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Identification and Prioritization of Critical Barriers to the Adoption of Robots in the Construction Phase with Interpretive Structural Modeling (ISM) and MICMAC Analysis

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Abstract

The adoption of robots in the construction phase can improve safety by replacing hazardous tasks and enhance productivity by automating repetitive work. Despite these advantages, adoption remains slow, constrained by economic, industrial, institutional, socio-cultural, and technological barriers. Wider acceptance is particularly urgent in construction, where fragmented processes, low profit margins, and safety risks make innovation both necessary and challenging. This study identified 22 critical barriers through a systematic literature review and categorized them into five dimensions. Beyond identification, the study prioritized these barriers using ISM and MICMAC analysis, clarifying which factors are fundamental drivers and which are outcome-related. The results showed that economic drivers occupy the base of the hierarchy and exert the greatest systemic influence, socio-cultural barriers emerge as highly dependent outcomes, and software usability acts as a linkage factor connecting technological immaturity with social acceptance. These findings reveal that barriers are interdependent rather than isolated and underscore the need for a structured prioritization framework. By applying ISM and MICMAC, this study presents a stepwise roadmap that differentiates fundamental drivers from outcome-related constraints, offering academic insights and practical guidance for policymakers to design strategies such as investment incentives, standardization, legal frameworks, and R&D expansion to accelerate adoption.

Keywords: construction robot; barrier factors; Interpretive Structural Modeling (ISM); MICMAC analysis

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1. Introduction

The construction industry is increasingly facing the necessity of adopting robotics due to persistent safety issues and an aging workforce [1]. Alongside advances in digital technologies, robotics and automation have enabled highly autonomous task execution through intelligent programming and control, becoming key elements in achieving faster and safer processes [2]. In construction, robots hold significant potential to improve productivity by replacing hazardous tasks, enhancing worker safety, and automating repetitive and inefficient processes.

Empirical evidence further highlights the growing role of robotics in improving safety and productivity. For example, Korea Western Power introduced autonomous inspection

robots that operate in hazardous areas of power plants, thereby reducing human exposure to dangerous environments [3]. According to the Korea Institute for Robot Industry Advancement, manufacturing firms that adopted robotics reported an average productivity increase of 56.49% and a defect reduction of 58.38% [4], with some companies such as Hanbit ENG achieving a 69.3% productivity increase and complete elimination of defects [5]. In addition, Jeong's Foods deployed autonomous mobile robots (AMRs) to automate nighttime logistics, alleviating labor shortages and stabilizing workflow [6]. These cases demonstrate tangible safety and efficiency gains, reinforcing the urgent need to analyze the barriers that continue to delay widespread adoption in the construction sector.

Nevertheless, the lack of sufficient data that reflects the diverse conditions of construction sites leads to degraded performance and quality uncertainty in computer vision (CV) models [7]. In addition, the application of 3D printing technology remains limited due to regulatory gaps [8]. As such, the adoption of new technologies in the construction industry remains slow. Robotic technology is also one such emerging field, where rapid advancements have been made, but its deployment in actual construction sites remains in the early stages. Many sites still rely on traditional practices, and this lag in technology adoption is closely related to the inherent characteristics of the construction industry, such as project-based structures, high uncertainty, procurement systems that emphasize short-term outcomes, as well as profitability uncertainty that discourages long-term investment in robotics.

Construction robots can be defined as systems introduced to automate and improve on-site operations classified into four categories [9]: off-site prefabrication systems, on-site automation and robotic systems, drones and autonomous vehicles, and wearable devices. For example, exoskeleton robots are designed to augment human strength in the back, shoulders, or legs, supporting tasks such as steelwork, refractory installation, and heavy material handling [10]. These technologies offer tangible benefits—hazard avoidance, replacement of repetitive tasks, and enhanced precision—but their practical utilization in construction remains limited.

This situation is not solely the result of technological immaturity. Rather, multidimensional barriers exist, including economic burdens, industrial structures, institutional deficiencies, socio-cultural resistance, and technological constraints. Critical barriers, in particular, directly determine the success or failure of projects and must be addressed as a priority in the technology adoption process. Comprehensive identification and structural analysis of such barriers are therefore essential foundations for promoting the adoption of construction robots.

Numerous studies have been conducted to identify the barriers hindering the adoption of construction robotics. For example, Law et al. [1] analyzed adoption factors from the perspectives of various stakeholders in a case study in Hong Kong and used the k-means clustering technique to derive 14 driving and 14 hindering factors. Delgado et al. [9] classified industry-specific barriers into economic, technological, and cultural dimensions, focusing on comprehensive categorization. Qu and Liu [11], focusing on the Chinese context, utilized the Interpretive Structural Modeling (ISM) method to structure barriers into four hierarchical levels. However, the scope of their study was limited, and the analysis lacked depth in interpretive insight.

Similar barriers have been reported in broader research on construction automation. Bock [12] identified issues such as high costs, lack of standardization, and cultural resistance but did not examine how these factors interact with one another. Sawhney et al. [13], within the Construction 4.0 framework, highlighted challenges in integrating robotics with BIM and IoT but did not conduct a prioritization of the barriers. Barbosa et al. [14], from a global perspective, emphasized lack of investment, regulatory hurdles, and the fragmented nature

of the industry as major constraints, yet their study remained focused on individual factors without exploring their interconnections. Tan et al. [15] applied ISM to analyze BIM-related barriers in prefabricated construction; however, its generalizability to robotics adoption is limited. The World Economic Forum (WEF) [16] pointed to institutional uncertainty and cultural resistance to innovation but failed to systematically explain the underlying structural issues.

As such, previous research has largely focused on identifying or classifying barriers, with limited attention given to their relative importance or structural interdependencies. In particular, there is a lack of studies exploring which barriers are more critical, and how specific factors may trigger or exacerbate others. Therefore, this study aims to address this gap by conducting a hierarchical structural analysis of 22 key barriers identified through a comprehensive literature review. The objective is to understand the interrelationships and priority among these factors and to derive practical strategic implications for the adoption of construction robotics. Understanding the relative importance and systemic interactions of these barriers is critical for developing effective solutions and strategic roadmaps for adoption.

To address this gap, this study applies Interpretive Structural Modeling (ISM) and the Matrix of Cross-Impact Multiplication Applied to Classification (MICMAC). ISM is well-suited for decomposing complex systems into hierarchical structures to reveal causal relationships among factors [17]. MICMAC analysis, by contrast, classifies factors based on their driving and dependence power, thereby clarifying their functional roles within the system. By combining the two methods, this study aims to systematically reveal the structural relationships among the critical barriers to construction robot adoption and, in turn, provide strategic insights for overcoming them.

The remainder of this paper is organized as follows. Section 2 presents the research methodology. Section 3 identifies the critical barriers from the literature and analyzes their interrelationships using ISM and MICMAC. Section 4 synthesizes the findings and discusses the academic contributions, practical implications, and directions for future research. Finally, Section 5 concludes the study by highlighting the key outcomes and suggesting avenues for future investigation.

2. Materials and Methods

ISM was selected as it provides a systematic way to organize the complex interrelationships among the identified barriers, helping reveal their hierarchical positions and causal pathways. Complementarily, MICMAC analysis was applied to quantify the driving and dependency strengths of each barrier and to categorize them into meaningful functional groups. The combined use of ISM and MICMAC was considered particularly appropriate for the construction industry context, where barriers to robot adoption are multidimensional and highly interdependent.

2.1. Interpretive Structural Modeling (ISM)

This study applied Interpretive Structural Modeling (ISM) to analyze the complex interrelationships among the barriers hindering the adoption of construction robots. The ISM technique is particularly effective for analyzing systems in which numerous factors interact simultaneously. It organizes these factors into hierarchical layers, distinguishing between core drivers and resultant outcomes [18–20]. In particular, the barriers to construction robot adoption are multidimensional, encompassing economic burdens, industrial constraints, institutional gaps, socio-cultural resistance, and technological limitations. Therefore, a systematic identification of both direct and indirect relationships among these factors was essential for prioritizing appropriate interventions.

