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Adoption of Lean Construction and AI/IoT Technologies in Iran's Public Construction Sector: A Mixed-Methods Approach Using Fuzzy Logic

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Abstract: The construction sector in Iran faces substantial inefficiencies, including high material wastage, posing environmental and economic risks. This study investigated the adoption of Lean Construction (LC) practices and AI/IoT technologies in Iran's public construction sector using a mixed-methods approach. This research examined the organizational, technical, and infrastructural factors across four key provinces—Tehran, Isfahan, Khorasan Razavi, and Fars—and employed fuzzy logic to address the uncertainties in adoption decisions. Data from 28 key stakeholder interviews were analyzed using Python 3.9, with libraries such as Pandas 1.3.3, NumPy 1.21.2, and skfuzzy 0.4.2 for the statistical analysis and NVivo 12 for the thematic coding. The analysis revealed that organizational readiness and leadership support were the critical drivers of adoption, particularly in Isfahan and Khorasan Razavi, which exhibited the highest adoption likelihood scores (0.5000). Tehran and Fars showed slightly lower scores due to regulatory barriers and financial limitations. The findings highlight the need for targeted leadership training, regulatory reforms, and infrastructure investments to accelerate the adoption of these technologies. This study aligned with the Sustainable Development Goals (SDG 9: Industry, Innovation, and Infrastructure and SDG 11: Sustainable Cities and Communities) by offering practical recommendations for advancing sustainable practices in Iran's construction sector. The insights provided have broader implications for other developing economies facing similar challenges, contributing to global efforts toward sustainable development.

Keywords: lean construction; AI/IoT adoption; fuzzy logic; sustainable development goals (SDGs); public construction; technology adoption in construction

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1. Introduction

The construction sector in Iran contributes approximately 41.8% of the nation's Gross National Product (GNP), making it a crucial economic driver. However, this sector faces significant challenges due to outdated practices, which lead to material waste, higher costs, and negative environmental impacts. These inefficiencies hinder the achievement of the Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation, and Infrastructure) and SDG 11 (Sustainable Cities and Communities) [1]. The sector's dependence on fragmented project delivery methods often results in delays, cost overruns, and poor resource allocation. As the demand for sustainable infrastructure grows, the need for more efficient construction practices becomes even more pressing [2,3].

Iran's public construction sector includes various sub-sectors, such as commercial, industrial, infrastructure, energy and utilities, institutional, and residential construction. These sub-sectors are interlinked, meaning that inefficiencies in one area can have widespread effects on the entire economy. Improving this sector's efficiency and sustainability is, therefore, critical. This improvement requires a thorough assessment of current practices, identifying opportunities for adopting Lean Construction (LC) practices and

AI/IoT technologies, and implementing strategies to boost productivity and drive economic growth [4].

The objective of this research was to bridge the gap in understanding the factors that influence the adoption of Lean Construction (LC) practices and AI/IoT technologies within Iran's public construction sector [5]. Specifically, this study examined how organizational, technical, and infrastructural variables impacted technology adoption, with a focus on regional variations across four provinces: Tehran, Isfahan, Khorasan Razavi, and Fars. By analyzing factors such as organizational readiness, leadership support, perceived benefits, and regulatory challenges, this study aimed to model these influences using fuzzy logic [6].

A mixed-methods approach was employed in this study by integrating qualitative interviews with a fuzzy logic-based analysis. The analysis utilized Python tools, like sk-fuzzy and NumPy, for a comprehensive evaluation, while descriptive statistics generated through Pandas 1.3.3 offered a detailed overview of the technology adoption landscape. The fuzzy logic analysis provided a nuanced understanding of how factors like organizational readiness and leadership engagement affect the likelihood of technology adoption. Additionally, qualitative thematic analysis, supported by NLTK 3.6.2 for text processing, revealed contextual barriers and facilitators, leading to deeper insights into regional adoption dynamics [7].

By focusing on these four key provinces, this study aligned with SDG 9 and SDG 11. Ultimately, this paper offers actionable recommendations for policymakers and industry professionals, providing insights that can inform global practices in similar developing contexts and contribute to broader efforts toward sustainable development in the construction sector.

2. Literature Review and Theoretical Framework

2.1. Lean Construction and AI/IoT Technologies

Globally, Lean Construction (LC) has emerged as an effective strategy for optimizing construction processes, minimizing waste, and enhancing project efficiency [8,9]. However, despite its global success, LC adoption in Iran has been slow due to barriers such as resistance to change, limited awareness, and inadequate training programs [10]. Moreover, advancements in Artificial Intelligence (AI) and the Internet of Things (IoT) offer significant potential for the construction industry, particularly for real-time data collection, predictive analytics, and automated decision-making [11]. Nevertheless, the integration of AI/IoT technologies in Iran is hampered by high implementation costs, a lack of technical expertise, and infrastructural shortcomings [12,13].

Lean Construction and AI/IoT technologies have emerged as essential innovations for enhancing efficiency, reducing waste, and promoting sustainability in construction projects [14,15]. Lean Construction, based on lean manufacturing principles, aims to eliminate non-value-adding activities [16], foster collaboration [16], and optimize project delivery to maximize value for stakeholders [17,18]. These principles are vital in addressing inefficiencies in traditional construction methods, especially as the demand for sustainable infrastructure grows [19,20].

Construction projects frequently face delays, material wastage, and communication gaps. Lean Construction helps resolve these issues by streamlining processes across the project lifecycle. However, as Albalkhy and Sweis [16] noted, regions like Jordan have limited adoption due to a lack of workforce training. According to Mano et al. [10], global barriers to LC adoption include organizational resistance and inadequate training, emphasizing the need for educational initiatives and improved readiness.

Techniques such as the Last Planner System (LPS) enhance project predictability and accountability by promoting collaboration, minimizing rework, and improving planning accuracy [21,22]. Value Stream Mapping (VSM) helps to eliminate waste by identifying inefficiencies and improving project outcomes [3]. However, resource limitations and insufficient training hinder the implementation of these methodologies in certain regions [16].

2.2. Integration of BIM with Lean Construction Practices

Building Information Modeling (BIM) has become a key technology in modern construction, providing a digital representation of the physical and functional characteristics of a facility. The integration of BIM with Lean Construction principles has proven to be highly effective in enhancing project efficiency, reducing waste, and improving communication between stakeholders. Studies by Sacks and Pikas [23] and Dave et al. [24] showed that the combination of BIM with lean methodologies significantly enhances project visualization, decision-making, and coordination, streamlining construction processes.

For example, González et al. [25] demonstrated that using BIM tools alongside Lean Constriction practices enhance planning and real-time problem solving, reducing delays and resource wastage. The integration of these technologies supports Lean Construction's objective of maximizing value by eliminating non-value-adding activities and fostering a collaborative project environment.

This combination of BIM and lean principles not only aligns with the goals of efficiency and sustainability but also sets the foundation for incorporating advanced technologies like AI and IoT into construction project management.

