\otimes}\, a_{ij}{}^{k}$is lower and $\overline{\otimes}\, a_{ij}{}^{k}$is upper grey number. The resulting grey matrix is:$\left[\otimes a_{ij}{}^{1}\right], \left[\otimes a_{ij}{}^{2}\right], \ldots, \left[\otimes a_{ij}{}^{e}\right]$.

Creating average grey-Relation Matrix: The average grey-relation matrix can be obtained by using below illustration:

$$\otimes \tilde{a}_{ij} = \left(\frac{\sum_k \underline{\otimes} a_{ij}{}^{k}}{e}, \frac{\sum_k \overline{\otimes} a_{ij}{}^{k}}{e}\right) \tag{2}$$

Developing crisp relation matrix: In this step, grey values are converted into crisp values using modified crisp scores defuzzification method explained in Patil et al. (2025). The crisp values are presented in Appendix A, **Table A3**.

Calculating the normalized direct-relation matrix: The crisp relation matrix is then converted into normalized direct-relation matrix using below illustration:

$$C = b \times D \tag{3}$$

Here D is:

$$D = \frac{1}{\max\limits_{1 \le i \le n} \sum_{j=1}^{n} b^{*}{}_{ij}} \tag{4}$$

The normalized direct-relation matrix is presented in Appendix A, **Table A4**.

Developing total relation matrix: The total relation matrix was computed from the normalized direct-relation matrix, capturing both direct and indirect effects among the blockades using below equation.

$$T = C \times (I - C)^{-1} \tag{5}$$

Here, I is the identity matrix. The total relation matrix is presented in Appendix A, **Table A5**.

Determining prominence and relation: The prominence and relation values for each blockade were calculated from the total relation matrix. These values help to visualize the interrelationships and identify the key drivers and dependents within the system.

$$R_i = \sum_{j=1}^{n} T_{ij} \ \forall i \tag{6}$$

$$D_j = \sum_{i=1}^{n} T_{ij} \forall j \tag{7}$$

Constructing the causal diagram: A causal diagram was constructed based on the prominence and relation values, providing a visual representation of the cause-and-effect relationships among the blockades. The values of R + D denote prominence and R - D denotes the Net effect. The positive values of R-D indicate cause blockades and negative values indicate effect blockades.

Calculating relative weights: The relative weights (RW) among the blockades can be calculated using below equations to make the rank order of blockades

$$rw_j = \sqrt{(R+D)^2 + (R-D)^2} \tag{8}$$

$$\widetilde{rw}_j = rw_j / \sum_{j=1}^{n} rw_j \tag{9}$$

4. Results and Discussions

4.1 Results of Grey-DEMATEL

The findings from the DEMATEL reveal that the Blockades hindering GenAI adoption in construction sector can be divided into two primary categories: cause and effect as shown in **Table 3** and **Table 4**.

Table 3. Weights for Blockades hindering GenAI adoption in construction sector.

Blockades hindering GenAI adoption	R	D	R+D	R-D	Weights	Nature
BIM and systems integration	4.44	3.39	7.82	1.05	0.09	Cause
Model accuracy and domain validity	4.87	4.26	9.13	0.61	0.11	Cause
Real time data processing	5.12	4.24	9.35	0.88	0.11	Cause
Structural behaviour simulation challenges	3.90	4.80	8.71	-0.90	0.10	Effect
Customizability for project-specific designs	4.00	4.25	8.25	-0.25	0.10	Effect
Regulatory validation and code compliance	3.71	4.35	8.06	-0.64	0.10	Effect
Computational resource requirements	4.44	4.31	8.76	0.13	0.10	Cause
Cross disciplinary collaboration challenges	4.27	4.05	8.32	0.23	0.10	Cause
Data quality and fragmentation	3.72	4.66	8.38	-0.94	0.10	Effect
Change detection and workflow management constraints	3.90	4.06	7.96	-0.17	0.09	Effect

Table 4. Ranking for blockades hindering GenAI adoption in construction sector.

Code	Blockades hindering GenAI adoption	Weights	Rank
A3	Real time data processing	0.111	1
A2	Model Accuracy and Domain Validity	0.108	2
A7	Computational resource requirements	0.103	3
A4	Structural behaviour simulation challenges	0.103	4
A9	Data Quality and Fragmentation	0.099	5
A8	Cross Disciplinary Collaboration challenges	0.098	6
A5	Customizability for Project-specific Designs	0.097	7
A6	Regulatory Validation and Code Compliance	0.095	8
A10	Change detection and Workflow Management constraints	0.094	9
A1	BIM and Systems Integration	0.093	10

Beyond identifying which blockades fall into the cause-and-effect groups, the DEMATEL model reveals important relational dynamics among them. The influence values show that real-time data processing (A3) exerts a strong causal effect on data integration (A9), validation and compliance (A6), and change detection (A10). This indicates that most downstream challenges are symptoms of inadequate data pipelines rather than independent problems. Similarly, model accuracy and domain validity (A2) strongly influence structural behavior simulation (A4) and customizability of designs (A5), suggesting that both issues originate from the foundational reliability of GenAI outputs rather than isolated modelling limitations.