The ISM procedure followed in this study was as follows:

- Factor identification: Based on an extensive literature review, 22 barrier factors to construction robot adoption were identified.
- Defining relationships: A panel of 17 experts, consisting of 9 academics and 8 industry professionals (contractors, and robot developers), was invited to independently assess pairwise relationships among the factors. All experts were based in South Korea, with an average of 12 years of professional experience, ensuring that both theoretical perspectives and practical insights were represented. Each expert provided written judgments, and the initial SSIM was constructed using a threshold-based majority aggregation, applying a tie-breaking rule (X > V > A > O). In cases of disagreement, the aggregated results were shared with all experts and agreement was confirmed, thereby combining systematic aggregation with a consensus confirmation step. The finalized relationships among the factors were represented using four directional symbols: V for "i influences j," A for "j influences i," X for "mutual influence," and O for "no relation.". The subsequent ISM and MICMAC calculations were implemented using custom Python 3.11.9 scripts, ensuring transparency and reproducibility.
- Development of SSIM: Based on expert evaluations, a Structural Self-Interaction Matrix (SSIM) was formulated to represent pairwise relationships among barriers.
- Initial reachability matrix: The SSIM outcomes were then translated into binary indicators (1 and 0) to produce the initial reachability matrix used for subsequent analysis.
- Application of transitivity: Indirect influences were incorporated by applying the transitivity principle of ISM. For example, if F1 influences F2 and F2 influences F3, then F1 is assumed to indirectly influence F3. This step ensures that hidden or secondary relationships are captured, thereby clarifying the complete hierarchical structure of barriers and strengthening the robustness of the model.
- Level partitioning: Hierarchical levels for all factors were identified by comparing the reachability and antecedent sets and examining their common elements.
- ISM model construction: Based on these results, a hierarchical structural model of the interrelationships among the factors was developed.

Through this process, ISM produced a hierarchical structure of the barriers to construction robot adoption, enabling a clear distinction between top-level outcome barriers and bottom-level root barriers. This allowed for the identification of strategic priorities, highlighting ISM's value in moving beyond simple factor listing toward a structured prioritization of interventions.

2.2. MICMAC Analysis

MICMAC analysis was subsequently applied using the Final Reachability Matrix obtained from ISM. This technique calculates each factor's driving power and dependence power, thereby classifying factors according to their functional roles [21]. While ISM emphasizes hierarchical structuring, MICMAC clarifies the role each factor plays within the system. This is particularly useful for analyzing the barriers to construction robot adoption, which involve diverse stakeholders and interdependent factors.

In MICMAC analysis, the identified factors were grouped into four functional categories based on their relative driving and dependency powers:

- Autonomous factors: These exhibit both low driving influence and low dependency, remaining largely detached from the overall system dynamics.
- Dependent factors: These possess limited driving capacity but strong reliance on other factors, making them outcome-oriented and symptomatic of deeper causes.
- Linkage factors: With high driving and dependency power, these factors are highly interactive and can amplify system fluctuations.

- Independent (driving) factors: These exert strong driving influence with little dependency, acting as core drivers that shape the system and require focused attention.

In this study, the 22 identified barrier factors were classified into these four categories. This enabled the differentiation of barriers that are fundamental and require immediate intervention (independent factors), those that are resultant and can be alleviated indirectly (dependent factors), and those that act as sensitive connectors with strong bidirectional effects (linkage factors).

The combined application of ISM and MICMAC moves beyond the simple identification of barriers, providing a comprehensive framework that simultaneously reveals their hierarchical structure and functional roles. This integrated approach thus provides a practical and evidence-based foundation for developing stepwise strategies and policy interventions to promote the adoption of construction robots.

3. Results

3.1. Identification of Critical Barrier Factors for the Adoption of Construction Robots

In this study, 22 barriers to the adoption of construction robots were identified through a systematic review of international literature published between 2015 and 2025. The literature search was conducted using Google Scholar, employing the following keywords: "construction robots" AND (barriers OR challenges OR influencing factors OR adoption). Inclusion criteria were: (1) peer-reviewed articles written in English, and (2) studies focusing on the application of robots in construction environments. Exclusion criteria included duplicate publications and studies related to non-construction industries. Following a review of titles, abstracts, and full texts, 30 relevant publications were selected for in-depth analysis. From these, 22 distinct barrier factors were extracted. Where overlapping or semantically similar terms were found, they were consolidated or refined based on thematic similarity to ensure clarity and avoid redundancy.

A barrier is defined as a factor that hinders or obstructs the execution of a system [22]. Critical barriers are those that exert a disproportionately strong influence on the success or failure of a project and thus must be identified and addressed as a priority in the process of technology adoption. In the case of construction robots, the barriers to adoption and utilization extend beyond technical limitations to include economic burdens, industrial characteristics, institutional deficiencies, socio-cultural resistance, and technological constraints. These factors do not operate in isolation but interact with each other, making a comprehensive identification and analysis essential for facilitating the effective adoption and activation of construction robots.

In this study, a systematic review of 30 international publications was conducted, from which 22 barrier factors were identified. These factors were categorized into five thematic dimensions: economic, industrial, institutional and policy, socio-cultural, and technological factors. This categorization moves beyond a simple listing of factors and enables a multidimensional interpretation of the structural challenges that hinder the adoption of construction robots in the construction industry.

The barrier factors in each category, along with their supporting references, are summarized in Table 1.

Table 1. Barriers to the Adoption and Activation of Construction Robots.

Division	No.	Barriers Factors	Refs.
Economic Factors	F1	High initial investment cost for robot adoption	[9,12,17,23–25]
	F2	Uncertainty in profitability and demand	[9,17,23–28]
	F3	Lack of business models and contract structures	[9,29,30]
	F4	Insufficient R&D investment	[9,12,23,31–33]
Industrial Factors	F5	Lack of worker capability to adopt robots	[9,23,28,32,34–37]
	F6	Limits in workforce transformation and training	[9,12,23,34–39]
	F7	Delay in digital transformation of the construction industry	[9,23,27,37,40–42]
	F8	Non-standardized site environments	[23,34,37–41,43]
	F9	Lack of robot-oriented design and process integration	[40–42]
Institutional and Policy Factors	F10	Absence of legal responsibility and standards	[12,23,41]
	F11	Lack of unified technical standards	[33,41–43]
	F12	Insufficient government support and incentives	[9,23,37,42]
	F13	Lack of leading cases in public procurement	[23,42,43]
	F14	Inadequate certification and regulatory systems for construction robots	[44,45]
Socio-Cultural Factors	F15	On-site resistance to change	[41–45]
	F16	Undefined human–robot collaboration systems	[46]
	F17	Lack of awareness of the value of robot utilization	[9,23,33,47]
	F18	Entrenchment of traditional work practices in the construction industry	[12,41,42,48]
Technical Factors	F19	Immature intelligent technologies for site perception and judgment	[41]
	F20	Hardware limitations unsuitable for narrow and variable work environments	[9,23–25,38]
	F21	Poor usability and accessibility of software	[9,16,23,33]
	F22	Absence of integrated operational platforms	[9,28,49]

3.1.1. Economic Factors

The economic environment exerts the most direct influence on whether construction robots are practically deployed in projects [23]. The first barrier (F1) is the high initial investment cost associated with robot adoption [24,25]. As technologies become more advanced, acquisition costs increase [2], which is especially burdensome for small- and medium-sized contractors. The second barrier (F2) is the uncertainty of profitability and demand [26–28]. When the return on investment is unclear and market demand is uncertain, firms hesitate to make active investments [9]. The third barrier (F3) relates to the lack of business models and contractual structures, as responsibilities and operational ownership are often ill-defined, slowing diffusion [29,30]. The final economic barrier (F4) is insufficient R&D investment, with both public and private sectors investing inadequately in development and pilot testing, leading to slow technological maturity [32,33]. Economic barriers go beyond financial constraints alone and are closely tied to the pace of technological innovation and industry-wide diffusion strategies. As such, they constitute the foremost challenges that must be addressed to promote the adoption of construction robots [23].