2.3. Integration of AI/IoT Technologies

Meanwhile, IoT technologies have revolutionized construction by enabling real-time monitoring, automation, and data sharing. IoT sensors collect and transmit data, offering insights into machinery performance, worker safety, and project progress [26]. For example, by tracking equipment metrics like temperature and vibration, IoT sensors help project managers anticipate maintenance needs, enhancing efficiency and sustainability [12].

Wearable IoT devices also monitor worker health and environmental conditions in real time, providing alerts in hazardous situations [27]. The combination of IoT and AI-powered predictive analytics supports informed decision-making, optimizing workflows and resource utilization [28]. AI further predicts equipment failures using historical data, allowing for proactive maintenance and minimizing downtime [29].

The integration of LC and AI/IoT technologies has transformed project management, aligning the real-time data flow with LC's focus on waste reduction and continuous improvement [15]. Predictive analytics from AI also help prevent delays and cost overruns, ensuring efficient project execution [30].

2.3.1. Applications of Lean and IoT Technologies in Construction

The practical applications of LC and IoT technologies have significantly improved the efficiency and sustainability in real-world projects. A prime example is the UK's Crossrail project, where drones and IoT sensors provided real-time data, allowing project managers to address delays and inefficiencies swiftly. This approach aligns with LC's goal of reducing waste and ensuring timely project completion, highlighting the potential of these technologies in large-scale infrastructure projects [9].

Another promising application is the use of digital twins—virtual models of physical structures powered by IoT data. As Moshood et al. [31] suggested, digital twins enable project managers to visualize performance, identify inefficiencies, and make data-driven decisions. This is especially beneficial for complex, multi-phase projects requiring collaboration across teams. For example, the Burj Khalifa project in Dubai used BIM and IoT to optimize resources, track progress, and improve safety [32,33].

In prefabrication and modular construction, IoT sensors are used to monitor the quality and progress of prefabricated components, ensuring they meet specifications before arriving on site. This minimizes rework, aligning with LC's focus on project efficiency [34]. Moreover, sensors in construction machinery predict maintenance needs, extending the equipment lifespan and reducing downtime [12].

IoT-enabled waste management systems have also shown their value in tracking material usage and waste production in real time. Benachio et al. [15] noted how this integration helps reduce waste and optimize resources, contributing to sustainability goals in construction. By combining LC principles with IoT-driven waste reduction strategies, the environmental impact of construction projects can be minimized [35].

However, most research focused on advanced economies, leaving gaps in applying these innovations to developing regions like Iran [36]. Traditional construction practices and limited access to technology create significant challenges in these areas. Albalkhy and Sweis emphasize the need for workforce training and organizational readiness to improve the adoption of lean practices in developing countries. Ref. [16] stresses the importance of training and organizational readiness for lean methods adoption in developing countries.

Faris et al. [20] advocated for context-specific strategies that consider infrastructure limitations, financial constraints, and workforce development needs. Tailored strategies are crucial for wider LC and IoT adoption in all regions, enhancing efficiency, sustainability, and competitiveness.

2.3.2. Existing Deficiencies and Obstacles

Despite the potential of LC and AI/IoT technologies, several barriers hinder their widespread adoption, particularly in developing regions like Iran. One of the main obstacles is organizational resistance. Albalkhy and Sweis [16] emphasized that workforce training and readiness are the key to facilitating LC adoption. However, in countries like Iran, many companies struggle to provide adequate training to implement these principles effectively. According to Mano et al. [10], cultural resistance often hinders the shift from traditional methods to technology-driven approaches. This resistance is often rooted in the perception that new technologies threaten established practices, making it difficult to integrate innovative techniques like LC and AI/IoT.

A lack of technological infrastructure is another significant barrier. Many developing regions face challenges in accessing the advanced digital tools required for AI/IoT integration [37]. Benachio et al. [15] and Cai et al. [12] also pointed out that the high implementation and maintenance costs create financial burdens for companies in less developed markets. This financial barrier further complicates the adoption of technology-driven construction methods.

Cultural and regulatory issues further block lean methods and IoT adoption. In regions with traditional hierarchies and rigid structures, adopting LC's collaborative and flexible principles is particularly challenging [37]. Moreover, without government support or incentives, companies may lack the motivation to invest in innovation, delaying advanced construction adoption [16].

2.3.3. Global Experiences and Knowledge of Global Projects

Global projects in more developed regions illustrate the potential of LC, BIM, and AI/IoT technologies, offering valuable lessons for their broader application in developing contexts [38]. For instance, in the UK's Crossrail project, the use of BIM, drones, and IoT sensors enabled real-time project monitoring, allowing project managers to swiftly identify and address inefficiencies [9]. Integrating these technologies with LC principles improves decision-making, reduces waste, and optimizes resource use [39].

Similarly, the Burj Khalifa project in Dubai successfully utilized BIM and IoT to manage the complexity of its multi-phased development [40]. Digital twin technology enabled real-time visualization and proactive adjustments, enhancing project coordination and efficiency.

In Qatar, digital twins and IoT systems have transformed project management in large-scale infrastructure projects [41]. Digital twins powered by IoT data support real-time project visualization and the early detection of inefficiencies, illustrating their synergy with LC principles [31,42].

In the United States, combining LC with prefabrication and modular construction has reduced material waste and improved project timelines [43]. IoT sensors verify the quality of prefabricated components, reducing rework and supporting lean efficiency principles [38].

These global examples demonstrate how the integration of LC, BIM, and AI/IoT technologies can significantly enhance project outcomes and resource management [44,45]. However, these advancements are typically limited to developed nations with robust technological infrastructures [15]. Developing regions like Iran face greater challenges due to infrastructure, financial, and organizational constraints, highlighting the need for targeted strategies to bridge this gap.

2.3.4. Challenges in Iran's Construction Industry

Iran's construction industry faces several challenges that impede the adoption of LC and AI/IoT technologies, including organizational, technological, financial, and regulatory factors that slow down the sector's modernization progress toward sustainability [46].

One major barrier is organizational resistance to change, with many firms adhering to traditional methods deeply rooted in their operational culture [47]. Although workforce training is crucial to overcoming resistance, inadequate training programs worsen the problem. Additionally, hierarchical management structures clash with the collaborative nature required for lean methodologies [16,48].

Technological deficiencies also hinder the adoption of advanced techniques [5]. IoT systems need a solid digital infrastructure, which is often lacking in regions like Iran [15]. Moreover, the financial burden of acquiring AI/IoT systems, coupled with the country's economic instability, further complicates implementation.

Sanctions and inflation exacerbate financial constraints, limiting firms' ability to modernize. Dadsena et al. [49] emphasized that financial viability is the key to technology adoption, yet government support and financial incentives are scarce. This lack of resources hampers efforts to enhance efficiency and sustainability.

Regulatory gaps continue to hinder technological adoption. Albalkhy and Sweis [16] argued that supportive policies are essential for innovation, but Iran's frameworks provide little incentive for lean or AI/IoT technologies. Without regulatory encouragement, adoption is likely to remain sluggish [5,38].

This research highlights the complex interplay of factors influencing technology adoption in Iran. Global best practices offer valuable lessons, but Iran's unique challenges demand targeted strategies to address both the logic of organizational and infrastructural issues, combined with mixed-methods research, to offer a robust framework to model these adoption factors and provide guidance for policymakers and industry leaders [49,50].