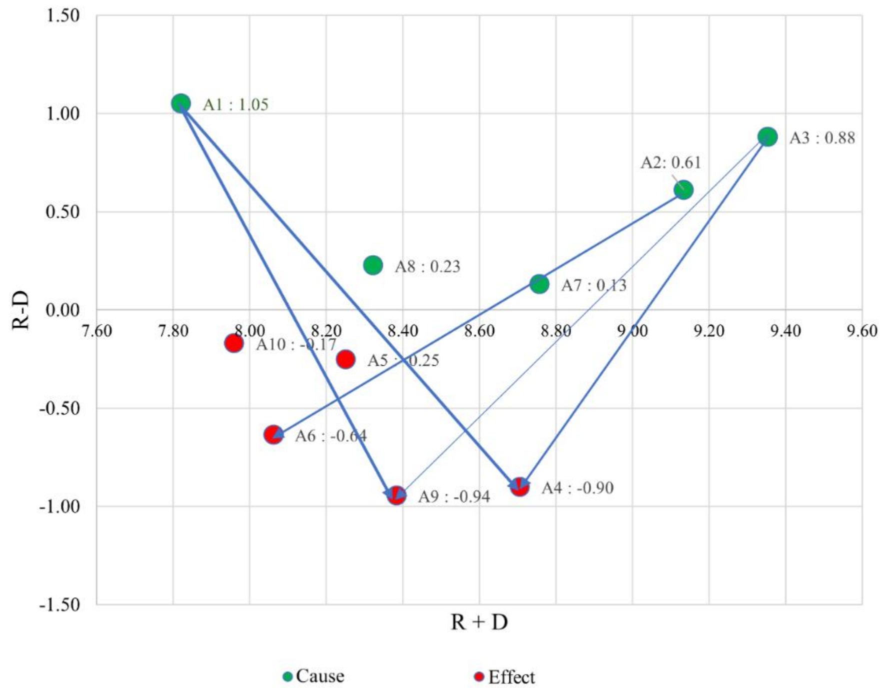

Figure 1. Causal interrelationship among blockades.

Computation resource requirements (A7) are another stringent cause of the workflow disruption. When organizations lack sufficient computational power, it hinders the smooth functioning of GenAI based framework. This, in turn, creates problems in maintaining proper coordination among team members leading to delayed responses in times of exigency. “Effect” blockades (A6, A9, and A10) depend largely on the core technology conditions. They take shape when the basic technical issues are left unresolved. This indicates that if the major technological issues are addressed timely and accurately, many other organizational and workflow problems following the technological issues become less severe and therefore tractable. Upon reflecting keenly, it can be easily noted that these patterns demonstrate a layered structure with the basic technical issues (A2, A3, and A7) forming the foundation leading to integration problems (A1, A9) which eventually cause workflow and compliance challenges (A6, A10). It is therefore essential to understand the relationships between the blockades in order to decipher which blockades are most important and how they influence the adoption of GenAI. But first, it is important to isolate the inherent issues that need to be solved in order to construct the application of GenAIs into organizations possible. Reflecting on **Figure 1**, the blockades, in the cause group, are the most important ones to be perceived because they are the ones that propagate the rest of them that is why they should be addressed as soon as possible. Arrows in **Figure 1** represent dominant causal relationships whose influence values exceed the threshold of 0.42.

4.2 Sensitivity Analysis

A sensitivity analysis was conducted to assess the robustness of the Grey-DEMATEL results. Given the variation in expertise and professional backgrounds of the selected expert panel, nine alternative scenarios were examined to evaluate the stability of the findings. These scenarios enabled an assessment of how changes in expert judgments influence the derived weights and rankings of the identified GenAI adoption blockades. The sensitivity analysis followed established procedures reported in prior studies (Dwivedi et al., 2022). Specifically, the input value of the highest-ranked causal blockade was systematically varied by 0.10. The corresponding changes in the weights of the GenAI adoption blockades are presented in **Table 5**, while variations in their rankings across scenarios are reported in **Table 6**. The rank movements under different scenarios are further illustrated in **Figure 2**. The results indicate that the rankings remain largely stable, with only minor deviations observed in, demonstrating that the findings are robust and not unduly influenced by individual expert bias.

Table 5. Weights change for different scenarios.