3.1.2. Industrial Factors

Industrial barriers are closely associated with the internal characteristics of the construction sector, such as workforce readiness, organizational structure, and the pace of digital transformation. Limited worker capability to adopt robots (F5) results in low levels of understanding and proficiency, creating challenges in operation and maintenance [34,37]. Changes in workforce structure and limited training opportunities (F6), due to an aging

workforce and shortages of new entrants, further delay adoption [35,38]. The delay in digital transformation within the construction sector (F7)—including the uptake of BIM, IoT, and sensor-based systems—remains a major obstacle compared with other industries [42]. Non-standardized site environments (F8) also create difficulties, as the variability of projects undermines stability and repeatability in robot control [37–39]. Finally, the lack of robot-oriented design and process integration (F9) presents a barrier [40], since robot applications are rarely considered in the planning and design stages, leading to interoperability issues [1,41]. Collectively, these industrial barriers reflect the structural challenges embedded within the construction industry, highlighting that robot adoption is not merely a matter of technology introduction but requires a paradigm shift in industry practice.

3.1.3. Institutional and Policy Factors

Institutional and policy barriers represent external conditions that restrict the adoption of construction robots. The absence of legal responsibility and standards (F10) increases the perceived risks for firms, particularly in cases of malfunction or accidents [2]. The lack of unified technical standards (F11) hampers interoperability across manufacturers and complicates system integration. Insufficient government support and incentives (F12) further exacerbate these challenges [37]. While financial support and tax incentives are proven drivers for technological diffusion [42], their absence discourages investment and delays market formation. The lack of leading cases in public procurement (F13) similarly restricts private sector adoption [42,43]. Lastly, inadequate certification and regulatory systems (F14) add uncertainty regarding the approval of new technologies for site deployment [50]. Institutional and policy barriers are beyond the capacity of individual firms to resolve and therefore require proactive leadership from governments and clients.

3.1.4. Socio-Cultural Factors

Socio-cultural barriers are subtle yet powerful obstacles that extend beyond technical challenges [26]. Resistance to change at the site level (F15) is exhibited by both managers and workers, making the introduction of new systems difficult [2,41]. Undefined human–robot collaboration systems (F16) create uncertainty in task allocation and safety management [46]. A lack of awareness of the value of robots (F17) is linked to inadequate preparation in organizational and educational settings [51]. Entrenchment of traditional work practices (F18) further constrains adoption, as a workforce accustomed to labor-intensive methods may be reluctant to accept automation [52]. These barriers can persist even when technical and institutional challenges are addressed, underscoring the need for strategies to improve social acceptance and cultural readiness in parallel with technological and regulatory interventions.

3.1.5. Technological Factors

Technological barriers relate directly to the performance and limitations of construction robots. Immature intelligent technologies for perception and judgment (F19)—including computer vision, SLAM, sensor fusion, and AI-based recognition—remain inadequate for coping with the complexity of dynamic construction environments. Hardware limitations (F20), such as restricted mobility in narrow or irregular spaces, further constrain deployment [24,25]. Poor usability and accessibility of software (F21), including navigation errors and non-intuitive interfaces, reduce practical applicability. The absence of integrated operational platforms (F22) prevents interoperability across different equipment and processes [53,54], limiting system-wide efficiency [27]. Although technological barriers are the most visible in practice, their impact is magnified when combined with economic, industrial, institutional, and socio-cultural factors. Accordingly, this study considers these technological barriers within a broader structural analysis of interrelated constraints.

3.2. Prioritization of Critical Barrier Factors for Adoption and Activation of Construction Robots

3.2.1. Structural Self-Interaction Matrix (SSIM)

To examine the interrelationships among the barriers to the adoption of construction robots, a survey was conducted with 17 experts based on South Korea. The panel was deliberately composed of diverse stakeholders—including contractors, robot developers, and academic researchers—and represented a heterogeneous composition, with professional experience ranging from 5 to 26 years. This ensured that the evaluation incorporated both theoretical perspectives and practical insights across multiple stakeholder groups.

Through the expert survey, contextual relationships between each pair of barrier factors were defined, and the Structural Self-Interaction Matrix (SSIM) was subsequently developed. SSIM serves as the starting point of the ISM procedure and provides a structured representation of causal relationships among factors, moving beyond simple frequency counts. In other words, SSIM systematically records how and in what direction one factor influences another.

To aggregate the individual judgments into a single SSIM, a threshold-based majority rule was applied. For each pair (i, j), the proportion of experts selecting "i influences j" (V or X) and "j influences i" (A or X) was calculated; if both directions exceeded 0.5, the relationship was assigned as X (mutual influence). If only one direction exceeded 0.5, it was assigned as V or A accordingly, and if both were below 0.5, the relationship was coded as O (no influence). In cases of exact ties, the priority order X > V > A > O was applied. The aggregated results were then shared with all experts for confirmation, ensuring transparency and consensus across the panel.

In this process, experts expressed the relationships between two factors using four symbols:

- V: Factor i influences factor j → (i, j) = 1, (j, i) = 0.
- A: Factor j influences factor i → (i, j) = 0, (j, i) = 1.
- X: Factors i and j influence each other → (i, j) = 1, (j, i) = 1.
- O: Factors i and j are unrelated → (i, j) = 0, (j, i) = 0.

This coding process captures not only the existence of influence but also its directionality, which is particularly critical for construction robot adoption barriers, as economic, institutional, and technological factors often intersect and exert directional effects on each other. Each relationship was then converted into binary values to form the Initial Reachability Matrix, where "influence exists" was coded as 1 and "no influence" as 0. This numerical transformation allows the SSIM to be used as quantitative input for the ISM procedure. It also provides the foundation for generating the Final Reachability Matrix and performing the level partitioning process in subsequent steps.

Accordingly, the SSIM is not merely a tabulation of survey results but a key mechanism for transforming expert judgments into structured data, ultimately enabling the construction of the ISM model. In this study, SSIM was developed for all 22 identified barriers to the adoption and activation of construction robots, and the results are presented in Table 2.

Table 2. Expert-evaluated Structural Self-Interaction Matrix (SSIM).

-	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22
F1	-	O	O	O	V	V	V	V	V	O	O	V	V	V	V	V	V	V	O	V	O	O
F2	O	-	O	O	V	V	V	V	V	O	O	V	V	O	V	V	V	V	O	O	O	O
F3	O	O	-	O	V	V	V	V	V	O	V	O	V	O	V	V	V	V	O	O	V	O
F4	O	O	O	-	V	V	V	V	V	O	O	V	V	O	V	V	V	V	V	O	O	O