By focusing on Iran's specific challenges, this research contributes to the global discourse on sustainable construction. Tackling these barriers could lead to more effective strategies for adopting technologies in developing regions facing similar obstacles, supporting a shift toward more efficient and sustainable construction practices.

3. Method

This research employed a mixed-methods approach to explore the adoption of LC practices and AI/IoT technologies in Iran's public construction sector. The integration of qualitative interviews and fuzzy logic-based analysis provides a comprehensive and multi-faceted understanding of the variables influencing technology adoption. Fuzzy logic was selected to handle the inherent uncertainties in construction industry decision-making. This methodology offers a flexible alternative to traditional decision-making models, which often impose rigid boundaries between variables (see Figure 1).

This figure illustrates the research methodology framework employed in this study, which integrated qualitative interviews and fuzzy logic analysis. The framework also aligned with the Sustainable Development Goals (SDGs) to assess the adoption of Lean Construction and AI/IoT technologies in Iran's public construction sector.

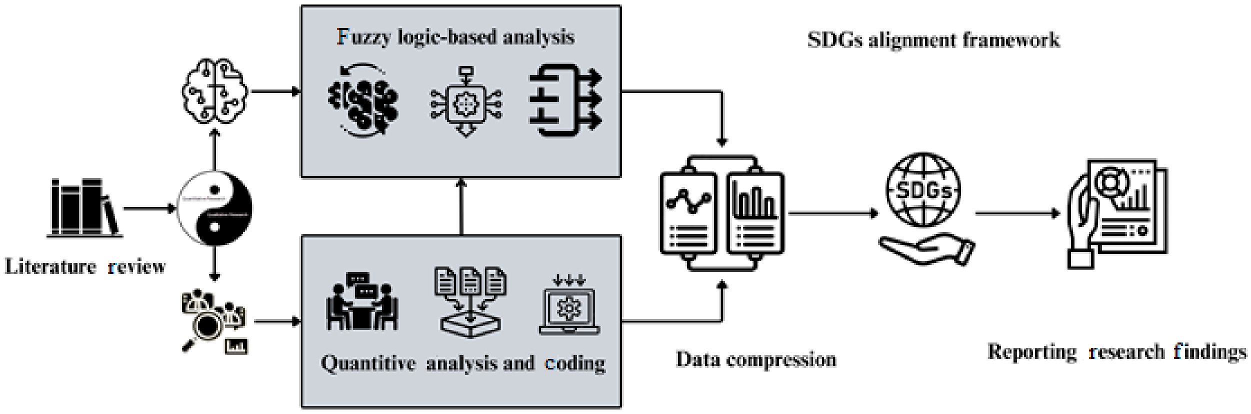

Figure 1. Research methodology framework for fuzzy logic-based and SDGs alignment analysis.

3.1. Qualitative Interviews and Coding

The qualitative phase involved semi-structured interviews with 28 key stakeholders, including government officials, project managers, and construction experts. The interviews aimed to uncover organizational, cultural, and infrastructural factors that influence technology adoption, focusing on leadership support, organizational readiness, and governmental regulation. NVivo 12 software was employed for the systematic coding and thematic analysis, which facilitated the identification of emergent themes.

The thematic analysis followed a structured process:

- Open coding involved identifying recurring concepts, like leadership challenges and financial constraints.
- Axial coding examined code relationships to form higher-order themes, such as organizational readiness.
- Selective coding refined key themes to align with research questions, highlighting leadership's role in adoption.

A participant from the western region emphasized, "Without strong leadership backing, any technology initiative will struggle to gain momentum" [51]. This highlights the role of leadership as a critical enabler of LC and AI/IoT adoption. Multiple rounds of peer debriefing validated the themes, ensuring their reliability and coherence [52].

3.2. Fuzzy Logic-Based Analysis

Fuzzy logic was employed to quantify the likelihood of technology adoption, addressing the uncertainties in subjective and multifaceted factors, such as organizational readiness, leadership support, and perceived benefits. Fuzzy logic offers a nuanced view of overlapping influences in technology adoption, unlike traditional regression models [53].

3.2.1. Fuzzy Logic Implementation

The fuzzy logic model was implemented using Python's skfuzzy 0.4.2 and NumPy 1.23.4. The process included four steps, as outlined in Figure 2.

Step 1 involved defining fuzzy sets for each variable, like organizational readiness, using triangular membership functions [54]. The mathematical representation was as follows:

$$\mu_{Low}(x) = \begin{cases} 0 & if\ x \leq a \\ \frac{x-a}{b-a} & if\ a < x < b \\ 1 & if\ x \geq b \end{cases} \quad (1)$$

where a (the lowest point of membership) and b (the peak point of full membership) define the range of values for the membership function.

For the other variables, such as perceived benefits (PBs), trapezoidal membership functions were used:

$$\mu_{Medium}(x) = \begin{cases} 0 & if\ x \leq a \\ \frac{x-a}{b-a} & if\ a < x \leq b \\ 1 & if\ b < x \leq c \\ \frac{d-x}{d-c} & if\ c < x \leq d \\ 0 & if x \geq d \end{cases} \tag{2}$$

where

- a: the lowest point of membership;
- b: the start of full membership;
- c: the end of full membership;
- d: the highest point.

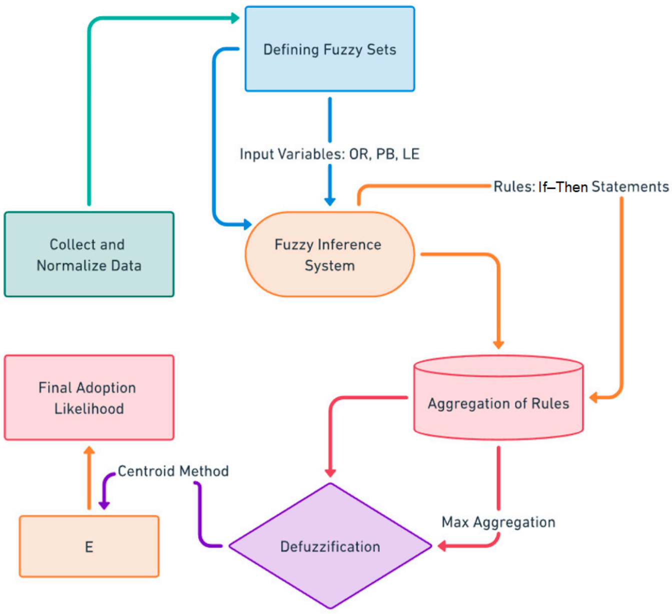

Figure 2. Process of implementing fuzzy logic for technology adoption analysis.