Code	Normal (A3: 0.111)	S1	S2	S3	S4	S5	S6	S7	S8	S9
		0.10000	0.090	0.080	0.070	0.060	0.050	0.040	0.030	0.020
A1	0.093	0.051	0.095	0.096	0.098	0.098667	0.099778	0.100889	0.102	0.103111
A2	0.108	0.071	0.110	0.111	0.113	0.113667	0.114778	0.115889	0.117	0.118111
A3	0.111	0.100	0.090	0.080	0.070	0.06	0.05	0.04	0.03	0.02
A4	0.103	0.064	0.105	0.106	0.108	0.108667	0.109778	0.110889	0.112	0.113111
A5	0.097	0.058	0.099	0.100	0.102	0.102667	0.103778	0.104889	0.106	0.107111
A6	0.095	0.054	0.097	0.098	0.100	0.100667	0.101778	0.102889	0.104	0.105111
A7	0.103	0.067	0.105	0.106	0.108	0.108667	0.109778	0.110889	0.112	0.113111
A8	0.098	0.060	0.100	0.101	0.103	0.103667	0.104778	0.105889	0.107	0.108111
A9	0.099	0.064	0.101	0.102	0.104	0.104667	0.105778	0.106889	0.108	0.109111
A10	0.094	0.053	0.096	0.097	0.099	0.099667	0.100778	0.101889	0.103	0.104111

Table 6. Ranks change for different scenarios.

Code	Normal	S1	S2	S3	S4	S5	S6	S7	S8	S9
		0.10000	0.090	0.080	0.070	0.060	0.050	0.040	0.030	0.020
A1	10	10	9	9	9	9	9	9	1	1
A2	2	2	1	1	1	1	1	1	2	2
A3	1	1	10	10	10	10	10	10	3	3
A4	3	4	2	2	2	2	2	2	4	4
A5	7	7	6	6	6	6	6	6	5	5
A6	8	8	7	7	7	7	7	7	6	6
A7	4	3	3	3	3	3	3	3	7	7
A8	6	6	5	5	5	5	5	5	8	8
A9	5	5	4	4	4	4	4	4	9	9
A10	9	9	8	8	8	8	8	8	10	10

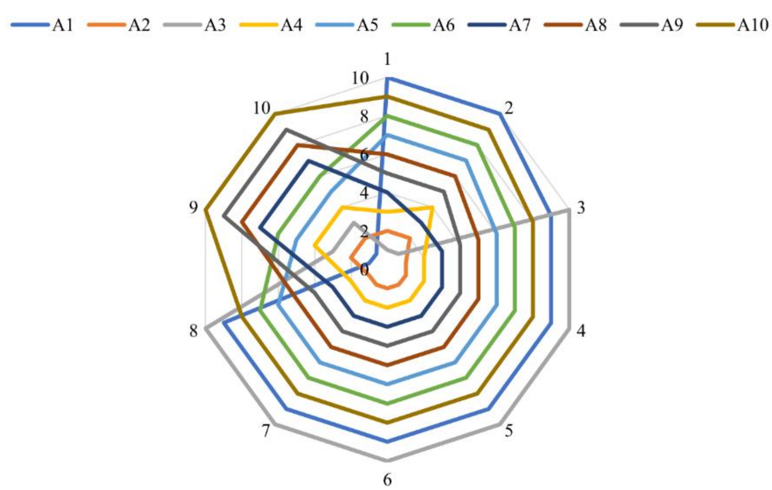

Figure 2. Sensitivity analysis for the scenario.

4.3 Interpretation of Influential Blockades

The topmost blockade amongst these is the problem of real-time data processing (A3). In construction projects, where decisions often need to be made on-the-fly, the ability to access and analyze data in real time is vital. Nonetheless, in India, the construction sector is still using the technology of outdated IT systems, disjointed data sources, and no integration between digital platforms which often discourages the sector from adopting LLMs. It is considered as a drawback of the LLMs, uniquely by this way, they are not capable of revealing the required information at the right time, and they do not even support the project in making decisions. To circumvent this problem, the construction industry needs to take immediate steps to digitize the supply chain operations and possibly upgrade the existing digital systems. This can facilitate smooth flow of real-time data and other important information between the operational units. A similar observation was made in the study conducted in the Ghanaian construction industry involving approximately 150 professionals, where real-time data processing was cited as the major obstacle in the adoption of new technologies such as IoT and AI. It was noticed that the inadequate and poorly equipped data systems that were slow, disconnected, and weak, could not monitor progress, or make timely decisions. Therefore, the professionals hesitated to adopt the new emerging technologies that need seamless supply of real-time information in order to function effectively (Maqbool et al., 2023).

Another closely related problem is model accuracy and validity (A2). Regardless of the country of origin, the construction sector worldwide is fraught with serious issues pertaining to exorbitant costs and safety concerns. This forces organizations to invest in technologies they can fully trust. GenAI based technologies rely on the availability of good quality, complete, consistent, and real-time data for efficient and accurate results or recommendations. Construction sector, due to its fragmented nature, suffers gravely from the availability of good quality and complete data. Because of the lack of trust in GenAI powered technologies, organizations are hesitant to adopt GenAI or just use it partially. In order to address the issue of distrust, GenAI based platforms can be trained on Indian construction projects and go through strong quality checks so that it gives accurate and project-specific results. A study on the use of Digital Twins (DTs) in industries reinforced the findings mentioned above. DTs has the ability to improve designs, manage projects, and provide real-time monitoring, subject to the availability of correct data. If the data is corrupt then the chances of misleading and unreliable results become considerably high affecting the construction safety and efficiency (Omrany et al., 2023).

