Critical Success Factors for the Adoption of Artificial Intelligence in Facilities Management: Second-Order Systematic Review

Robson Quinello[1*], *Benny Kramer Costa*[1,2]

Abstract

The application of Artificial Intelligence (AI) in Facilities Management (FM) has grown significantly, driven by the pursuit of resource optimization, automation, and operational efficiency. However, specialized literature remains in an early stage, hindering a comprehensive understanding of the Critical Success Factors (CSFs) that influence the adoption of this technology in the sector. To address this gap, this study conducts a Second-Order Systematic Review (SOSR) to identify and consolidate the main CSFs associated with the adoption of AI in FM. The analysis is grounded in a conceptual model based on the TOEH theoretical framework (Technology–Organization–Environment–Human), which enables a multidimensional reading of both facilitators and barriers. Key challenges include system interoperability, data quality, the reliability of AI models, and building typology diversity, issues exacerbated by technological fragmentation and a lack of standardization, which hinder integrated solutions. Regulatory concerns regarding data privacy and governance, combined with limited workforce training, further hinder large-scale adoption. Conversely, innovations such as digital twins, explainable AI, robotics, and cybersecurity for smart buildings emerge as drivers of transformation. The findings provide valuable insights for FM managers, technology providers, and policymakers, contributing to the development of effective strategies for integrating AI in the Facilities Management sector.

Keywords: artificial intelligence, facilities management, critical success factors, technology adoption, CSF-TOEH framework.

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Introduction

Facilities Management (FM) is a multidisciplinary field that integrates people, processes, and technologies to optimize the functionality of built environments and the efficiency of organizational operations (ISO 41001:2018; Pedral Sampaio et al., 2022; Moghayedi et al., 2024; Quinello & Nascimento, 2025). According to Amos et al. (2021), the scope of FM can be segmented into hard services and soft services. Hard services encompass structural and technical aspects such as building maintenance, HVAC systems, energy management, and utilities. Soft services, in turn, encompass functions related to occupant wellbeing, including cleaning, security, reception, and workspace management. These activities are essential to ensure the operational continuity and efficiency of buildings, with Operations and Maintenance (O&M) accounting for 80% to 85% of the total lifecycle costs of built environments, as noted by Benbya et al. (2020). In 2022, buildings were responsible for 34 percent of global energy demand and 37 percent of energy and process-related carbon dioxide (CO_2) emissions (UNEP, 2023).

Given its operationally intensive nature, FM has historically relied on data to support decision-making, which has facilitated the progressive incorporation of AI as a tool for automation, resource optimization, and enhancement of building efficiency (Pedral Sampaio et al., 2022). Since the 1960s, the sector has adopted technological solutions, beginning with Supervisory Control and Data Acquisition (SCADA) systems, followed by Computer Aided Design (CAD), and more recently, Building Information Modeling (BIM), which has established a robust digital foundation for asset management (Ilter & Ergen, 2015; Wong et al., 2018; Biswas et al., 2024).

The transition from reactive approaches to more initiative-taking models gained momentum with the dissemination of systems such as the Building Automation System (BAS) and Computer-Aided Facility Management (CAFM) at the end of the twentieth century. Although advanced for their time, these systems were based on fixed rules and lacked the adaptive and predictive capabilities inherent to modern AI. The increasing complexity of buildings, coupled with rising demands for efficiency, has driven the development of solutions such as Digital Twins (DT), which enable real-time simulation and optimization of infrastructure performance (Arseculаratne et al., 2024).

Recent studies have highlighted the benefits of such technologies. Abdelalim et al. (2024) identified a 25% reduction in maintenance costs and a 20% decrease in energy consumption through the use of DT, in addition to significant improvements in operational efficiency. Nevertheless, despite the growing volume of data generated by sensors and integrated systems, FM managers still face considerable challenges related to data integration and strategic analysis (Dahanayake & Sumanarathna, 2022; Lawal et al., 2025). Despite these hurdles, FM has evolved into a data-driven field, increasingly focused on making predictive decisions and providing occupant-centered experiences. The convergence of AI, IoT, and BIM is shaping a new era of operations (Pedral Sampaio et al., 2022; Olimat et al., 2023). However, the adoption of these technologies remains uneven and is constrained by fragmented barriers, which limit structured decision-making among sector professionals.