Step 2: Fuzzy inference system (FIS): A Mamdani-type inference system was used with the rules structured as follows: "IF Organizational Readiness is High AND Leadership Support is High, THEN Adoption Likelihood is High". The minimum operator was used for AND conditions, while the maximum operator was used for OR conditions [55].

$$\mu_{Adaptation\ Likelihood} = \min(\mu_{OR}, \mu_{PB}) \tag{3}$$

For the OR condition, the maximum operator was applied:

$$\mu_{Adaptation\ Likelihood} = \max(\mu_{OR}, \mu_{PB}) \tag{4}$$

Step 3: Aggregation of rules: outputs from different fuzzy rules were aggregated using the maximum aggregation method; this allowed the system to combine the outputs from various fuzzy rules (adoption likelihood) [56], which was aggregated as follows:

$$\mu_{Adaptation\ Likelihood} = \max(\mu_1, \mu_2, \ldots, \mu_n) \tag{5}$$

where n represents the number of fuzzy rules applied in the system.

Step 4: Defuzzification: The fuzzy outputs were converted into crisp values using the centroid method, which calculates the center of gravity for the aggregated membership function [57]. The formula used for defuzzification is

$$z_{crisp} = \frac{\int_{\Omega} x.\mu_{output}(x)dx}{\int_{\Omega} \mu_{output}(x)dx} \tag{6}$$

where

- z_{crisp} is the defuzzified output (the crisp value);
- $x.\mu_{output}(x)$ is the aggregated membership function for the fuzzy output (for example, adoption likelihood);
- Ω is the range over which the fuzzy set is defined;
- x is the variable (such as the likelihood score).

The resulting crisp value represents the likelihood of technology adoption for each region, accounting for factors such as organizational readiness and leadership support. The process is illustrated in Figure 2, showing how fuzzy logic was used to derive a crisp value for the technology adoption likelihood from the input variables, such as organizational readiness, perceived benefits, and leadership engagement.

This diagram explains the steps in using fuzzy logic, from defining the fuzzy sets to calculating the adoption likelihood in different provinces of Iran, including key factors such as organizational readiness, leadership engagement, and perceived benefits.

3.2.2. Justification for Using Fuzzy Logic

Fuzzy logic was chosen for its effectiveness in handling uncertainties and qualitative data. Regression models, decision trees, or other conventional methods often fail to capture the complex, overlapping relationships between factors influencing technology adoption, such as leadership support and cultural resistance. Fuzzy logic allows for a more flexible framework, enabling a deeper understanding of the nuanced dynamics at play in technology adoption within the construction sector.

3.3. Data Comparison

Combining qualitative interview insights with fuzzy logic-based analysis enabled a strong comparison. This cross-examination revealed consistencies and discrepancies between stakeholder perceptions and the modeled likelihood of adoption. For instance, the interviews identified leadership challenges as a key barrier, which was confirmed by the fuzzy logic analysis that showed a lower adoption likelihood in regions with weaker leadership support. This comparative approach enriched the overall analysis and provided a more holistic understanding of the factors that influenced LC and AI/IoT adoption.

3.4. Alignment with Sustainable Development Goals (SDGs)

This research was firmly aligned with the SDGs, specifically SDG 9 and SDG 11. By examining the adoption of LC and AI/IoT technologies, this study contributes to building resilient infrastructure and fostering sustainable urbanization in Iran's public construction sector. The actionable insights generated from this study—such as enhancing leadership support and organizational readiness—are directly applicable to achieving these SDGs in Iran and other developing nations.

4. Finding and Results

This section explores the complex factors that influenced the adoption of LC and AI/IoT technologies within Iran's public construction sector. By employing a mixed-methods approach that combined semi-structured interviews and fuzzy logic analysis, this study uncovered the intricate relationships that shaped technology adoption. The objective was to highlight how organizational readiness, perceived benefits, and leadership support interacted to either facilitate or hinder the integration of these technologies in the construction industry. Fuzzy logic offered detailed insights into the link between organizational readiness and perceived benefits, enhancing the understanding of adoption dynamics.

4.1. Overview of Thematic Analysis

The thematic analysis conducted in this study shed light on the factors that influenced the adoption of LC and AI/IoT technologies in Iran's public construction sector. By engaging 28 participants from various roles and provinces, this research addressed several gaps in the existing literature—particularly the need for region-specific analyses in a context marked by diverse leadership, regulatory, and infrastructure challenges. Focusing on Tehran, Isfahan, Khorasan Razavi, and Fars gave a deeper understanding of the adoption process often missed in earlier studies. Figure 3 compares the intensity of leadership challenges, regulatory constraints, financial limitations, and compatibility factors across the provinces of Tehran, Isfahan, Khorasan Razavi, and Fars. The data highlight the regional variations that influenced the adoption of Lean Construction and AI/IoT technologies. The radar graph represents each axis corresponding to a specific challenge or benefit, measured on a scale from 0 (none) to 5 (maximum intensity). This provides a comparative view of each province's readiness and the obstacles faced in adopting LC and AI/IoT technologies. Figure 1 visualizes the intensity of leadership challenges, regulatory constraints, financial limitations, and potential benefits across the provinces Tehran, Isfahan, Khorasan Razavi, and Fars. This comparative view provides a detailed overview of each province's readiness and obstacles in adopting LC and AI/IoT technologies.

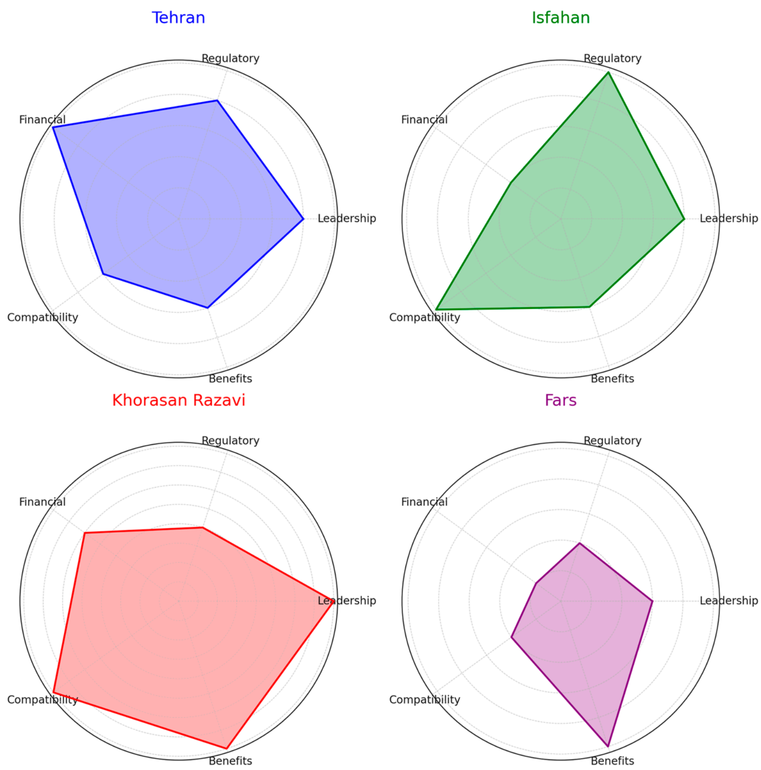

Figure 3. Comparative analysis of leadership, regulatory, financial, and compatibility factors across provinces.

The radar charts compare the leadership, regulatory, financial, and technology compatibility factors across the Tehran, Isfahan, Khorasan Razavi, and Fars provinces. This analysis highlighted key challenges that impacted the adoption of Lean Construction and AI/IoT technologies.