Table 2. *Cont.*

-	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22
F5	A	A	A	A	-	O	O	O	O	A	A	A	O	A	O	O	O	O	A	A	A	A
F6	A	A	A	A	O	-	O	O	O	A	A	A	O	A	O	O	O	O	A	A	A	A
F7	A	A	A	A	O	O	-	O	O	A	A	A	O	A	O	O	O	V	A	A	A	A
F8	A	A	A	A	O	O	O	-	O	A	A	A	O	A	O	O	O	O	A	A	A	A
F9	A	A	A	A	O	O	O	O	-	A	A	A	O	A	O	O	O	O	A	A	A	A
F10	O	O	V	O	V	V	V	V	V	-	O	O	V	O	V	V	V	V	O	O	O	O
F11	O	O	V	O	V	V	V	V	V	O	-	O	V	O	V	V	V	V	O	O	O	O
F12	O	O	O	O	V	V	V	V	V	V	V	-	V	O	V	V	V	V	O	O	O	O
F13	A	A	A	A	O	O	O	O	O	A	A	A	-	A	O	O	O	O	A	A	A	A
F14	O	O	O	O	V	V	V	V	V	O	O	O	V	-	V	V	V	V	O	O	O	V
F15	A	A	A	A	O	O	O	A	O	A	A	A	O	A	-	O	O	O	A	A	A	A
F16	A	A	A	A	O	O	O	O	O	A	A	A	O	A	O	-	O	O	A	A	A	A
F17	A	A	A	A	O	O	O	O	O	A	A	A	O	A	O	O	-	O	A	A	A	A
F18	A	A	A	A	O	O	O	O	O	A	A	A	O	A	O	O	O	-	A	A	A	A
F19	O	O	O	O	V	V	V	V	V	O	V	O	V	V	V	V	V	V	-	O	O	V
F20	O	O	V	O	V	V	V	V	V	O	V	O	V	O	V	V	V	V	O	-	O	O
F21	O	O	O	O	V	V	V	V	V	O	O	O	V	O	V	V	V	V	O	O	-	O
F22	O	O	O	O	V	V	V	V	V	O	O	O	V	O	V	V	V	V	O	O	O	-

3.2.2. Reachability Matrix

After developing the SSIM, a Reachability Matrix was constructed to represent its quantitative equivalent. This matrix captures both the direct links among factors and their indirect interconnections, offering a structured means to visualize the complexity of their interactions [17]. In contrast to the SSIM, which reflects qualitative expert assessments, the Reachability Matrix converts these judgments into a numerical framework suitable for systematic quantitative evaluation.

The Reachability Matrix is expressed as a binary adjacency form, where each pairwise relation is denoted by either 1 or 0. A value of 1 signifies that factor *i* affects factor *j*, whereas a 0 denotes the absence of such influence [17]. This binary conversion reduces relational complexity while retaining the essential structural properties of the network.

A key step in this process involves applying transitivity, which captures indirect relationships [18]. For example, when F1 affects F2 and F2 affects F3, F1 is inferred to have an indirect influence on F3. Through transitivity, hidden relational chains can be revealed, deepening the understanding of system-wide interdependencies. Accordingly, the Final Reachability Matrix integrates both direct and indirect relationships, providing a more complete representation of the system's interaction dynamics.

From this final matrix, each factor's driving and dependency strengths are derived. Driving strength is measured by the row total—indicating the extent to which a factor influences others—while dependency strength is obtained from the column total, representing how much a factor is affected by others. These two indices form the analytical basis for the MICMAC, which groups factors into autonomous, dependent, linkage, and independent categories [55].

Hence, the Reachability Matrix serves not as a mere intermediate step but as a key mechanism translating expert knowledge into an organized quantitative dataset [56].

It supports the exploration of causal linkages among barriers and provides the essential input for the MICMAC analysis. Table 3 presents the initial binary Reachability Matrix, and Table 4 shows the final version incorporating transitivity.

Table 3. Computed initial reachability matrix derived from expert evaluations.

-	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22
F1	1	0	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0	1	0	0
F2	0	1	0	0	1	1	1	1	1	0	0	1	1	0	1	1	1	1	0	0	0	0
F3	0	0	1	0	1	1	1	1	1	0	1	0	1	0	1	1	1	1	0	0	1	0
F4	0	0	0	1	1	1	1	1	1	0	0	1	1	0	1	1	1	1	1	0	0	0
F5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
F8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
F9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
F10	0	0	1	0	1	1	1	1	1	1	0	0	1	0	1	1	1	1	0	0	0	0
F11	0	0	1	0	1	1	1	1	1	0	1	0	1	0	1	1	1	1	0	0	0	0
F12	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0	0	0
F13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
F14	0	0	0	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	0	0	0	1
F15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
F16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
F17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
F18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
F19	0	0	0	0	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	0	0	1
F20	0	0	1	0	1	1	1	1	1	0	1	0	1	0	1	1	1	1	0	1	0	0
F21	0	0	0	0	1	1	1	1	1	0	0	0	1	0	1	1	1	1	0	0	1	0
F22	0	0	0	0	1	1	1	1	1	0	0	0	1	0	1	1	1	1	0	0	0	1

Table 4. Reachability matrix refined through transitivity (Final version).

-	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22
F1	1	0	1 *	0	1	1	1	1	1	1 *	1 *	1	1	1	1	1	1	1	0	1	1 *	1 *
F2	0	1	1 *	0	1	1	1	1	1	1 *	1 *	1	1	0	1	1	1	1	0	0	1 *	0
F3	0	0	1	0	1	1	1	1	1	0	1	0	1	0	1	1	1	1	0	0	1	0
F4	0	0	1 *	1	1	1	1	1	1	1 *	1 *	1	1	1 *	1	1	1	1	1	0	1 *	1 *
F5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
F8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
F9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
F10	0	0	1	0	1	1	1	1	1	1	1 *	0	1	0	1	1	1	1	0	0	1 *	0
F11	0	0	1	0	1	1	1	1	1	0	1	0	1	0	1	1	1	1	0	0	1 *	0
F12	0	0	1 *	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0	1 *	0
F13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
F14	0	0	0	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	0	0	0	1
F15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
F16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
F17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
F18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
F19	0	0	1 *	0	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	0	1 *	1
F20	0	0	1	0	1	1	1	1	1	0	1	0	1	0	1	1	1	1	0	1	1 *	0
F21	0	0	0	0	1	1	1	1	1	0	0	0	1	0	1	1	1	1	0	0	1	0
F22	0	0	0	0	1	1	1	1	1	0	0	0	1	0	1	1	1	1	0	0	0	1

Note: Entries marked with an asterisk indicate relationships added through the application of transitivity.

3.2.3. Level Partitions

Table 5 presents the Reachability Set, Antecedent Set, and Intersection Set derived from the Reachability Matrix. The definitions of these sets are as follows:

- Reachability Set (factors influenced by a given element): Includes a specific factor together with all other factors it can directly or indirectly affect.
- Antecedent Set (influencing factors): Comprises a specific factor and all other factors that can exert influence upon it.
- Intersection Set (common factors between reachability and antecedent sets): Represents the overlap between the reachability and antecedent sets—those factors that both influence and are influenced by others.

Table 5. Hierarchical-level assignment (Iteration 1).