(1) Universidade Nove de Julho, São Paulo, Brazil
(2) Universidade de São Paulo, Brazil
*Corresponding author: robson.quinello@sp.senai.br

In this context, identifying Critical Success Factors (CSFs) emerges as an essential analytical tool. Defined by Rockart (1979) as elements whose presence is vital for the success of an initiative, CSFs function as intervening variables that mitigate uncertainty and structure decision-making in complex environments (Alias et al., 2014; Dora et al., 2022). The Technology–Organisation–Environment–Human (TOEH) model, an evolution of the TOE framework proposed by Tornatzky & Fleischer (1990), has been widely adopted in the literature to categorize such factors, incorporating the human dimension as a fundamental component of technological adoption (Orji et al., 2019; Lok et al., 2022).

Within the technological dimension, CSFs include data availability and quality, the sector's digital maturity, and the interoperability of legacy and new systems (Pedral Sampaio et al., 2022; Hou et al., 2024). At the organizational level, factors such as top management support, innovation culture, and strategic alignment are frequently cited as determinants (Lee et al., 2021; Mishra et al., 2024). Environmentally, factors such as expected return on investment (ROI), regulations, and market conditions directly influence the feasibility of adoption (Vaiste, 2020; Marocco et al., 2024). Finally, the human dimension encompasses technical training, reskilling, knowledge transfer, and stakeholder engagement (Merhi, 2023; Moghayedi et al., 2024).

Given this scenario, this article seeks to answer, based on an extensive review of the scientific literature, the following research questions:
(RQ1) What is the chronological trajectory of AI applications in FM?
(RQ2) What are the emerging applications and future opportunities for the FM sector?
(RQ3) What are the main challenges faced in the adoption of these technologies?
(RQ4) What are the necessary conditions for the successful adoption of Artificial Intelligence in Facilities Management, based on a conceptual model of Critical Success Factors grounded in the TOEH framework?

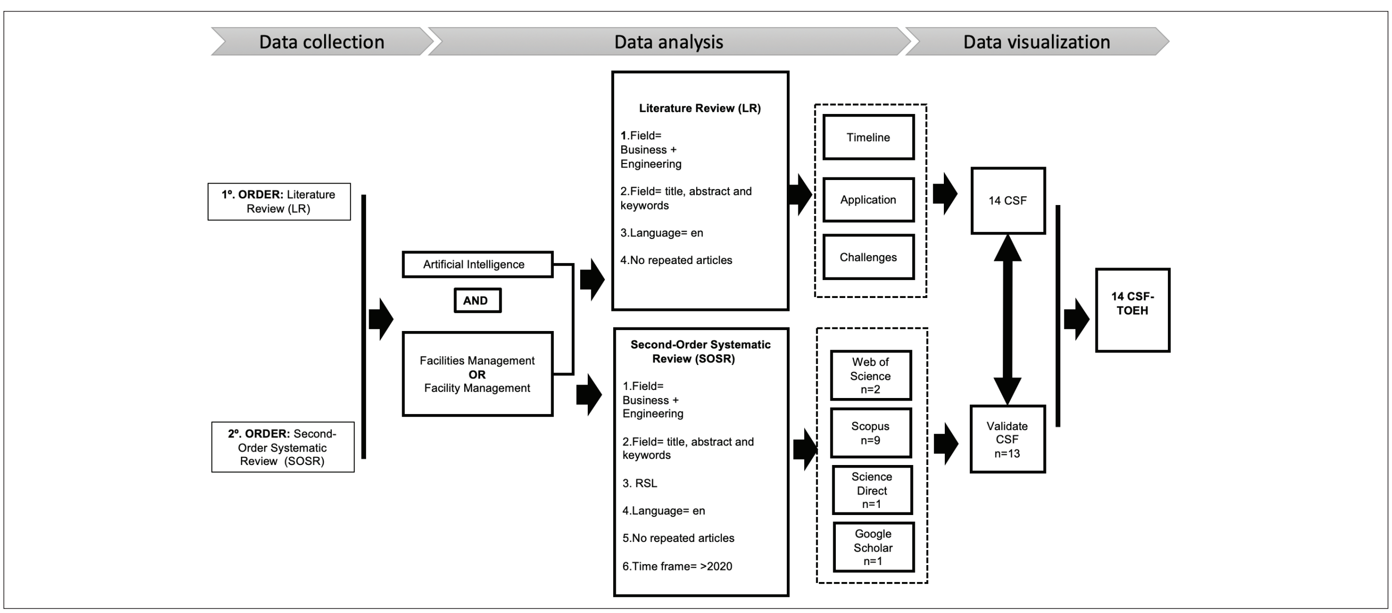
Methodology

This study employs a methodological approach based on the Second-Order Systematic Review (SOSR) for the non-empirical validation of Critical Success Factors (CSFs), as illustrated in Figure 1. This technique involves systematically mapping and analyzing CSFs previously identified in the scientific literature through the cross-synthesis of published Systematic Literature Reviews (SLRs). Unlike meta-analyses, which aggregate quantitative data from primary studies, or first-order SLRs, focused on the direct analysis of empirical evidence, SOSR operates at a higher meta-analytical level, where the objects of investigation are the systematic reviews themselves. This approach requires strict criteria regarding the methodological quality, thematic relevance, and practical applicability of the studies analyzed.