4.1.1. Leadership and Organizational Readiness

Leadership support is a key factor in technology adoption. In Tehran and Isfahan, 64.29% of the participants identified a lack of strategic leadership as a significant barrier, with leadership challenges rated at 4 and 5, respectively. The findings demonstrate that hierarchical structures in these regions limited the flexibility needed for the integration of LC and AI/IoT technologies. In contrast, Fars, rated lower at 3, had fewer leadership barriers, indicating a more proactive approach. Khorasan Razavi also faced leadership challenges (rated 4), but the participants emphasized the importance of training initiatives, which helped mitigate some barriers. Addressing region-specific leadership gaps is crucial for improving technology adoption in these areas (see Table 1).

Table 1. Regulatory and leadership challenges by province.

Province	Regulatory Environment Challenges	Leadership Challenges
Tehran	High	High (4)
Isfahan	Very high	High (5)
Khorasan Razavi	Low	High (4)
Fars	Low	Moderate (3)

4.1.2. Regulatory and Governmental Support

Outdated regulations in Isfahan pose severe challenges to adopting LC and AI/IoT technologies. The regulatory environment in Isfahan was rated as highly challenging (5), compared with 4 in Tehran, where modernization efforts were underway. In contrast, Khorasan Razavi and Fars, with more flexible local governance, experienced fewer regulatory challenges (both rated 2). This regional variation in regulatory barriers highlights the need for targeted reforms that reflect the specific challenges of each province (see Table 1).

4.1.3. Financial and Infrastructure Constraints

Financial limitations and infrastructure readiness were key factors that influenced the adoption likelihood. Tehran, with its significant financial challenges (rated 5), faced leadership delays that exacerbated these issues. In Isfahan, the financial constraints were less severe (rated 2) due to supportive government programs. Khorasan Razavi, which faced moderate financial challenges (rated 3), struggled with severe infrastructure limitations (compatibility rated 4), which hindered the integration of new technologies. Fars, with financial constraints rated 1 and compatibility challenges rated 2, was better positioned for technology adoption, and emerged as the region most prepared for the transition to LC and AI/IoT technologies (see Table 2).

Table 2. Financial constraints and compatibility by province.

Province	Financial Constraints	Compatibility Challenges
Tehran	Significant (5)	Moderate (4)
Isfahan	Low (2)	High (5)
Khorasan Razavi	Moderate (3)	High (4)
Fars	Low (1)	Low (2)

4.1.4. Perceived Benefits

Despite the challenges, the participants acknowledged the potential benefits of LC and AI/IoT technologies, such as cost savings and efficiency improvements. The perception of these benefits was the strongest in Fars and Isfahan, where the adoption readiness was higher. In Tehran, 50% of the participants saw the potential for cost savings and efficiency gains, even in the face of leadership and regulatory challenges. The focus on regional differences in perceived benefits offered a more comprehensive view of the opportunities for technology adoption across provinces (see Tables 3 and 4).

Table 3. Distribution of responses related to perceived benefits and barriers.

Theme	Frequency	Percentage (%)
Cost savings	14	50.0
Efficiency gains	14	50.0
Resistance to change	28	100.0
Infrastructure limitations	17	60.71

Table 4. Key challenges and benefits by province.

Province	Key Challenges	Potential Benefits
Tehran	Financial constraints, leadership challenges	Cost savings, efficiency gains (4)
Isfahan	Regulatory and compatibility challenges	Efficiency gains (5)
Khorasan Razavi	Leadership and compatibility challenges	Improved communication (4)
Fars	Minimal financial and regulatory barriers	Reduced project timelines, high benefits (5)

4.1.5. The Path Forward

To address these challenges, a region-specific approach is essential. Tehran and Isfahan must focus on leadership development and regulatory reforms to reduce the barriers to adoption, while Khorasan Razavi should prioritize infrastructure modernization and financial support to address its compatibility issues. Fars, already the best-positioned region, can serve as a model for technology adoption, with its proactive government engagement and modern infrastructure facilitating the smooth integration of new technologies.

By addressing these region-specific barriers—leadership training, regulatory flexibility, financial support, and infrastructure upgrades—Iran's construction sector can fully realize the transformative potential of LC and AI/IoT technologies, leading to greater efficiency, cost savings, and sustainability.

4.2. Fuzzy Logic Analysis of Adoption Likelihood

The fuzzy logic analysis focused on four key variables—leadership support, organizational readiness, perceived benefits, and regulatory challenges—that influenced the adoption of LC and AI/IoT technologies in Iran's public construction sector. This analysis was conducted across four provinces: Tehran, Isfahan, Khorasan Razavi, and Fars. Using a Mamdani-type fuzzy inference system, these variables were modeled with fuzzy sets to address uncertainties in subjective assessments, like leadership effectiveness and the perceived benefits of technology adoption. The defuzzification process provided actionable insights into each province's likelihood of adopting these technologies. The heatmap in Figure 4 illustrates the correlation between the four key factors that influenced adoption. Leadership support and perceived benefits showed a high correlation across all provinces, while regulatory challenges presented a relatively weaker correlation with other factors, particularly in Fars and Khorasan Razavi, where the local governance was more supportive.

This heatmap depicts the correlations between leadership support, regulatory challenges, organizational readiness, and perceived benefits across the four provinces in Iran. This visualization helps to understand the relationships between these factors in Lean Construction and AI/IoT adoption.

Table 5 summarizes the crisp adoption likelihood scores for each province, indicating the overall readiness for technological change. Fars had the lowest likelihood (0.4973), while Isfahan and Khorasan Razavi exhibited the highest readiness (0.5000). Tehran, with a score of 0.4987, demonstrated moderate readiness, but with notable challenges, particularly in regulatory reform.

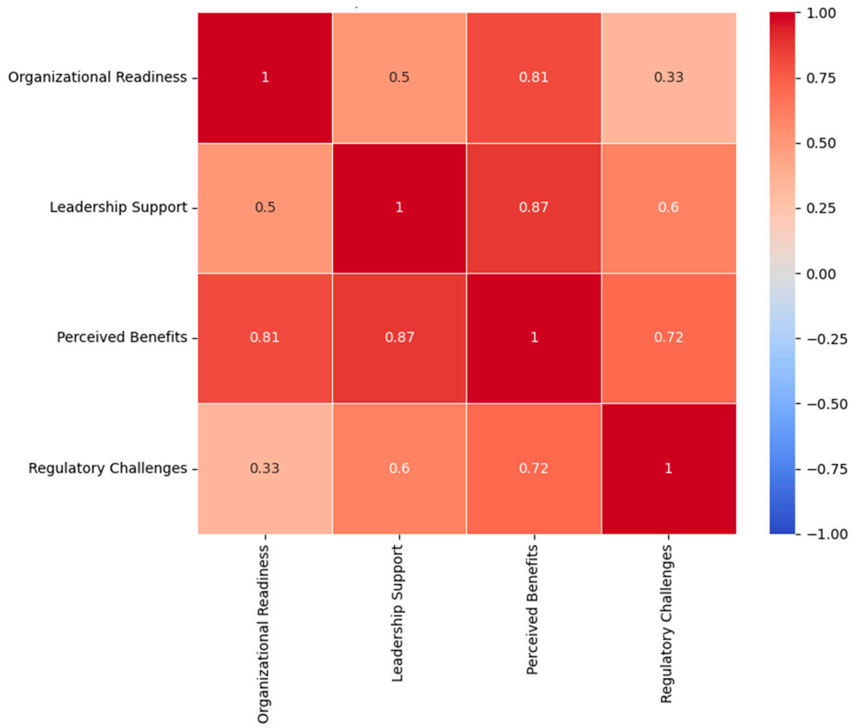

Figure 4. Heatmap of correlation between variables that affected technology adoption.