Label	Factors Influenced	Influencing Factors	Common Factors	Level
F1	F1 F3 F5 F6 F7 F8 F9 F10 F11 F12 F13 F14 F15 F16 F17 F18 F20 F21 F22	F1	F1	0
F2	F2 F3 F5 F6 F7 F8 F9 F10 F11 F12 F13 F15 F16 F17 F18 F21	F2	F2	0
F3	F3 F5 F6 F7 F8 F9 F11 F13 F15 F16 F17 F18 F21	F1 F2 F3 F0 F11 F12 F19 F20	F3 F11	0
F4	F3 F4 F5 F6 F7 F8 F9 F10 F11 F12 F13 F14 F15 F16 F17 F18 F19 F21 F22	F4	F4	0
F5	F5	F1 F2 F3 F4 F5 F10 F11 F12 F14 F19 F20 F21 F22	F5	1
F6	F6	F1 F2 F3 F4 F6 F10 F11 F12 F14 F19 F20 F21 F22	F6	1
F7	F7 F18	F1 F2 F3 F4 F7 F10 F11 F12 F14 F19 F20 F21 F22	F7	0
F8	F8 F15	F1 F2 F3 F4 F8 F10 F11 F12 F14 F19 F20 F21 F22	F8	0
F9	F9	F1 F2 F3 F4 F9 F10 F11 F12 F14 F19 F20 F21 F22	F9	1
F10	F3 F5 F6 F7 F8 F9 F10 F11 F13 F15 F16 F17 F18 F21	F1 F2 F4 F10 F12	F10	0
F11	F3 F5 F6 F7 F8 F9 F11 F13 F15 F16 F17 F18 F21	F1 F2 F3 F4 F10 F11 F12 F19 F20	F3 F11	0
F12	F3 F5 F6 F7 F8 F9 F10 F11 F12 F13 F15 F16 F17 F18 F21	F1 F2 F4 F12	F12	0
F13	F13	F1 F2 F3 F4 F10 F11 F12 F13 F14 F19 F20 F21 F22	F13	1
F14	F5 F6 F7 F8 F9 F13 F14 F15 F16 F17 F18 F22	F1 F4 F14 F19	F14	0
F15	F15	F1 F2 F3 F4 F8 F10 F11 F12 F14 F15 F19 F20 F21 F22	F15	1
F16	F16	F1 F2 F3 F4 F10 F11 F12 F14 F16 F19 F20 F21 F22	F16	1
F17	F17	F1 F2 F3 F4 F10 F11 F12 F14 F17 F19 F20 F21 F22	F17	1
F18	F18	F1 F2 F3 F4 F7 F10 F11 F12 F14 F18 F19 F20 F21 F22	F18	1
F19	F3 F5 F6 F7 F8 F9 F11 F13 F14 F15 F16 F17 F18 F19 F21 F22	F4 F19	F19	0
F20	F3 F5 F6 F7 F8 F9 F11 F13 F15 F16 F17 F18 F20 F21	F1 F20	F20	0
F21	F5 F6 F7 F8 F9 F13 F15 F16 F17 F18 F21	F1 F2 F3 F4 F10 F11 F12 F19 F20 F21	F21	0
F22	F5 F6 F7 F8 F9 F13 F15 F16 F17 F18 F22	F1 F4 F14 F19 F22	F22	0

In ISM, level partitioning serves as a key step for progressively identifying hierarchical relationships among the factors. A factor whose intersection set matches its reachability set is classified as a top-level element, meaning it is influenced by other factors but does not affect any additional ones at lower levels. After determining the top-level factors, they are excluded from subsequent iterations, and the same procedure continues until all factors are placed within their respective hierarchical tiers.

Thus, level partitioning is not merely a mathematical operation but a process that clarifies how barriers to construction robot adoption are arranged hierarchically from root causes to resultant outcomes. Top-level factors (Level 1) are those that are primarily influenced by others and represent outcome-related barriers, whereas bottom-level factors (Level n) are those that influence many other factors and represent fundamental root barriers. This hierarchical structure provides insights beyond the relative importance of individual factors by revealing which barriers play more fundamental structural roles within the system.

Accordingly, the level partitioning results serve as the foundation for visualizing the ISM structural model and for interpreting the characteristics of factors at each level. More importantly, they reveal not only the prioritization of barriers but also the causal pathways and transitive mechanisms underlying the adoption of construction robots. Table 5 through 11 present the results of each iteration of the level partitioning process.

In the first iteration (Table 5), factors F5, F6, F9, F13, F15, F16, F17, and F18 were identified as Level 1 (top-level) factors. These factors mainly represent site-level and socio-cultural barriers, such as insufficient worker capability, resistance to change, entrenched traditional practices, and lack of robot-oriented design and processes, all of which are outcome-driven in nature. In the second iteration (Table 6), F7 and F8 were classified as Level 2 factors. In the third iteration (Table 7), F21 and F22 were placed in Level 3, while in the fourth iteration (Table 8), F3, F11, and F14 were categorized as Level 4. Subsequently, F10, F19, and F20 were identified as Level 5 factors (Table 9), and F12 emerged as the sole Level 6 factor (Table 10). Finally, F1, F2, and F4 were classified as Level 7 (bottom-level) factors (Table 11).

Table 6. Hierarchical-level assignment (Iteration 2).

Label	Factors Influenced	Influencing Factors	Common Factors	Level
F1	F1 F3 F7 F8 F10 F11 F12 F14 F20 F21 F22	F1	F1	0
F2	F2 F3 F7 F8 F10 F11 F12 F21	F2	F2	0
F3	F3 F7 F8 F11 F21	F1 F2 F3 F4 F10 F11 F12 F19 F20	F3 F11	0
F4	F3 F4 F7 F8 F10 F11 F12 F14 F19 F21 F22	F4	F4	0
F7	F7	F1 F2 F3 F4 F7 F10 F11 F12 F14 F19 F20 F21 F22	F7	2
F8	F8	F1 F2 F3 F4 F8 F10 F11 F12 F14 F19 F20 F21 F22	F8	2
F10	F3 F7 F8 F10 F11 F21	F1 F2 F4 F10 F12	F10	0
F11	F3 F7 F8 F11 F21	F1 F2 F3 F4 F10 F11 F12 F19 F20	F3 F11	0
F12	F3 F7 F8 F10 F11 F12 F21	F1 F2 F4 F12	F12	0
F14	F7 F8 F14 F22	F1 F4 F14 F19	F14	0
F19	F3 F7 F8 F11 F14 F19 F21 F22	F4 F19	F19	0
F20	F3 F7 F8 F11 F20 F21	F1 F20	F20	0
F21	F7 F8 F21	F1 F2 F3 F4 F10 F11 F12 F19 F20 F21	F21	0
F22	F7 F8 F22	F1 F4 F14 F19 F22	F22	0

Table 7. Hierarchical-level assignment (Iteration 3).

Label	Factors Influenced	Influencing Factors	Common Factors	Level
F1	F1 F3 F10 F11 F12 F14 F20 F21 F22	F1	F1	0
F2	F2 F3 F10 F11 F12 F21	F2	F2	0
F3	F3 F11 F21	F1 F2 F3 F4 F10 F11 F12 F19 F20	F3 F11	0
F4	F3 F4 F10 F11 F12 F14 F19 F21 F22	F4	F4	0
F10	F3 F10 F11 F21	F1 F2 F4 F10 F12	F10	0
F11	F3 F11 F21	F1 F2 F3 F4 F10 F11 F12 F19 F20	F3 F11	0
F12	F3 F10 F11 F12 F21	F1 F2 F4 F12	F12	0
F14	F14 F22	F1 F4 F14 F19	F14	0
F19	F3 F11 F14 F19 F21 F22	F4 F19	F19	0
F20	F3 F11 F20 F21	F1 F20	F20	0
F21	F21	F1 F2 F3 F4 F10 F11 F12 F19 F20 F21	F21	3
F22	F22	F1 F4 F14 F19 F22	F22	3

Table 8. Hierarchical-level assignment (Iteration 4).

Label	Factors Influenced	Influencing Factors	Common Factors	Level
F1	F1 F3 F10 F11 F12 F14 F20	F1	F1	0
F2	F2 F3 F10 F11 F12	F2	F2	0
F3	F3 F11	F1 F2 F3 F4 F10 F11 F12 F19 F20	F3 F11	4
F4	F3 F4 F10 F11 F12 F14 F19	F4	F4	0
F10	F3 F10 F11	F1 F2 F4 F10 F12	F10	0
F11	F3 F11	F1 F2 F3 F4 F10 F11 F12 F19 F20	F3 F11	4
F12	F3 F10 F11 F12	F1 F2 F4 F12	F12	0
F14	F14	F1 F4 F14 F19	F14	4
F19	F3 F11 F14 F19	F4 F19	F19	0
F20	F3 F11 F20	F1 F20	F20	0

Table 9. Hierarchical-level assignment (Iteration 5).