Although it shares similarities with the umbrella review as defined by Grant & Booth (2009), this study diverges in its purpose: it does not aim to consolidate clinical evidence or provide immediate normative recommendations but rather to carry out a conceptual and theoretical validation of CSFs applicable to the adoption of AI in FM. This conceptual emphasis, combined with the field's applied nature, lends originality to the approach.

A distinctive feature of this study is the selection of SLRs focused on specific AI applications in FM, such as sustainability, predictive maintenance, interoperability, and energy management. This ensures a high degree of alignment with applied contexts, thereby increasing the external validity and practical utility of the validated factors. Compared to studies such as Schmid et al. (2024), which also employ SOSR, and Barbosa et al. (2024), who adopted a systematic literature review with meta-analysis, the present work differs in that, while those authors seek to consolidate evidence around a construct or set of practices, this study aims to test the robustness and recurrence of CSFs across convergent contexts, using them as the basis for a structured and replicable conceptual model within the domain of AI in FM.

Figure 1. Applied Methodology



Source: Elaborated by the authors (2025)

In the first instance, the literature review on AI applied to FM involved a broad selection of articles published in indexed journals and normative reports, including ISO 41001:2018, the primary global standard for FM systems. The goal of this initial review was to identify challenges and opportunities related to AI adoption in FM, considering multiple perspectives, including building automation, operational efficiency, sustainability, and digital transformation. The search prioritized recent publications (post-2020) in English, reflecting the advancement of AI applications in the sector, without excluding earlier studies that provided conceptual and methodological foundations. This phase facilitated a discussion of the historical trajectory, opportunities, and challenges associated with AI in FM.

In the second order, the insights from the first-order review were cross-referenced with the only available SLRs focused on AI in FM, ensuring the analysis was grounded in consolidated studies. To guarantee methodological rigor and replicability, the SLRs were retrieved from Scopus, Science Direct, Web of Science and Google Scholar using the following search string:

"artificial intelligence" AND "facilities management" OR "facility management" AND "Systematic Literature Review"

The inclusion and exclusion criteria were as follows:

(i) Period: Post-2020 (including earlier studies when conceptually essential);

(ii) Inclusion criteria: SLRs on AI applied to FM, in English, published in peer-reviewed journals;

(iii) Exclusion criteria: Non-peer-reviewed papers, publications unrelated to AI and FM, and duplicate studies.

The evidence collected (n=13) was organized into four analytical axes, which structure the subsequent discussion:

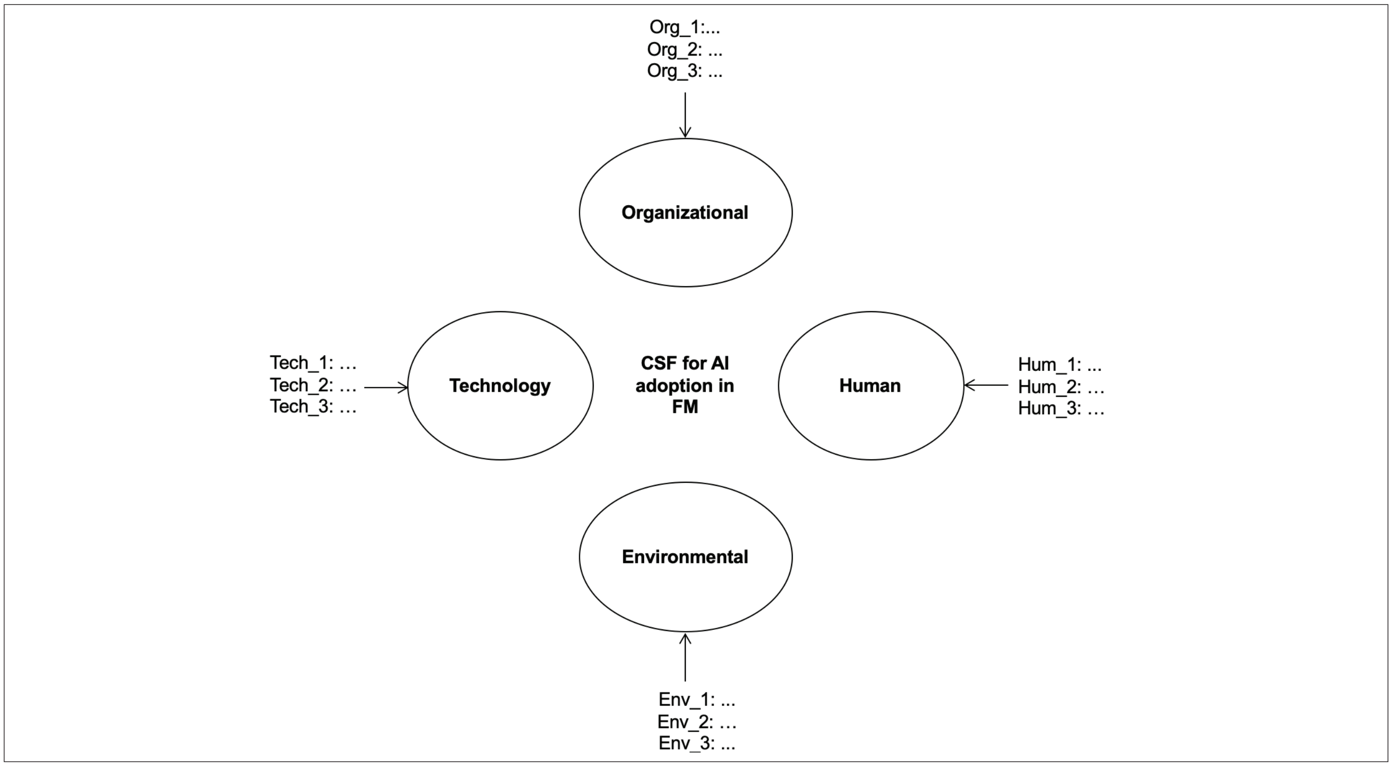
- Evolution of AI in FM, including the timeline of digital technology adoption in the sector;
- Emerging trends and opportunities, such as DT, Explainable AI (XAI), and intelligent automation;
- Technical, human, and regulatory challenges, including interoperability, data governance, and infrastructure constraints;
- Development of a conceptual model for AI adoption in FM, based on CSFs aligned with the TOEH framework.

The final stage involved the construction and validation of the conceptual model of CSFs, grounded in the four dimensions of the TOEH, integrating theoretical contributions from the TOE model (Tornatzky & Fleischer, 1990) and the HOT model. The conceptual foundations include works by Orji et al. (2019), Dora et al. (2022), Loo et al. (2023), and Merhi (2023).

The TOEH model, as illustrated in Figure 2, encompasses the following domains:

- Technological (Tech): Covers technologies, processes, and solutions used in AI adoption, with emphasis on innovation and system integration (Nilashi et al., 2016);
- Organizational (Org): Encompasses resources, leadership, culture, and institutional capabilities that directly influence adoption feasibility (Wicaksono et al., 2022);
- Environmental (Env): Considers external factors such as regulation, economic conditions, and ethical/social barriers (Yadegaridehkordi et al., 2018);
- Human (Hum): Refers to professional training, reskilling, stakeholder engagement, and collaborative interfaces (Orji et al., 2019).

Figure 1. Proposed Conceptual Model



Source: Elaborated by the authors (2025)

This model aims to provide a robust conceptual framework to help managers and decision-makers assess the feasibility of AI adoption in the FM sector.

Literature Review: First Order

3.1 Evolution of Artificial Intelligence Applications in Facilities Management (RQ1)

As emphasized by Quinello and Nascimento (2025), it is crucial to distinguish the chronology of AI applications in FM from the broader timeline of technological advancements within the sector. Technologies such as SCADA, BIM, BAS, CAFM, IoT, and RFID were widely adopted before the integration of AI. Still, they lacked core attributes such as machine learning, autonomous decision-making, predictive inference, and the ability to process large-scale, high-velocity, and heterogeneous datasets (i.e., big data and unstructured information). The systematic application of AI in facilities management (FM) is relatively recent. It can be divided into three distinct periods: pre-2018, 2018–2021, and post-2021, based on the definition of AI as systems capable of simulating human intelligence, analyzing complex patterns through extensive data and advanced algorithms (Russell & Norvig, 2020). The introduction of generative AI in 2014, mainly through Pretrained Foundation Models (PFMs) such as ChatGPT (Zhou et al., 2024), marks a significant turning point in this trajectory, enabling content creation, personalized decision-making, and novel human-machine interaction paradigms. Nevertheless, the quality of such interactions still depends heavily on the user's technical expertise and domain competence, which is a critical aspect in the FM context.