Table 5. Crisp adoption likelihood scores by province.

Province	Crisp Adoption Likelihood
Fars	0.4973
Isfahan	0.5000
Khorasan Razavi	0.5000
Tehran	0.4987

4.2.1. Fuzzy Logic Analysis of Qualitative Data

The comparison highlighted strengths and challenges in the studied regions. Fars demonstrated a relatively low likelihood of adoption due to significant regulatory barriers, weak leadership support, and financial constraints. Furthermore, the lack of access to skilled professionals in this province further contributed to its lower score in the analysis. Figure 5 presents a pair plot, highlighting the distribution and relationships between key factors, such as the leadership support, organizational readiness, and regulatory challenges across provinces. The data visualization helps illustrate how these factors varied between regions, providing a more in-depth understanding of Fars's position relative to the others.

The pair plots illustrate the distributions and relationships between variables like leadership support, organizational readiness, and regulatory challenges across Tehran, Isfahan, Khorasan Razavi, and Fars. This visualization aids in understanding the regional variations in technology adoption readiness.

In contrast, Isfahan displayed strong leadership support and high organizational readiness, despite encountering some regulatory hurdles. The perceived benefits of adopting LC and AI/IoT technologies in Isfahan boosted its overall readiness for implementation, as reflected in its high scores. Figure 6 shows how leadership support, organizational readiness, and regulatory challenges correlated with the adoption likelihood in each province, emphasizing Isfahan's relatively better performance in terms of the readiness and leadership effectiveness.

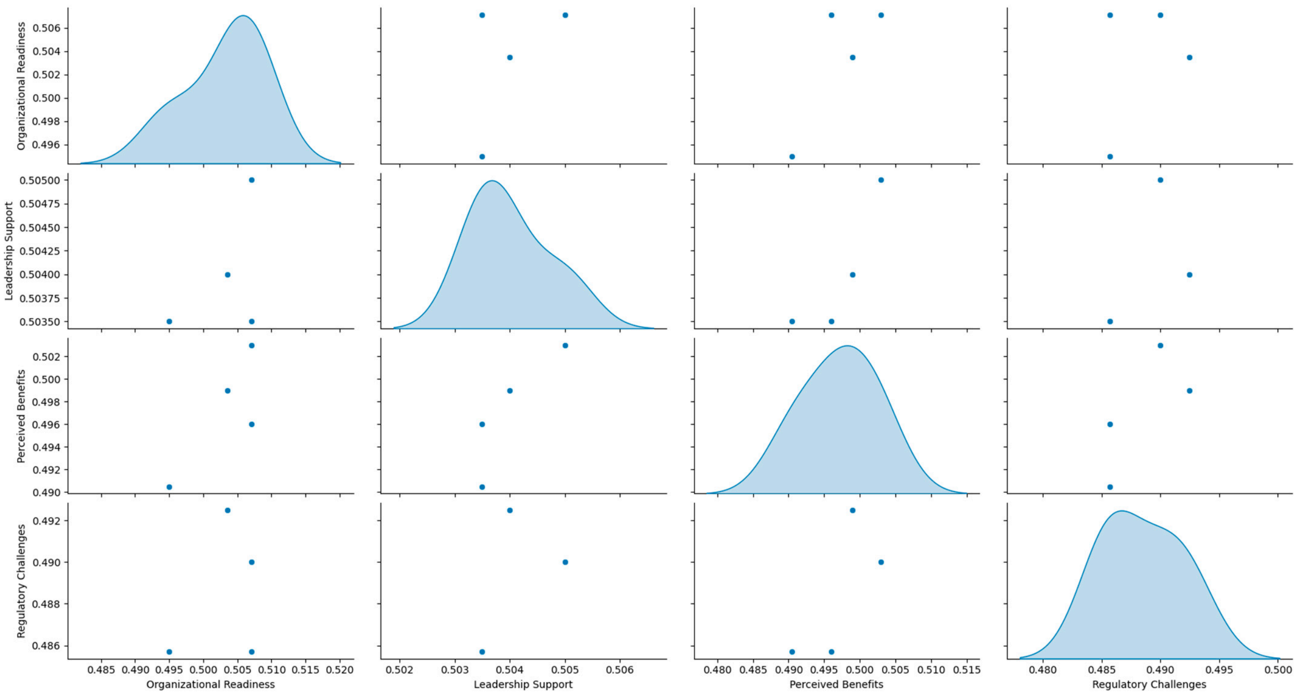

Figure 5. Pair plot of factor distributions and relationships across provinces.

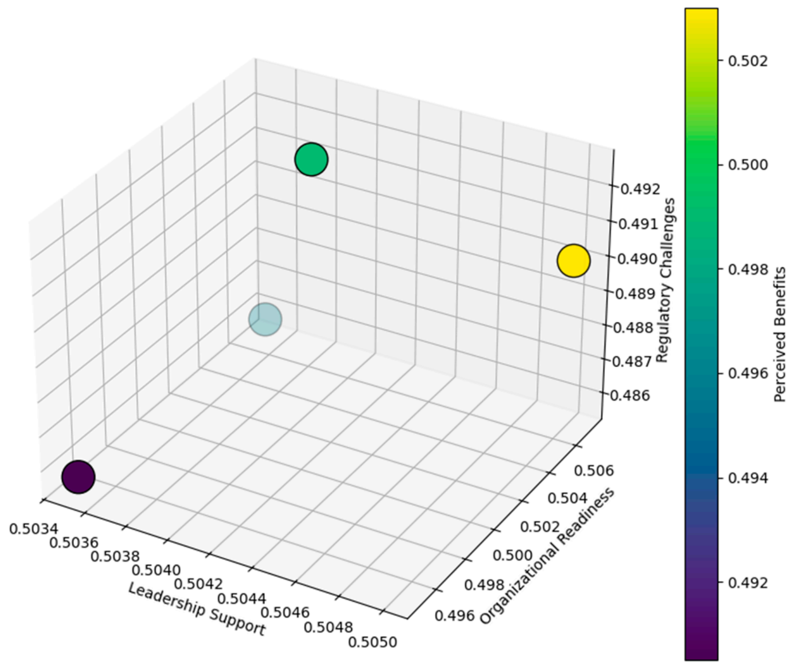

Figure 6. Leadership, readiness, and regulatory challenges impacts on adoption likelihood.