Another important blockade in the “cause” category is huge computational power required (A7) to develop and operate GenAI. These models need exorbitant investments in digital infrastructure, particularly in strong servers, advanced graphics processing units (GPUs), and scalable cloud services, all of which are required for a robust and effective GenAI based framework. The small construction companies, especially the ones operating in the remote parts of India, find themselves bereft of the funds needed to invest in the digital infrastructure. The high costs and investments discourage the construction organizations from including digital tools in their OSCM and instead choose to go with the manual work. This problem can be partially alleviated and the adoption of GenAI can be promoted with cheaper cloud computing alternatives and government aid. Recent research on the propensity of the construction sector to adopt Blockchain Technology solidified the observation that the huge investment capital can prove a significant hurdle in the adoption process (Perera et al., 2020).

Another concerning challenge is the difficulty of using GenAI to simulate structural behavior (A4). In order to attain success in construction projects, it is absolutely necessary to conduct simulations of designs ensuring safety and compliance with regulations. As stated above, one of the major caveats with using GenAI is its stringent requirement of complete, consistent, and timely information. Most often the information pertaining to the materials, site conditions, and structural rules is either unavailable or only partially available, especially in the context of India. This confuses the output from GenAI, and the results are often misleading or completely inaccurate. This problem is further aggravated in developing country such as India where there is dearth of digitized historical data and the engineering standards are not often consistent. The immediate solution to remedy the problem mentioned above is to collaborate with universities, incorporate better data systems, and use standardized datasets. These steps would promote better simulations ensuring the correctness of the outputs from GenAI and thus encourage organizations to ponder seriously on adopting GenAI in OSCM.

Lack of collaboration across various disciplines within the construction sector (A8) is another major blockade hindering the adoption of GenAI. Every participant, from architects to engineers, contractors, and project managers need to work together to make the best optimum use of technologies such as IoT, GenAI, etc. But the industry often operates separately where isolated groups work with no proper communication amongst each other coupled with the resistance to new technology. Because of this disconnect many stakeholders do not completely understand how AI can actually benefit them and hence do not show any interest in learning about them. This problem can be averted to a large extent by imparting digital training, encouraging teamwork across disciplines, and shared platforms where new technologies are used with regular workflows. The study conducted with the Singapore construction firm revealed a similar finding showing that poor collaboration infused with weak data and information sharing was one of the most severe barriers to using smart technologies. This problem, coupled with regulatory issues and fuzzy data ownership impeded digital transformation in the sector (Hwang et al., 2022).

On the contrary, blockades in the effect group result from the blockades in the cause group. One prominent blockade here is the difficulty in integrating data from various sources (A9). For GenAIs to function optimally, they require seamless access to data generated across multiple platforms, such as project management systems, on-site sensors, and historical construction records. Yet, data silos, incompatible formats, and lack of interoperability are responsible for this failure of integration, and the models produce suboptimal results. Implementing the data protocols that are standardized and the middleware solutions that enable seamless data integration may overcome this blockade. It has been highlighted that the primary blockade in adopting Industry 4.0 technologies within the construction industry is data integration, as the effective utilization of diverse data sources is crucial for optimizing processes and enhancing decision-making (Li et al., 2023).

Another important blockade is the issue of providing customizability in building designs (A5). Due to the uniqueness of each construction project, the GENAI must be able to develop the required projects while considering the particular regional traditions, regulatory rules, and client requests. Nevertheless, the current shortcomings of such models make it impossible for them to create fully personalized solutions that are exactly the same as the local construction practices, thus making them less useful in practice. Improving the adaptability of GenAIs by training them on modular frameworks that can be tailored for certain projects becomes the central point required to solve the problem.

Regulatory Validation and Code Compliance (A6) is the other main blockade that emerges from the limited cause-related breakthroughs. The sector operates on very strict regulations and GenAIs can only be effective if they can comprehend and correctly use the guidelines in designs. The existing lack of integration between regulatory databases and GENAI outputs hampers their effectiveness. Solving this problem would involve the development of AI models that can automatically check the designs against the code and quickly point out noncompliance.

The lack of efficient systems for detecting changes and managing them within project timelines (A10) emerged as another blockade hindering the adoption of GenAI. The framework based on GenAI is a useful tool for detecting anomalies early and rectify it before the situations worsen. But because communication is sporadically fragmented and the data systems are disconnected from each other, the use of GenAI is challenging. A possible solution for this problem can be to use automated tools that detect changes using real-time data to spot the discrepancies and address it in a timely fashion.

Finally, the integration of GenAI and BIM is still at a very early stage of inclusion. It has been observed that GenAI and BIM often do not work smoothly together. Adding to the issue is the fact that many professionals still find it very difficult to understand the fundamentals of both GenAI and BIM. Because of this, a holistic advantage of the integration of GenAI and BIM is still unattainable. Better and focused training programs can help organizations to disseminate the knowledge of the technical "know-how" of new technologies to the workforce. This finding is reinforced from the observation made in Agrawal et al. (2023), where the lack of skilled workforce was equated directly with the hindrance to adopt new technologies at workplace.