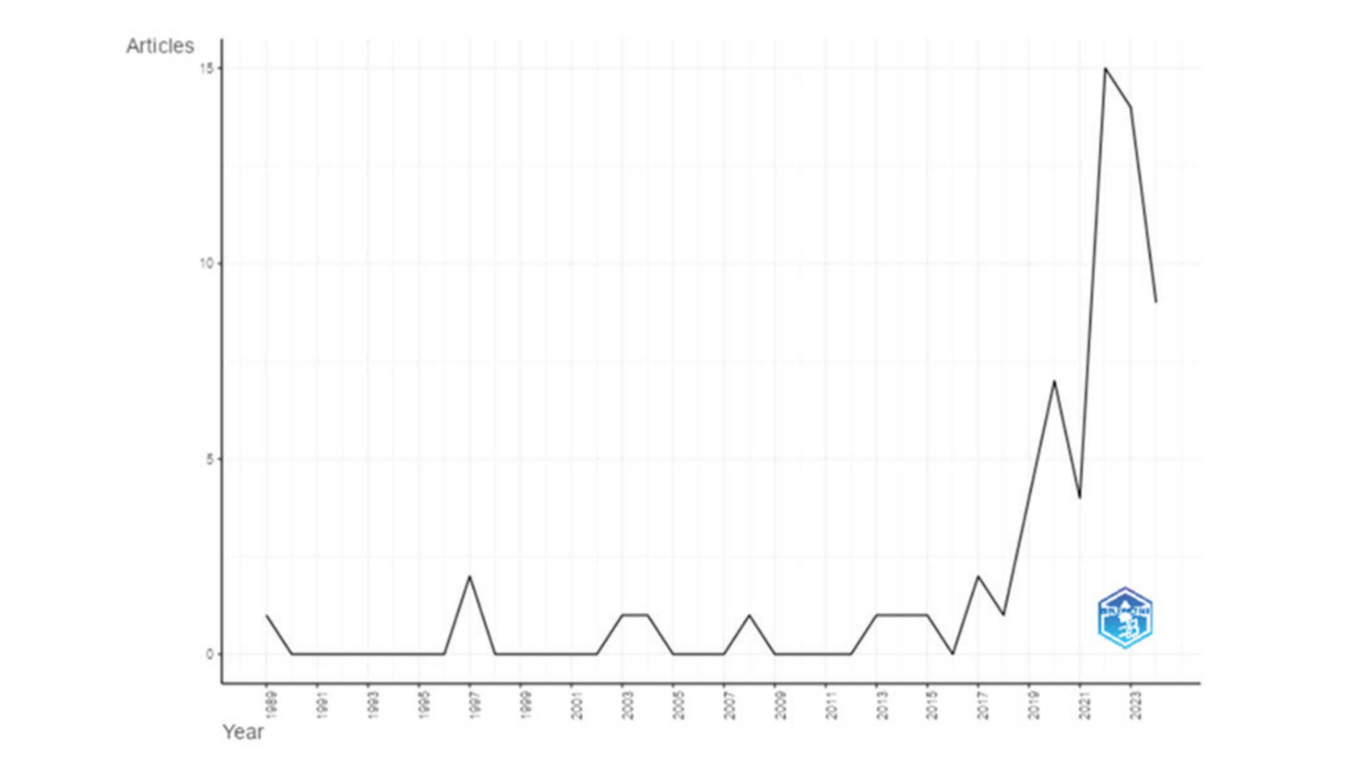
Below is a chronological synthesis of the scientific literature on AI in FM (Figure 3):

- Pre-2018 – Foundational Studies and Initial Exploration: Research remained limited and fragmented, focusing on specific domains such as BIM and task scheduling (Cao et al., 2014), with few empirical validations (Vaiste, 2020; Pedral Sampaio et al., 2022).

- 2018–2021 – Technological Integration and Thematic Expansion: A notable surge in AI applications driven by IoT and BIM, particularly in predictive maintenance and HVAC systems (Cheng et al., 2020; Bouabdallaoui et al., 2021), along with early efforts in predictive modeling using DT (Dahanayake & Sumanarathna, 2022). Significant advances also occurred in initiatives targeting energy efficiency and sustainability (Lu et al., 2021; Yayla et al., 2022; Pedral Sampaio et al., 2022).