Khorasan Razavi emerged with strong leadership and organizational readiness, which contributed to its high likelihood score for adoption. However, the participants indicated that access to technology education and training remained a critical area that required improvement. While regulatory challenges were present, they were less severe compared with the other provinces, enabling Khorasan Razavi to maintain its favorable position. The regulatory environment in Khorasan Razavi allowed for more flexibility, which contributed positively to its overall score.

Tehran exhibited strong leadership support and organizational readiness, but it faced substantial regulatory barriers. Outdated policies and high compliance costs were frequently cited by participants as major obstacles that hindered the adoption of new technologies. Furthermore, the brain drain of skilled professionals from the region posed an additional challenge that required urgent attention through targeted training programs. Figure 7, a 3D surface plot, visually compares the key factors across provinces, showing how regions like Isfahan and Khorasan Razavi outperformed Fars and Tehran in terms of overall readiness and leadership support. Table 6 provides an overview of the factor contributions to the adoption likelihood by province. Organizational readiness emerged as the most significant factor, with an average score of 0.5071, indicating a solid foundation for adopting new technologies. Leadership support averaged 0.5036, though weaker results were seen in Fars and Tehran, highlighting the need for leadership development programs to foster stronger executive support for technological innovation. Perceived benefits averaged 0.4964, with certain provinces, particularly Fars, showing uncertainty regarding the advantages of these technologies. Regulatory challenges had the lowest average score of 0.4857, where Khorasan Razavi and Tehran experienced the most severe barriers, indicating a need for focused policy interventions.

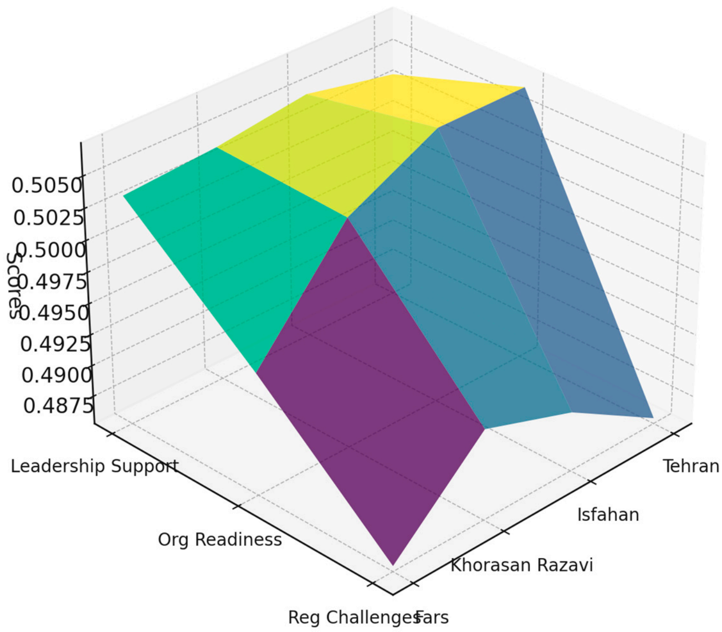

Figure 7. Three-dimensional surface plot of provincial comparison in adoption readiness and leadership support. The legend is same with Figure 6.

Table 6. Factor contributions to adoption likelihood by province.

Province	Organizational Readiness	Leadership Support	Perceived Benefits	Regulatory Challenges
Fars	0.4950	0.5035	0.4905	0.4857
Isfahan	0.5071	0.5050	0.5030	0.4900
Khorasan Razavi	0.5035	0.5040	0.4990	0.4925
Tehran	0.5071	0.5035	0.4960	0.4857

This comparison chart details the impact of leadership readiness and regulatory challenges on the likelihood of adopting Lean Construction and AI/IoT technologies across Tehran, Isfahan, Khorasan Razavi, and Fars provinces.

This 3D surface plot compares the readiness for adopting Lean Construction and AI/IoT technologies across Tehran, Isfahan, Khorasan Razavi, and Fars, with an emphasis on leadership support and organizational preparedness.

4.2.2. Policy and Practical Implications

The fuzzy logic analysis underscored the importance of addressing leadership gaps and regulatory barriers. Leadership development programs in Fars and Tehran are essential to bolster the executive support for innovation. Additionally, regulatory reforms are needed to modernize policies and reduce compliance costs in Tehran and Khorasan Razavi. Addressing these issues could improve the readiness for adopting LC and AI/IoT technologies.

There is a clear need for targeted training programs to address the shortage of skilled professionals in Tehran and improve access to expertise in Fars. By upskilling the local workforce, these provinces can enhance their organizational readiness and improve their adoption rates.

Finally, Isfahan and Khorasan Razavi could serve as model provinces, sharing best practices with regions facing greater challenges. Cross-provincial knowledge-sharing platforms could accelerate technology adoption across Iran's public construction sector.

4.3. Comparison of Findings and SDGs Alignment

The integration of qualitative and fuzzy logic analysis provided a holistic understanding of the factors influencing the adoption of LC and AI/IoT technologies in Iran's public construction sector. The combined findings reveal clear region-specific challenges and opportunities across Tehran, Isfahan, Khorasan Razavi, and Fars.

4.3.1. Comparison of Findings

Leadership challenges were a major barrier in Tehran and Isfahan, as identified by 64.29% of the participants and supported by the fuzzy logic analysis, which showed leadership support scores of 0.5035 and 0.5050, respectively. In Khorasan Razavi, 60.71% of the participants reported financial constraints, reflected in the fuzzy logic analysis as moderate organizational readiness. These results indicate that leadership support and regulatory reforms are critical areas for improvement in Tehran and Khorasan Razavi, while Fars demonstrated fewer barriers but still required enhancements in leadership support (see Table 7).

Table 7. Provincial comparison of leadership, organizational readiness, and regulatory challenges.

Province	Leadership Support	Organizational Readiness	Regulatory Challenges	Financial Constraints
Tehran	0.5035	0.5071	0.4857	5
Isfahan	0.5050	0.5071	0.4900	2
Khorasan Razavi	0.5040	0.5035	0.4925	3
Fars	0.5035	0.4950	0.4857	1

4.3.2. Alignment with SDGs

This analysis directly supported SDG 9 (Industry, Innovation, and Infrastructure) and SDG 11 (Sustainable Cities and Communities). The results show that Khorasan Razavi, despite its regulatory challenges, had strong leadership and organizational readiness, making it well-suited to adopting innovative technologies and aligned with SDG 9. However, provinces like Tehran and Isfahan required significant regulatory reforms, as outdated regulations and high compliance costs were identified as barriers by 71.43% of the participants.

Fars, with its minimal financial and regulatory hurdles, was positioned to achieve the SDG 11 goal by streamlining project timelines and improving communication. This region is poised to lead the country in adopting LC and AI/IoT technologies (see Table 8).

Table 8. SDGs alignment by province.