4.3 Linking "Cause" Blockades to Operational KPIs (Cost, Schedule, Safety, Productivity, Service Levels)

Although the causal analysis identifies the influential "cause" blockades, their operational value becomes clearer when connected to measurable outcomes. Each major cause blockade—real-time data processing (A3), model accuracy and domain validity (A2), computational resource requirements (A7), cross-disciplinary collaboration challenges (A8), and BIM/systems integration (A1)—directly influences core OSCM KPIs such as cost, schedule adherence, safety, productivity, and service levels.

4.3.1 Real-Time Data Processing (A3) → Schedule, Safety, Productivity

When real time data is available, the GenAI based framework can intimate the teams about delays, resource problems, or safety risks. This helps in restoring safety at workplace, organization in team work, and avert mishaps. Managers are enabled to make better and faster decisions and reduce wasted time leading to higher productivity and better schedules.

4.3.2 Model Accuracy and Domain Validity (A2) → Cost, Safety, Rework, Quality

When GenAI is employed in the supply chain operations, it produces accurate results thereby reducing mistakes in understanding designs, estimating quantities, planning schedules, and detecting risks. This assists in cutting down expenses and incorrect usage of materials. When accuracy is ensured, the structural and safety-related errors are significantly minimized. This makes the construction sites safer to work and regulatory requirements are met.

4.3.3 Computational Resource Requirements (A7) → Productivity, Cost, Service Levels

The high computing power strengthens GenAI in making quicker and more accurate decisions. Consequently, procurement plans, risk reports, and compliance documents can be generated by such systems with minimal delay. The near-instantaneous outputs produced by GenAI-based systems significantly enhance operational efficiency and productivity. This has special utility for the contractors who are supposed to deliver reports or updates to clients timely and accurately. AI-generated analysis helps the contractors to respond faster, provide better service, and build trust with clients.

4.3.4 Cross-Disciplinary Collaboration Challenges (A8) → Schedule, Cost, Productivity

A lack of collaboration among architects, engineers, and contractors can compromise work quality, particularly when errors are not identified in a timely manner and consequently propagate unnoticed. GenAI finds it difficult to operate when the information it receives is incomplete, inconsistent, and outdated. Therefore, collaboration between teams can help reduce delays, promote speedy approvals, and ensure smooth information flow between teams leading to cost effectiveness and more reliable project schedules.

4.3.5 BIM and Systems Integration (A1) → Schedule, Productivity, Cost

The disconnected systems affect the operations severely as thoroughly integrated systems are required for GenAI to provide correct designs, organized planning, and optimal use of site data. When the systems are well integrated, GenAI can rapidly create documents, spot potential clashes, and update designs more smoothly. This speeds up the transition from the design to the construction phase and reduces the cost associated with manually rectifying mismatched information.

Implementing preventive and remedial actions to address the "cause" blockades helps build a robust foundation that GenAI needs to function well. When the "cause" blockades are alleviated the corresponding "effect" blockades like fragmented data, slow workflows, and regulatory approval problems, also start to decrease. This provides overarching benefits at the same time such as lower costs, more reliable schedules, better safety, and higher productivity.

5. Implications

This study discusses the issues and identifies major blockades impeding the adoption of GenAI in the Indian construction sector unlike the past research that focused mainly on the adoption of some common technologies such as BIM or DT in industries. Several blockades unique to the adoption of GenAI is considered in this study namely high computation needs, concerns about model accuracy for different types of construction projects, and difficulty in creating design outputs, that differ from the BIM and DT literature that enlisted the banal challenges such as system compatibility, regulatory requirements, and keeping data consistent. The challenges are even more severe for a country like India where the data systems are fragmented and access to real time data is almost an impossibility. This makes it worse for the GenAI based framework to operate smoothly as compared to BIM or DT tools, which rely less on real-time data. Upon comparing the blockades, it can be inferred that GenAI posits some extra difficulties. Specifically, it needs sophisticated data systems, stronger technology, and more coordinated teamwork than earlier AI tools. Hence, it can be deduced that GenAI is more complex to adopt than the technologies studied before. These challenges are amplified in India because the underlying conditions required for GenAI—standardised data pipelines, interoperable systems, and digital workflow maturity—are less developed than in many global construction markets. The study demonstrates that the blockades affecting the adoption of GenAI in the construction sector of India is a consequence of issues inherent to technology, organizational challenges, and external factors. This observation aligns with the Technology–Organization–Environment (TOE) framework, which posits that digital adoption depends not only on technological readiness but also on organizational preparedness and the supportiveness of the external environment. The results are also in alignment with the socio-technical systems theory which postulates that technology operates successfully only when it is coupled with organized workflows, skilled people, and good governance. In this study it is shown that the identified ten blockades such as weak data processing, low computing power, and poor model accuracy affect organizational factors such as lack of teamwork, low digital skills, and unstructured workflows. The problems mentioned above are particularly rampant in emerging economies such as India which is characterized by its fragmented regulatory and infrastructure system, all of which make the adoption of GenAI even more challenging.