- Post-2021 – Case Studies and Emerging Technologies: Practical validations of AI applications in maintenance and energy management (Olimat et al., 2023; Ajayi et al., 2024), increased regional focus in adoption trends (Moghayedi et al., 2024), growing concern with ethics and governance (Vaiste, 2020), and the integration of advanced technologies such as blockchain, federated learning, and XAI (Beltrán et al., 2023). Recent studies also provide quantitative evidence, such as a 20% reduction in energy consumption through intelligent HVAC control (Hanafi et al., 2024).

Figure 3. Scientific Production on AI in Facilities Management



Source: Elaborated by the authors (2025)

3.2. Applications of Artificial Intelligence in Facilities Management (RQ2)

Artificial Intelligence (AI) has revolutionized Facilities Management (FM) by utilizing big data and advanced machine learning (ML) algorithms to enhance efficiency, sustainability, and operational innovation. These advances are reflected in a wide range of practical applications, both in established domains and in disruptive, emerging technologies.

- Predictive maintenance is a key application that uses real-time data instead of scheduled or corrective methods to forecast failures, reduce costs, and improve reliability (Pohl et al., 2022; Yan et al., 2022). AI-driven predictive strategies can cut unplanned failure costs by up to 98% (Pedral Sampaio et al., 2022). IoT sensors supply ML models with operational data such as temperature, vibration, and current to detect component deterioration, allowing for timely interventions and longer asset lifespans (Al-Aomar & Abel, 2023).

- Neural networks, SVMs, and CNNs have achieved high accuracy in fault prediction for HVAC, elevators, and electrical systems (Arsecularatne et al., 2024). CNNs improve energy management in smart buildings (Alijoyo, 2024), and time-series learning enhances prediction, reducing costs and increasing reliability.

- Energy management is another vital area, as buildings account for nearly 48% of global energy consumption (Marinakis & Doukas, 2018; Rizvi, 2023; Abdelalim et al., 2024; Zhu & Xiao, 2024; Nainwal & Sharma, 2025). AI analyzes historical and environmental data to autonomously optimize HVAC, lighting, and loads (Wong et al., 2018; Rafsanjani et al., 2024). Adaptive models utilize weather, occupancy, and user preferences to reduce carbon emissions. Digital twins simulate scenarios to support decision-making (Pedral Sampaio et al., 2022). Integration with renewables like solar and wind enhances energy efficiency (Bin Abu Sofian et al., 2024; Ding et al., 2024).

- Space optimization benefits from AI and IoT sensors that monitor occupancy and enable dynamic reconfiguration, reducing underutilization (Zeleny et al., 2024; Mena-Martinez et al., 2024). AI-powered systems adjust comfort settings based on feedback. The post-pandemic context has increased the adoption of systems for air quality and crowd monitoring (Lok et al., 2022). These approaches support Occupant-Centric Design by adapting buildings to user behavior (Rafsanjani et al., 2024).

- AI, BIM, and Digital Twins: Integrating AI with Building Information Modeling (BIM) and Digital Twins (DT) facilitates advanced simulation, fault prediction, and continuous optimization (Wang & Chen, 2024). Studies report up to 25% reductions in maintenance and 20% in energy costs through DTs (Abdelalim et al., 2024). However, issues related to interoperability, data standardization, and cybersecurity still persist (Ige et al., 2024). BIM-IoT-AI integrated platforms have demonstrated notable benefits in large facilities (Arsecularatne et al., 2024).

- Robotic Automation and Augmented Reality (AR): AI-powered robotics automates cleaning, surveillance, and maintenance, providing cost savings and consistent quality (Lim et al., 2024). Drones perform inspections using computer vision, while cleaning robots optimize resource utilization. AR tools enable technicians to access real-time data through smart glasses, thereby enhancing accuracy and speeding up interventions (Salman & Ahmad, 2025). These innovations propel FM 4.0, integrating AI, IoT, and automation for cognitive, predictive operations (Nota et al., 2021).

In summary, the convergence of AI, advanced data analytics, and emerging technologies such as robotics and augmented reality is reshaping the strategic landscape of FM. These innovations are not only driving significant operational efficiencies and sustainability improvements but are also creating a more adaptable and occupant-focused built environment. As the sector continues to adopt digital transformation, AI serves as a catalyst for new business models, deeper platform integration, and more resilient, future-ready FM practices.