Province	SDG 9	SDG 11	Key Challenges	Potential Benefits
Tehran	Moderate	Moderate	Regulatory barriers, brain drain	Cost savings, efficiency gains
Isfahan	High	High	Regulatory hurdles, compatibility	Efficiency gains
Khorasan Razavi	High	Moderate	Infrastructure, regulatory issues	Improved communication
Fars	High	Very high	Minimal barriers	Reduced project timelines

5. Discussion

5.1. Benefits of Lean Construction and AI/IoT Technologies

The integration of LC practices with AI/IoT technologies has proven to offer significant advantages in enhancing operational efficiency across Iran's construction sector [5]. This synergy streamlines workflows, reduces waste, and directly impacts both cost efficiency and project timelines [58]. This study's fuzzy logic analysis indicates that Tehran and Isfahan were well-positioned to leverage these technologies, with organizational readiness scores of 0.5071 and 0.5050, respectively. Real-time monitoring enabled by AI/IoT supported immediate interventions in construction processes, minimizing delays from unforeseen issues [59]. This supports SDG 9 by fostering sustainable industrialization and innovation with digital tools [60]. These capabilities align with SDG 9, which aims to promote sustainable industrialization and innovation by leveraging advanced digital tools. Furthermore, findings continue to support the view that LC enhances resource optimization, reducing material waste and contributing to SDG 12 [15,61].

Another key advantage identified in this study was the reduction in material waste. The integration of LC's focus on resource optimization with AI/IoT's precision in data collection enables Iranian construction firms to improve resource allocation and reduce overconsumption. The fuzzy logic analysis showed that Tehran and Isfahan demonstrated greater efficiency in resource management, which reinforced the goals of SDG 12. These findings echo those of prior studies, highlighting the role of AI in resource management and sustainability efforts [12,62,63].

5.2. Integration of Digital Twin Technology with AI/IoT

Building on the benefits of AI/IoT technologies, integrating digital twin (DT) models into Iran's construction sector can further optimize resource management and decision-making. Digital twin technology creates digital replicas of physical assets, facilitating real-time data exchange with IoT devices and enabling predictive maintenance and efficient project monitoring [64]. Implementing DT models could address existing challenges, such as improving project timelines and minimizing material waste, thus aligning with the objectives of SDG 9 and SDG 11.

5.3. International Application of Study Findings

Although this study specifically focused on the adoption of Lean Construction (LC) practices and AI/IoT technologies in Iran, its findings have significant implications for other developing countries with similar socio-economic and infrastructural challenges. Many nations in regions such as the Middle East, North Africa, and South Asia face comparable barriers to technology adoption, including financial constraints, cultural resistance, and regulatory hurdles like those encountered in Iran.

The strategies identified in this research could therefore be applicable in accelerating the adoption of LC and AI/IoT technologies in the construction sectors of countries like Turkey, India, and Egypt. Emphasizing leadership support, targeted training, and financial incentives are universally relevant factors that can drive technology integration across diverse contexts. Lessons learned from Iran's experience in overcoming these obstacles can guide policymakers and industry leaders in creating more favorable environments for sustainable infrastructure development in their respective regions.

5.4. Challenges of Implementing Lean Construction and AI/IoT Technologies

Despite the benefits, this study identified significant challenges in adopting LC and AI/IoT technologies, particularly in regions with less developed infrastructure, like Fars and Khorasan Razavi. High adoption costs and financial constraints hinder smaller construction firms in these areas from fully implementing these advanced technologies. Fuzzy logic analysis highlighted these financial limitations and the lower organizational readiness scores in Fars (0.4950) and Khorasan Razavi (0.5035) correlated with reduced adoption rates, slowing the progress toward achieving SDG 9 [47,65,66].

Cultural resistance also emerged as a significant barrier, especially in areas where traditional labor practices prevailed. Workers and management often view AI/IoT technologies as threats to job security, which intensifies the reluctance to adopt these innovations. Overcoming this resistance requires targeted technical training to equip workers with the skills necessary to adapt to new technologies [18,47,67–69].

5.5. Recommendations for Overcoming Adoption Challenges

To address these challenges, several strategies are recommended. Financial incentives, such as government subsidies or low-interest loans, could ease the burden on smaller firms in regions like Fars and Khorasan Razavi, encouraging investment in new technologies. Targeted training programs for both management and labor are essential to bridge knowledge gaps and reduce the resistance to adoption. Furthermore, leadership development programs focused on digital literacy could significantly boost the adoption rates in regions with lower technical skills [9,33,70].

Establishing a national framework for digital transformation in the construction sector is also crucial to ensure the consistent adoption of AI/IoT and LC technologies across all regions. A cohesive national strategy would support SDG 9 by fostering innovation and SDG 11 by promoting sustainable urban development practices [71].

5.6. Practical Lessons Learned from Implementing Lean Construction and AI/IoT Technologies

Several practical lessons emerged from this study. Strong leadership is essential in overcoming financial and cultural barriers to adopting LC and AI/IoT technologies. Regions where leadership prioritized innovation, like Tehran, showed higher success rates in technology adoption. Early stakeholder involvement and robust infrastructure support also play pivotal roles in facilitating smooth technology integration. Practical training initiatives are vital to empowering workers to embrace these innovations without fearing job displacement [72–74].

6. Conclusions

This study underscored the significant impact of Lean Construction (LC) and AI/IoT technologies in advancing operational efficiency and sustainability within Iran's construction sector. The findings indicate that Tehran and Isfahan were particularly well positioned to implement these innovations, largely due to their robust organizational support and leadership engagement, which aligned with Sustainable Development Goals (SDGs) 9 and 11. In contrast, provinces such as Fars and Khorasan Razavi encountered considerable challenges, including financial constraints, lower levels of organizational readiness, and cultural resistance.

The fuzzy logic analysis highlighted the pivotal role of leadership support and regulatory reforms as crucial factors for promoting technology adoption. To address these barriers, targeted policy interventions and leadership development initiatives are recommended, which could drive broader adoption and encourage sustainable practices throughout the sector. Future research should investigate the long-term impacts, extend the geographical focus of this study, and incorporate alternative analytical methods to achieve a more comprehensive understanding of how LC and AI/IoT technologies could transform the construction industry.

Despite the valuable insights gained from this study, several limitations must be acknowledged. This research was geographically confined to the provinces of Tehran, Isfahan, Fars, and Khorasan Razavi, which limits its applicability to other regions or countries with different economic and cultural circumstances. Although engagement with key stakeholders was undertaken, this study did not fully capture the perspectives of smaller contractors, laborers, and government policymakers, potentially narrowing this study's conclusions.

While the fuzzy logic approach proved effective in handling uncertainties in decision-making, neural networks could offer deeper insights into the complexities of technology adoption. This study primarily focused on the short- to medium-term impacts of LC and AI/IoT technologies, indicating a need for future research into their long-term effects on productivity and sustainability. Neural networks, with their capacity to process large datasets and identify patterns in complex, non-linear relationships, could significantly enhance this analysis, potentially revealing correlations and dependencies that fuzzy logic models might overlook.

Future research should expand to include comparative studies across multiple countries to better understand the adaptability of these strategies in diverse cultural and economic settings. A broader scope could refine the framework for global implementation, making it relevant to both developed and developing nations. Extending this study's methodology to different regions would enrich the understanding of how LC and AI/IoT technologies could reshape the global construction industry. Additionally, involving a wider range of participants, including smaller contractors and policymakers, would enhance the robustness and applicability of the findings, ensuring that the insights are relevant across a variety of socio-economic contexts.

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