5.1 Prioritizing Technological and Organizational Readiness

The DEMATEL technique highlights the blockades that need immediate attention. The study revealed that the most severe blockades that propagate many other issues were real-time data processing, model reliability, and high computing requirements. This underscores the need for companies to strengthen their digital and data infrastructures. In other words, organizations must ensure access to well-integrated project data, establish robust data governance protocols, and adopt cost-effective computing solutions for training and deploying LLMs. Organizational capability occupies a pivotal space as well. Lack of collaboration between architects, engineers, contractors, and managers is found to have a profound impact in the adoption tendencies. When teams work in isolation from each other, the necessary information flow is hindered that impact the effective functioning of GenAI or any other digital framework. Organizations are recommended to invest in improving digital skills, encourage teamwork across departments, and establish clear AI-friendly workflows that promotes the propensity of organizations to adopt GenAI.

5.2 Implications for the Wider Construction Ecosystem

The findings also highlight the importance of institutional environment support to facilitate the GenAI adoption from India's perspective. The role of government bodies and regulators are crucial in order to achieve this. Standard rules must be put in place, together with ensuring that BIM, LLMs, and other data systems can work together smoothly, and update regulatory databases. These initiatives can pave the way for GenAI to be integrated seamlessly for compliance and documentation tasks. In a country like India many small contractors, suppliers, and workers often work independently with limited coordination. Because of this the large contractors who manage large projects hold a lot of power. The decisions taken by them to invest in digital tools, setting requirements for suppliers, and training workers can go a long way with either speeding up or slowing down the GenAI adoption across the whole industry. This gives the large firms an upper hand in trying GenAI for tasks like document verification, contract review, schedule planning, and risk identification.

The blockades identified above impact the small and medium enterprises (SMEs) even more severely. Since they do not have advanced computers, digitally skilled workforce, or an overall high functioning digital system, it gets challenging for them to comprehend GenAI application let alone adopting it. The easier course of action for them might be to start with easier, lower-cost options such as creating tender documents or automating routine reports. Thereafter gradually introducing GenAI with the assistance of large contractors in the form of training can help SMEs to gain confidence without spending huge sums. The role of technical providers cannot be sidelined, especially in the context of adopting digital tools. They must design GenAI tools that address the needs of the construction OSCM categorically. In simple words, such GenAI based tools should be designed that can run smoothly on low resource settings, can be integrated easily with the other construction software, and explain how AI makes decisions that are especially important for safety and regulatory approval. Training GenAI models on Indian design data and building codes can remedy several problems associated with the accuracy and validation of the models.

5.3 Integrating Theory with Practice

The implications clearly indicate that adopting a sophisticated technology like GenAI in the construction sector of India extends beyond just installing new software. It requires understanding of the interconnection between the changes in technology, teamwork, and the broader industry environment. The TOE framework establishes the severe impact exerted by weak digital systems and poor coordination in the adoption of GenAI in organizations. Socio-technical systems theory directs the organizations to redesign their workflows, improve workers' skills, and set up better governance in order to use new emerging technologies like GenAI optimally.

The technique employed in this study grey-DEMATEL, clearly identifies the blockades that need immediate attention. Specifically, the main "cause" blockades such as the ones related to the data issues and computing limits should be tended to first so that the other related or "effect" blockades can be consequently addressed. The findings offer real world insight by charting out a roadmap for the stakeholders to advance GenAI adoption in the Indian construction supply chain.

5.4 Stakeholder Specific Implications

Table 7 consolidates the major recommendations to the prominent stakeholders in the construction supply chain management.

Table 7. Recommended strategies mapped to key stakeholder groups.

Identified strategy	Policymakers / Regulators	Large contractors	SMEs	Technology providers
Cloud adoption & digital infrastructure	Create incentives (subsidies, tax support) for cloud migration; establish data-security guidelines.	Invest in scalable cloud systems for real-time data; integrate IoT and BIM with cloud platforms.	Adopt cost-efficient subscription-based cloud services; participate in industry cloud programs.	Provide affordable cloud packages tailored to construction; ensure interoperability with BIM/GENAI tools.
Workforce training & digital literacy	Fund skill-development programs; mandate AI-readiness modules in professional accreditation.	Conduct cross-functional training for engineers, architects, and site teams on AI tools.	Upskill workforce through modular, low-cost training programs; partner with local institutes.	Develop training toolkits and simulation sandboxes for safe GENAI/BIM experimentation.
Regulatory integration & compliance automation	Modernize codes for digital submissions; standardize compliance databases.	Integrate GENAI-based regulatory checks into workflows; adopt automated compliance engines.	Use AI-powered compliance guides to reduce manual burden.	Build models aligned with regional codes; develop APIs for automated code checking.
Improving data integration & interoperability	Promote standardized data protocols for construction (BIM–GENAI interface standards).	Invest in unified data layers to avoid siloed systems.	Use plug-and-play middleware solutions for data consolidation.	Create integration-ready systems and support open data standards.
Enhancing model accuracy & trust	Develop guidelines for AI validation; encourage transparency in AI audits.	Implement project-specific model testing; maintain internal data governance.	Participate in shared-data pools to improve local model accuracy.	Train models on regional datasets; release explainable-AI diagnostics.
Reducing computational barriers	Introduce AI-infrastructure support schemes for SMEs; promote shared compute centers.	Deploy hybrid cloud–edge architectures for real-time operations.	Use cloud-based computing services as an alternative to capital-intensive infrastructure investments.	Offer lightweight model versions requiring lower compute power.
Improving cross disciplinary collaboration challenges	Encourage collaborative platforms in public projects; mandate data-sharing frameworks.	Adopt integrated digital collaboration systems across teams.	Join shared digital collaboration platforms with contractors.	Build multi-user co-creation environments (AI–BIM integration).