Label	Factors Influenced	Influencing Factors	Common Factors	Level
F1	F1 F10 F12 F20	F1	F1	0
F2	F2 F10 F12	F2	F2	0
F4	F4 F10 F12 F19	F4	F4	0
F10	F10	F1 F2 F4 F10 F12	F10	5
F12	F10 F12	F1 F2 F4 F12	F12	0
F19	F19	F4 F19	F19	5
F20	F20	F1 F20	F20	5

Table 10. Hierarchical-level assignment (Iteration 6).

Label	Factors Influenced	Influencing Factors	Common Factors	Level
F1	F1 F12	F1	F1	0
F2	F2 F12	F2	F2	0
F4	F4 F12	F4	F4	0
F12	F12	F1 F2 F4 F12	F12	6

Table 11. Hierarchical-level assignment (Iteration 7).

Label	Factors Influenced	Influencing Factors	Common Factors	Level
F1	F1	F1	F1	7
F2	F2	F2	F2	7
F4	F4	F4	F4	7

Through this stepwise process, the barriers were hierarchically classified, with top-level factors interpreted as resultant barriers and bottom-level factors as fundamental driving barriers. Specifically, the top-level factors (F5, F6, F9, F13, F15, F16, F17, F18) are predominantly associated with workforce capability, socio-cultural resistance, and process deficiencies, reflecting outcome-related obstacles that are largely the manifestation of other underlying factors. In contrast, the bottom-level factors (F1, F2, F4)—high initial investment cost, uncertainty in profitability and demand, and insufficient R&D investment—represent fundamental economic and structural drivers that influence the entire system. This finding demonstrates that beneath the visible site-level and cultural challenges lie deeper economic and institutional constraints that serve as root causes of resistance and slow adoption. Accordingly, while short-term efforts should focus on alleviating site-level resistance and technical difficulties, long-term strategies must prioritize strengthening institutional frameworks and financial incentives to address these structural drivers.

3.2.4. ISM Model

Building upon the level-partitioning results, an ISM was developed to visualize the hierarchical linkages among the key barriers affecting construction robot adoption. The model generated in this study is illustrated in Figure 1, which presents a seven-tier hierarchy consisting of eight factors at the uppermost level and three at the base. Directional arrows depict the influence pathways between factors, emphasizing that the barriers are interconnected components of a multi-layered system rather than independent or isolated obstacles.

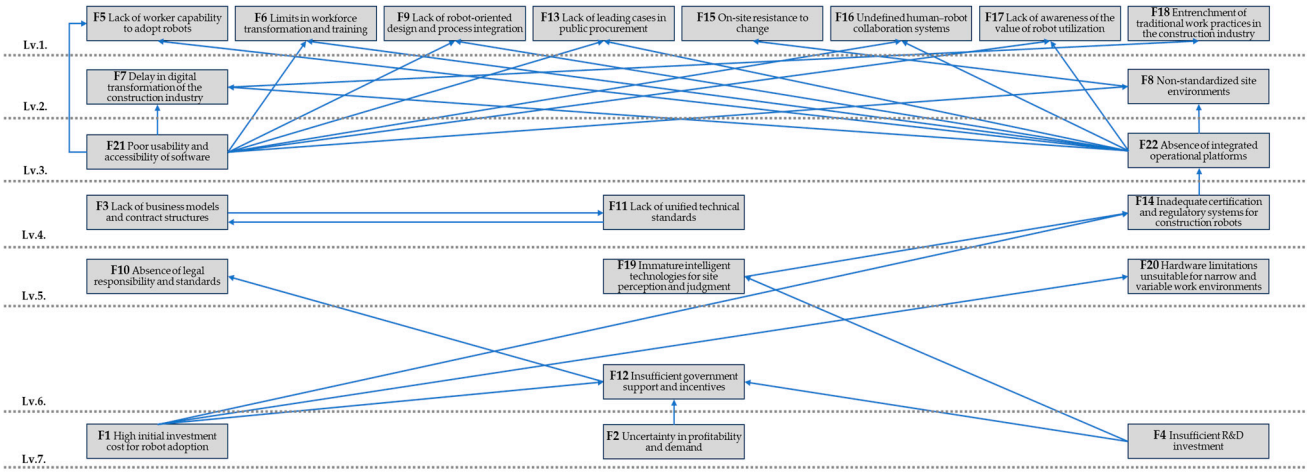


Figure 1. ISM model.

At the top level (Level 1), the following eight factors were identified:

- F5: Lack of worker capability to adopt robots.
- F6: Limits in workforce transformation and training.
- F9: Lack of robot-oriented design and process integration.
- F13: Lack of leading cases in public procurement.
- F15: On-site resistance to change.
- F16: Undefined human–robot collaboration systems.
- F17: Lack of awareness of the value of robot utilization.
- F18: Entrenchment of traditional work practices in the construction industry.

These factors are primarily associated with social acceptance and organizational readiness, rather than direct technological or financial interventions. Accordingly, they can

be interpreted as outcome-related barriers that are likely to be alleviated gradually once underlying root causes are addressed.

In contrast, the bottom level (Level 7) is dominated by economic factors:

- F1: High initial investment cost for robot adoption.
- F2: Uncertainty in profitability and demand.
- F4: Insufficient R&D investment.

These factors represent the fundamental barriers that directly hinder initial adoption and exert influence over many other factors. Economic burdens and limited investment delay technological maturity, which in turn reinforces resistance at the site level and slows institutional and regulatory reform. As such, these bottom-level factors function as the driving barriers in the ISM model and must be prioritized for intervention.

The intermediate levels (Levels 2–6) comprise industrial, institutional, and technological barriers. For instance, F7 (delay in digital transformation of the construction industry) and F8 (non-standardized site environments) were positioned at Level 2, acting as mediators between technological readiness and social acceptance. F21 (immature intelligent technologies) and F22 (absence of integrated platforms) were classified as Level 3, serving as critical connectors between on-site applicability and higher-level acceptance factors. Factors F3, F10, F11, F14, F19, and F20 were placed at Levels 4 and 5, reflecting legal responsibility, technical standards, certification systems, and hardware constraints; these indicate that improvements in socio-cultural acceptance cannot be achieved without a stable institutional and technical foundation. Finally, F12 (insufficient government support and incentives) was uniquely positioned at Level 6, highlighting the pivotal role of policy intervention in reinforcing economic and technological foundations.

The ISM model thus confirms that without addressing the underlying economic and technological drivers, it is difficult to achieve improvements in acceptance-related barriers. In the short term, efforts should focus on enhancing workforce training and awareness at the site level, while in the long term, strategies must prioritize financial incentives, stronger government support, and accelerated technological maturity. Consequently, the ISM model serves as a structural basis for prioritizing policy interventions to promote the adoption and activation of construction robots.

3.2.5. Results of MICMAC Analysis

The MICMAC analysis was performed using the calculated driving and dependency strengths of each factor. As illustrated in Figure 2, the factors were grouped into four distinct clusters. On the horizontal axis, driving strength indicates how strongly a factor influences others, whereas the vertical axis represents dependency strength, reflecting the degree to which a factor is affected by other elements. Based on these two dimensions, the factors were categorized into four functional groups—autonomous, dependent, linkage, and independent. This classification complements the hierarchical results derived from ISM and helps clarify the systemic role that each factor plays within the overall framework.

Autonomous factors have both weak driving and weak dependency strength, showing minimal connection or interaction with other variables. However, in this study, no factors were classified into this cluster. This finding suggests that all 22 identified barriers exert a substantive influence on the adoption and activation of construction robots, thereby supporting the validity and comprehensiveness of the factor set derived in this study.

Dependent factors possess limited driving capacity but strong reliance on others, indicating that their behavior is largely determined by external influences. In this study, ten factors—F5, F6, F7, F8, F9, F13, F15, F16, F17, and F18—were classified as dependent. These factors primarily reflect workforce limitations, resistance to change, delays in digital transformation, non-standardized site environments, and the absence of robot-oriented

design and processes. As such, they are outcome-related barriers, largely shaped by underlying economic, institutional, and technological conditions. Direct interventions targeting these barriers may be less effective, as their alleviation depends heavily on addressing the root causes at lower levels.