3.3. Constraints and Challenges to Emerging Technologies (RQ3)
Although FM has traditionally integrated digital technologies, from process digitization to sensor-based data gathering, the adoption of AI still faces major structural and multi-layered challenges, as shown in recent research:

- Human and organizational barriers: Successful AI adoption requires more than just technical changes; it calls for cultural, educational, and organizational transformation. Many FM professionals lack training in data analytics, which limits effective AI use (Marocco et al., 2024; Mishra et al., 2024). Ethical and privacy concerns about sensitive occupant data also create resistance, emphasizing the need for strong governance (Ahumada-Sanhueza et al., 2025). Upskilling through online platforms and VR is making progress (Lok et al., 2023), but low early involvement in digital implementation still hampers results (Dixit et al., 2019).

- Data integration and interoperability: AI in FM relies on diverse data sources such as IoT, legacy systems, and historical records, which are often isolated, hindering analytics (Wong et al., 2018). The lack of interoperability between BIM, DT, and operational systems remains a significant challenge (Matarneh et al., 2019; Ozturk, 2020; Pedral Sampaio et al., 2022). While semantic ontologies and standardized taxonomies are suggested, integration costs and contractual barriers, especially for SMEs, still pose problems (Lok et al., 2022; Asare et al., 2022). Manual processes for inspections and updating as-built records further obstruct automation (Ilter & Ergen, 2015; Dahanayake & Sumanarathna, 2022; Lawal et al., 2025). Nevertheless, as Naghshbandi (2016) points out, "construction does not understand FM". The disconnect between construction practices and operational routines continues to impede substantial progress. Thus, FM digitalization requires new outsourcing models and open, interoperable technologies.

- Data quality and availability: AI performance heavily relies on data quality. Many older buildings lack sensors and infrastructure for real-time data collection, which weakens predictive algorithms (Ilter & Ergen, 2015; Arsecularatne et al., 2024). While RFID and smart sensors are recommended, privacy and data security remain ongoing concerns (Dahanayake & Sumanarathna, 2022; Hisamuddin et al., 2023; Lawal et al., 2025). There is a need for algorithms to clean, integrate, and update data, along with advanced analytics training.

- Complexity in modeling building systems: Buildings are intricate cyber-physical environments; their performance relies on many interconnected variables, both internal and external. Hybrid models, which combine physics and ML, show promise (Arsecularatne et al., 2024) but are still underused. Modeling human behavior, occupant preferences, and patterns requires context-aware, interdisciplinary AI models (Antonino et al., 2019).

- Technological Implications: Legacy buildings often lack digital infrastructure, making the integration of smart platforms expensive and complicated (Ilter & Ergen, 2015). Sensor reliability is critical; miscalibration and hardware failures can destabilize models. Large-scale deployments require robust architectures, such as edge and cloud computing (Arsecularatne et al., 2024). Vendor lock-in and proprietary standards limit interoperability, despite harmonization efforts like ISO 19650. Research into open systems and modular platforms is essential (Wong et al., 2018).

- Methodological limitations: The literature mainly consists of case studies and lacks standardized frameworks for scalable AI implementation in FM (Pedral Sampaio et al., 2022; Arsecularatne et al., 2024). AI models often act as "black boxes" (Hassija et al., 2024), which limits transparency and validation. There is a need for explainable AI (XAI) and for evaluation metrics that consider financial, environmental, and user-centered impacts. Incorporating expert domain knowledge remains uncommon but is increasingly recommended (Pedral Sampaio et al., 2022).

- Regulatory and governance gaps: Regulation of AI in FM is still evolving, leading to uncertainty around compliance, privacy, and accountability (Wong et al., 2018). Data protection laws, such as GDPR and LGPD, restrict how occupant data is handled (European Commission, 2023). Cybersecurity threats are rising as automation and connectivity increase; protocols need to be established from the beginning (Ige et al., 2024). Legal liability remains unclear, with no definitive provisions for autonomous systems in current standards. There is a movement toward making AI systems auditable and approved by regulators, similar to practices in sectors like healthcare. Ethical governance should steer policy (Gupta & Parmar, 2024).