6. Conclusion and Future Scope

The current study aims at identifying major blockades in the adoption of GenAI in the Indian OSCM. It is well established that including new sophisticated technologies like GenAI has the potential of revamping the construction OSCM in numerous ways still the industry finds itself unable to embrace it holistically. The study employs GREY-DEMATEL technique to analyze the blockades and classify them into "cause" and "effect" categories. It was found that real time data processing is the most severe of the blockades in the "cause" category. Some of the related issues that make the real time decision making particularly challenging for the construction organizations are the outdated or legacy IT systems, scattered data sources, and poor integration platforms. Model accuracy and domain validity emerges as the second most influential blockade stemming from the poor-quality data and differences in the nature of the construction projects. High computational requirements coupled with difficulty in simulating structural behavior, weak collaboration between project teams, and the lack of historical data are found to impact the adoption behavior. The prominent “effect” blockades revealed were data integration difficulties, Customizability for Project-specific designs, Regulatory Validation Concerns, and BIM and Systems Integration Compatibility.

The study suffers from some limitations that can be considered as the future research opportunities. Only six experts from the Indian construction sector were considered for the qualitative data. This small group can limit the generalizability of the findings and induce possible bias in the outputs. To address this issue, future studies must focus on experts from different regions, types of construction activities, and organizational roles such as contractors, policymakers, technology providers, and global specialists. Future researchers must consider exploring sector-specific applications of GenAIs in construction sub-sectors, developing localized data models for regional needs, integrating GenAIs with advanced technologies like BIM and IoT, assessing long-term impacts, addressing ethical concerns, creating governance frameworks, fostering workforce adaptation, and analyzing SME adoption costs.

Appendix A

Table A1. Linguistics scale.

Linguistic attributes	**Grey numbers**
No influence (NI)	[0, 0]
Very low influence (VLI)	[0, 0.25]
Low influence (LI)	[0.25,0.5]
High influence (HI)	[0.5, 0.75]
Very high influence (VHI)	[0.75, 1]

Table A2. Grey matrix obtained from expert 1.

Code	**A1**		**A2**		**A3**		**A4**		**A5**		**A6**		**A7**		**A8**		**A9**		**A10**	
A1	0.00	0.00	0.50	0.75	0.50	0.75	0.50	0.75	0.75	1.00	0.75	1.00	0.50	0.75	0.50	0.75	0.50	0.75	0.75	1.00
A2	0.5	0.75	0	0	0.8	1	0.5	0.8	0.5	0.8	0.3	0.5	0	0.3	0.8	1	0.5	0.8	0.8	1
A3	0.75	1.00	0.75	1.00	0.00	0.00	0.00	0.25	0.25	0.50	0.50	0.75	0.00	0.25	0.75	1.00	0.75	1.00	0.50	0.75
A4	0.25	0.50	0.25	0.50	0.25	0.50	0	0	0.25	0.50	0.8	1	0.25	0.50	0	0.3	0.8	1	0	0.3
A5	0.25	0.50	0.00	0.25	0.50	0.75	0.00	0.25	0.00	0.00	0.3	0.5	0.3	0.5	0.00	0.25	0.00	0.25	0.00	0.25
A6	0.75	1	0	0.3	0.3	0.5	0	0.3	0	0.3	0	0	0	0.3	0.5	0.8	0	0.3	0	0.3
A7	0.00	0.25	0.00	0.25	0.00	0.25	0.75	1.00	0.00	0.25	0.75	1.00	0.00	0.00	0.75	1.00	0.50	0.75	0.25	0.50
A8	0.75	1	0.3	0.5	0	0.3	0.5	0.8	0	0.3	0.5	0.8	0.3	0.5	0	0	0.5	0.8	0	0.3
A9	0.25	0.50	0.00	0.25	0.50	0.75	0.3	0.5	0.00	0.25	0.50	0.75	0.25	0.50	0.75	1.00	0.00	0.00	0.00	0.25
A10	0	0.25	0.5	0.8	0.5	0.8	0.5	0.8	0	0.3	0	0.3	0.5	0.8	0.5	0.8	0.8	1	0	0

Table A3. CFCS method to find crisp values.