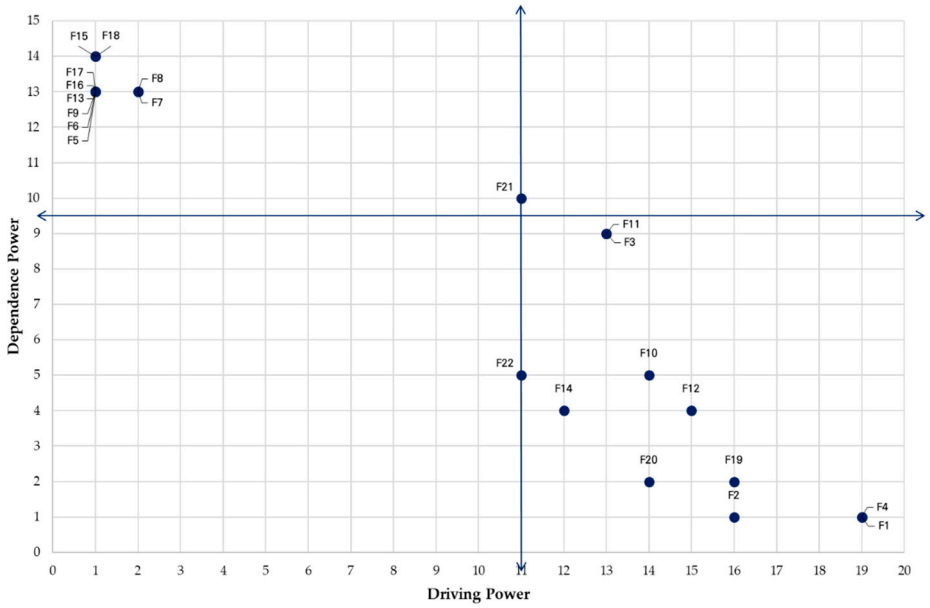


Figure 2. Results of MICMAC analysis.

Linkage factors combine strong driving and dependency strengths, making them highly interactive and sensitive elements that can intensify instability within the system. In this study, only one factor, F21 (poor usability and accessibility of software), was identified as a linkage factor. F21 is closely connected with both higher-level acceptance factors (e.g., resistance to change and awareness of robot value) and lower-level technological factors (e.g., immature intelligent technologies, absence of integrated platforms). Consequently, even minor improvements or setbacks in this factor may produce cascading effects across the system. If left unmanaged, linkage factors such as F21 can significantly increase uncertainty in the adoption process.

Independent factors demonstrate high driving influence with low dependency, functioning as dominant forces that shape the system while remaining largely unaffected by other components. Eleven factors—F1, F2, F3, F4, F10, F11, F12, F14, F19, F20, and F22—fell into this cluster. These include economic barriers (high initial investment cost, uncertainty in profitability and demand, insufficient R&D investment), institutional barriers (absence of legal responsibility, lack of unified technical standards, insufficient government support, inadequate certification and regulatory systems), and technological barriers (immature intelligent technologies, hardware limitations, absence of integrated platforms). Independent factors represent the fundamental drivers that structurally constrain the adoption of construction robots. Therefore, they should be the highest priority for policy and industrial interventions. Without effectively addressing these independent barriers, improvements in dependent socio-cultural factors cannot be achieved.

4. Discussion

This study applied the ISM–MICMAC framework to examine the hierarchical relationships and functional dynamics among 22 key barriers influencing the adoption of construction robots. The analysis grouped these barriers into four functional categories—autonomous, dependent, linkage, and independent—providing an integrated under-

standing that goes beyond the simple identification or ranking of factors reported in earlier research.

No autonomous factors were identified in this study. Although autonomous factors are typically peripheral variables with little influence on the system, the absence of such factors here suggests that all 22 barriers exert a substantive impact on the adoption and activation of construction robots. This finding supports the comprehensiveness and validity of the identified barrier set.

A total of ten dependent factors (F5, F6, F7, F8, F9, F13, F15, F16, F17, and F18) were identified. These included social and cultural barriers such as limited worker capability and training (F5, F6), resistance to change (F15), and entrenched traditional practices (F18), as well as industrial barriers such as delays in digital transformation (F7), non-standardized site environments (F8), and the lack of robot-oriented design and process integration (F9). In addition, the absence of leading public procurement cases (F13) reflects an institutional gap. These barriers were found to be outcome-related, characterized by low driving power but high dependence. While they appear most visible at the site level, they are in fact shaped by underlying economic, institutional, and technological drivers. As such, they are unlikely to be effectively resolved without first addressing the root causes at lower levels.

The ISM model (see Figure 1) illustrates how fundamental drivers and linkage factors interact to produce dependent outcomes. For example, F1 (high initial investment cost) influences F9 (lack of robot-oriented design and process integration), which in turn contributes to F18 (entrenchment of traditional practices). Although F1 and F18 are not directly connected, the transitivity principle of ISM suggests that financial burdens constrain design and process innovation, and without such innovation, site operations continue to rely on traditional practices. This demonstrates that economic drivers are not merely cost issues but exert cascading effects on design innovation and cultural practices. Another example is F19 (immature intelligent technologies), which links to F21 (poor software usability) and further extends to F17 (lack of awareness of the value of robotics). This path shows how technological immaturity propagates through software usability, reducing workers' recognition of robotic benefits.

Only one linkage factor was identified: F21 (poor usability and accessibility of software). This factor serves as a hub connecting socio-cultural barriers (e.g., resistance to change, lack of awareness of robot value) with technological barriers (e.g., immature intelligent technologies, absence of integrated platforms). For example, non-intuitive software interfaces may reinforce worker resistance (F15, F17) while also amplifying technological limitations (F19, F22). With high driving and dependence power, linkage factors are highly interactive and unstable; small improvements or setbacks can trigger cascading effects throughout the system. If left unmanaged, F21 could significantly increase uncertainty in the adoption process.

The largest cluster comprised eleven independent factors (F1, F2, F3, F4, F10, F11, F12, F14, F19, F20, and F22). These included economic barriers such as high initial investment costs (F1), uncertainty in profitability and demand (F2), and insufficient R&D investment (F4); institutional barriers such as the absence of legal responsibility (F10), lack of unified technical standards (F11), insufficient government support and incentives (F12), and inadequate certification and regulatory systems (F14); and technological barriers such as immature intelligent technologies (F19), hardware limitations (F20), and the absence of integrated platforms (F22). These independent factors are fundamental drivers that shape the entire system. With high driving power and low dependence, they represent the most strategic targets for intervention. Without addressing these barriers, improvements in dependent socio-cultural factors are unlikely to be realized.

The MICMAC analysis (see Figure 2) further indicates variation in the relative influence of barriers. For example, F1 (high initial investment) and F4 (insufficient R&D) each recorded the highest driving scores (19), confirming their role as dominant systemic drivers. In contrast, factors such as F5–F9 and F13–F18 showed high dependence scores ($\geq$13), illustrating their subordinate position in the hierarchy and their reliance on deeper economic or institutional conditions. Linkage factors such as F21, with balanced driving (11) and dependence (10), highlight areas where small changes may generate disproportionate ripple effects. These distinctions emphasize that not all barriers exert influence equally, and interventions must be prioritized accordingly

These findings are broadly consistent with previous studies. For instance, refs. [1,11] emphasized socio-cultural barriers, but the present study demonstrates that these are not standalone causes; rather, they are the resultant manifestations of economic and institutional root barriers. Similarly, the industrial limitations noted by [9] were confirmed here as dependent factors, underscoring that their resolution depends on addressing deeper structural drivers. Thus, this study extends prior research by systematically clarifying the hierarchical and functional roles of barriers.

Economic barriers are not only conceptual but are also reflected in industry and research data. A recent framework study showed that acquisition costs for construction robots can reach several hundred thousand USD per unit and are compounded by maintenance and software update expenses, imposing a substantial burden on contractors [57]. Case-based analyses similarly highlight that the net economic benefit of single-task robots is highly sensitive to productivity gains and task context [58]. Moreover, industry reports note that ROI is often calculated on a per-project basis rather than across a multi-project lifecycle, which amplifies profitability uncertainty and discourages scaling [59]. These findings illustrate how economic drivers such as high initial investment and uncertain profitability directly translate into practical challenges, aligning with the concerns repeatedly raised in our survey and seminar discussions. While broader industry-wide data remain limited, the convergence of empirical studies, industry reports, and practitioner insights confirms that economic barriers form the root constraints to construction robot adoption.

The hierarchical structure identified in this study does more than simply classify barriers; its theoretical significance is reinforced when interpreted through established technology adoption theories such as TAM and UTAUT. By comparing each barrier with the core constructs of these models, a more refined understanding can be gained of how structural factors shape user perception and adoption intentions in the context of construction robotics. For example, economic barriers such as high initial investment costs and profitability uncertainties (F1, F2) undermine perceived usefulness in TAM and performance expectancy in UTAUT, leading stakeholders to question the practical value of adoption. Institutional deficiencies (F10–F14) correspond to weak facilitating conditions, where insufficient standards, unclear legal responsibility, and limited incentives restrict the translation of adoption intentions into actual use. Technological immaturity and usability issues (F19–F22) reduce perceived ease of use in TAM and effort expectancy in UTAUT, thereby increasing the burden of learning and implementation. Socio-cultural barriers (F5–F18) are closely tied to social influence, as resistance to change, lack of awareness, and entrenched practices directly affect decision-making. Finally, industrial barriers (F7–F9) weaken both facilitating conditions and performance expectancy, since delayed digital transformation and non-standardized site environments reduce the anticipated benefits of adoption. By mapping the ISM–MICMAC results to TAM and UTAUT constructs, this study not only reinterprets structural barriers within established theoretical frameworks but also demonstrates the potential to extend and enrich these models.

Academically, the study contributes a novel analytical framework by combining ISM and MICMAC to simultaneously reveal the hierarchical structure and functional classification of construction robot adoption barriers. This moves beyond prior approaches that only identified or ranked factors, enabling the differentiation of fundamental drivers versus outcome-related barriers.

Practically, the results provide a basis for developing strategies in policy and industry contexts. Independent factors—particularly high initial investment costs, profitability uncertainties, insufficient R&D, institutional deficiencies, and technological immaturity—must be prioritized as the most urgent challenges. Dependent factors can then be addressed through workforce training, change management, and awareness programs. Linkage factors, such as software usability, require targeted interventions to ensure stability across the system.

Based on the ISM–MICMAC analysis, practitioners and policymakers can establish intervention priorities in the sequence of independent → linkage → dependent factors. First, independent factors with the highest driving power should be addressed as the most urgent barriers. In this study, these include economic and institutional barriers (F1, F2, F4, F10–F14). To mitigate these drivers, initial investment burdens and profitability uncertainties can be alleviated through subsidies, tax incentives, and expanded government investment, while deficiencies in standards and certification can be reinforced by developing unified technical guidelines and clarifying legal responsibilities. Second, linkage factors characterized by both high driving and dependence power are critical for maintaining system stability. In this study, these are represented by software usability (F21) and platform integration (F22). At this stage, UI/UX improvements, expanded pilot projects, and R&D informed by user feedback are required. Third, dependent factors with high dependence power can be effectively improved once higher-level drivers have been addressed. These include limited worker capability (F5, F6), resistance to change (F15), and entrenched traditional practices (F18), which can be gradually mitigated through training, awareness programs, and change management initiatives after the necessary economic and technological foundations have been established.

At the policy level, the findings indicate several strategic directions:

- Mitigating economic burdens through subsidies, tax incentives, and investment support to reduce initial entry barriers.
- Strengthening institutional foundations by clarifying safety certification procedures, establishing legal responsibility, and developing unified technical standards.
- Accelerating technological maturity through expanded R&D investment and pilot projects, with particular emphasis on software usability and platform development.
- Enhancing social acceptance by implementing training and awareness programs for contractors and workers, alongside expanding pilot projects to demonstrate benefits.

These stepwise strategies reflect the structural insights derived from ISM and MICMAC analysis, highlighting the importance of intervening in the order of independent drivers, linkage factors, and dependent outcomes for effective adoption of construction robots. In the long term, if fundamental economic and institutional barriers are not resolved, investment in research and technology development may stagnate and the absence of unified standards may further delay large-scale adoption. Conversely, sustained efforts in training, awareness, and pilot projects can gradually reshape organizational culture and worker acceptance, generating a more favorable environment for robotics. Thus, the proposed interventions are not only immediate remedies but also long-term strategies for ensuring continuous improvement in adoption readiness.

5. Conclusions

This study identified 22 critical barriers to the adoption and activation of construction robots through an extensive literature review and categorized them into five dimensions: economic, industrial, institutional and policy, socio-cultural, and technological. Using ISM and MICMAC analyses, the study examined their structural relationships and functional roles, developing a hierarchical model that clarifies their interdependencies.

The analysis revealed that fundamental economic drivers—such as F1 (high initial investment), F2 (profitability uncertainty), and F4 (insufficient R&D)—occupy the base of the hierarchy and exert the strongest driving power. In contrast, socio-cultural outcomes, such as resistance to change and entrenched practices, emerge as highly dependent factors shaped by these deeper drivers. Linkage elements, including software usability (F21), connect technological immaturity with social acceptance, underscoring their pivotal role in the adoption process. This highlights the varying degrees of influence among barriers and underscores the need for a structured prioritization approach. These findings clarify the structural dynamics of adoption barriers and provide insights into addressing real-world challenges such as reducing cost burdens, closing standardization gaps, and improving workforce acceptance in construction projects.

From an academic perspective, this study moves beyond prior research that merely listed or ranked barriers. By integrating ISM and MICMAC, it systematically identified both hierarchical relationships and functional roles, providing a new analytical framework for understanding the multidimensional nature of construction robot adoption barriers. Moreover, by mapping the identified hierarchy to established models such as TAM and UTAUT, the study demonstrates its theoretical significance and lays a foundation for future empirical validation.

From a practical perspective, the findings provide a stepwise roadmap for developing policies and institutional measures to accelerate construction robot adoption. The results suggest the following sequence: (1) address independent economic and institutional drivers through investment support, standards, and certification reforms; (2) stabilize linkage factors such as software usability and platform integration through targeted R&D and pilot programs; and (3) mitigate dependent socio-cultural outcomes through training, awareness, and change management once the structural foundations are in place. This tiered strategy offers actionable guidance for both policymakers and industry stakeholders. In practice, these measures can reduce financial pressure in the short term, improve technological stability in the medium term, and enhance social acceptance in the long term.

This study has certain limitations. First, the analysis relied on expert surveys, which may not fully represent the views of all relevant stakeholders. Second, the structural model is static and does not capture temporal or dynamic changes. Future research should therefore include broader stakeholder groups—such as contractors, workers, and robot developers—and validate the findings through real-world pilot implementations. In addition, cross-country comparative studies and empirical analyses linking ISM–MICMAC results with TAM and UTAUT constructs could further enrich theoretical understanding and enhance international relevance.

In conclusion, this study provides a systematic framework for understanding the multidimensional barriers to construction robot adoption and a structured foundation for prioritizing interventions. By aligning the proposed stepwise roadmap with the hierarchical structure, this study bridges theoretical modeling and real-world application, offering both practical relevance and academic insight.

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