Code	**A1**		**A2**		**A3**		**A4**		**A5**		**A6**		**A7**		**A8**		**A9**		**A10**	
A1	0.00	0.00	0.54	0.79	0.38	0.63	0.46	0.71	0.33	0.58	0.21	0.46	0.63	0.88	0.25	0.50	0.25	0.50	0.33	0.58
A2	0.33	0.58	0.00	0.00	0.33	0.58	0.58	0.83	0.42	0.67	0.54	0.79	0.42	0.67	0.38	0.63	0.54	0.79	0.38	0.63
A3	0.54	0.79	0.29	0.54	0.00	0.00	0.42	0.67	0.46	0.71	0.29	0.54	0.38	0.63	0.58	0.83	0.54	0.79	0.63	0.88
A4	0.25	0.50	0.25	0.50	0.33	0.58	0.00	0.00	0.33	0.58	0.50	0.75	0.25	0.50	0.29	0.54	0.54	0.79	0.25	0.50
A5	0.29	0.54	0.42	0.67	0.42	0.67	0.38	0.63	0.00	0.00	0.21	0.46	0.38	0.63	0.33	0.58	0.25	0.50	0.33	0.58
A6	0.33	0.58	0.29	0.54	0.21	0.46	0.21	0.46	0.38	0.63	0.00	0.00	0.08	0.33	0.33	0.58	0.54	0.79	0.46	0.71
A7	0.17	0.42	0.21	0.46	0.46	0.71	0.54	0.79	0.33	0.58	0.71	0.96	0.00	0.00	0.46	0.71	0.21	0.46	0.42	0.67
A8	0.42	0.67	0.46	0.71	0.33	0.58	0.33	0.58	0.54	0.79	0.42	0.67	0.25	0.50	0.00	0.00	0.29	0.54	0.25	0.50
A9	0.04	0.29	0.42	0.67	0.54	0.79	0.42	0.67	0.21	0.46	0.21	0.46	0.58	0.83	0.21	0.46	0.00	0.00	0.08	0.33
A10	0.13	0.38	0.46	0.71	0.25	0.50	0.46	0.71	0.29	0.54	0.25	0.50	0.42	0.67	0.25	0.50	0.46	0.71	0.00	0.00

Table A4. Normalized direct relation matrix.

Normalized	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	0.00	0.13	0.09	0.12	0.08	0.06	0.15	0.06	0.06	0.08
A2	0.08	0.00	0.08	0.14	0.10	0.13	0.10	0.09	0.13	0.09
A3	0.13	0.07	0.00	0.10	0.11	0.07	0.09	0.14	0.13	0.15
A4	0.06	0.06	0.08	0.00	0.08	0.12	0.06	0.07	0.13	0.06
A5	0.07	0.10	0.10	0.09	0.00	0.06	0.09	0.08	0.06	0.08
A6	0.08	0.07	0.06	0.06	0.09	0.00	0.03	0.08	0.13	0.11
A7	0.05	0.06	0.11	0.13	0.08	0.17	0.00	0.11	0.06	0.10
A8	0.10	0.11	0.08	0.08	0.13	0.10	0.06	0.00	0.07	0.06
A9	0.02	0.10	0.13	0.10	0.06	0.06	0.14	0.06	0.00	0.03
A10	0.04	0.11	0.06	0.11	0.07	0.06	0.10	0.06	0.11	0.00

Table A5. The total group influence matrix.

Total relation matrix	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	0.291863	0.481198	0.4513	0.521893	0.444	0.43505675	0.5	0.412863958	0.463965	0.42954
A2	0.396013	0.402664	0.479	0.577182	0.494	0.52871429	0.5	0.467350139	0.559465	0.46823
A3	0.451458	0.496645	0.4227	0.571135	0.523	0.49928846	0.52	0.524729376	0.577697	0.53342
A4	0.317117	0.384517	0.3995	0.362514	0.399	0.43639723	0.39	0.375681309	0.471611	0.36855
A5	0.333895	0.423698	0.4225	0.460196	0.332	0.39386012	0.42	0.393685124	0.424967	0.39469
A6	0.318834	0.380312	0.3602	0.400097	0.39	0.30893916	0.34	0.36622164	0.453231	0.39069
A7	0.340652	0.419745	0.4631	0.52638	0.446	0.52390355	0.37	0.451574941	0.460742	0.44674
A8	0.376349	0.455949	0.4291	0.476147	0.471	0.45292298	0.42	0.336667001	0.457037	0.4
A9	0.268098	0.395658	0.4248	0.441921	0.362	0.3749849	0.43	0.351350904	0.339662	0.32698
A10	0.291011	0.421166	0.3837	0.465769	0.39	0.39447562	0.42	0.367900836	0.455741	0.30604

Conflicts of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors would like to thank the editor and anonymous reviewers for their comments that help improve the quality of this work.

AI Disclosure

The author(s) declare that no assistance is taken from generative AI to write this article.

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