The evolution of AI in FM is intrinsically tied to overcoming technical, human, regulatory, and methodological challenges. Based on the review conducted in this section, 14 CSFs were identified as directly influencing AI adoption in the sector:

- Data availability: Widely highlighted as the structural foundation for predictive maintenance, energy optimization, and machine learning applications (Pedral Sampaio et al., 2022; Abdelalim et al., 2024; Arsecularatne et al., 2024).
- Building infrastructure: Identified as a physical barrier, especially in legacy buildings lacking sensors and connectivity (Ilter & Ergen, 2015; Wong et al., 2018; Arsecularatne et al., 2024).
- Technological maturity of the sector: Associated with the early-stage digital transformation in FM and low interoperability between systems (Pedral Sampaio et al., 2022; Lawal et al., 2025)

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- System interoperability: Cited as a key obstacle to integration between BIM, DT, IoT sensors, and management platforms (Wong et al., 2018; Matarneh et al., 2019; Ozturk, 2020; Arsecularatne et al., 2024).
- Integration with IT: Evidenced by the need for effective communication across operational systems, middleware, and edge/cloud computing infrastructure (Lok et al., 2022; Arsecularatne et al., 2024).
- Organizational culture of innovation: Essential for reducing internal resistance to AI adoption, supported by ongoing training and institutional openness to data-driven practices (Lok et al., 2023; Marocco et al., 2024).
- Top management support: A key enabler for resource allocation, institutional legitimacy, and innovation promotion (Mishra et al., 2024).
- Strategic alignment: Necessary for integrating AI as a driver of digital transformation within institutional goals (Mishra et al., 2024).
- Expected ROI and cost: A decisive factor in evaluating the economic viability of AI solutions (Asare et al., 2022; Abdelalim et al., 2024; Lawal et al., 2025).
- External economic factors: Reflected in the financial limitations faced by SMEs in adopting emerging technologies due to high integration costs (Asare et al., 2022).
- Governance and compliance: Emphasized in discussions on data protection, cybersecurity, and legal accountability, particularly under GDPR and LGPD (Wong et al., 2018; Ige et al., 2024; Gupta & Parmar, 2024).
- Training and reskilling: Deemed essential for enabling FM professionals to operate and interpret AI-based systems (Dixit et al., 2019; Lok et al., 2023).
- Knowledge transfer among stakeholders: Crucial for overcoming communication gaps between technical teams, managers, and technology vendors (Naghshbandi, 2016).
- User engagement: Particularly relevant in occupant-centric applications, such as space optimization, thermal comfort, and responsive environments (Lok et al., 2022; Rafsanjani et al., 2024).

Ultimately, the potential of AI to transform FM depends on a comprehensive approach that tackles not only technological progress but also the related issues of data governance, infrastructure updates, organizational readiness, and regulatory compliance. The fourteen Critical Success Factors identified, covering data availability, system integration, digital culture, management support, user engagement, and ethical governance, outline the complex environment FM leaders must navigate. Only through fostering cross-disciplinary cooperation, investing in capacity development, and aligning strategic goals with responsible innovation can organizations fully harness AI to create sustainable value and resilience in the built environment (Wong et al., 2018; Lok et al., 2023; Pedral Sampaio et al., 2022; Marocco et al., 2024).

Non-Empirical Validation of Critical Success Factors: Second-Order Review

Following the completion of the first-order literature review (LR), a non-empirical validation phase was conducted exclusively through the analysis of Systematic Literature Reviews (SLRs). The primary objective of this stage was to verify whether the CSFs previously identified were consistently reflected in the most relevant SLRs published between 2020 and 2025, aiming to support the construction of a robust and validated final framework.

A search was conducted across Scopus, Science Direct, Web of Science, and Google Scholar databases, resulting in a final sample of 13 SLR articles, comprising more than 1,200 secondary references. A recurring finding across these reviews was the absence of consolidated frameworks that systematically organize critical success factors (CSFs) for AI adoption in facilities management (FM) in an operational and replicable manner, reinforcing the core purpose of this study. Table 1 summarizes the findings, using a binary coding system based on the explicit presence of each CSF term in the text. High explicitly (1) requires literal occurrence, low explicitly (0) means the term is absent or only implicit.

Table 1. Results from the Second-Order Systematic Review

Dimension	CSF	Lee et al. (2021)	Pedral Sampaio et al. (2022)	Zhang et al. (2022)	Egwim et al. (2024)	Hou et al. (2024)	Lim et al. (2024)	Moghayedi et al. (2024)	Ohene et al. (2024)	Scaife (2024)	Wang et al. (2024)	Wettewa et al. (2024)	Quinello & Nascimento (2025)	Salman & Ahmad (2025)
Technological	Data Availability	1	1	1	1	1	1	1	1	1	1	1	1	1
	Building Infraestructure	1	1	1	1	1	1	1	1	1	1	1	1	1
	Sector Technological Maturity	0	1	1	0	0	0	1	1	0	0	0	1	1
	Systems Interoperability	1	1	1	0	1	1	0	1	1	1	1	1	1
Organizational	IT Integration	1	1	1	0	1	1	0	1	1	1	1	1	1
	Innovation Culture	0	0	0	0	0	0	1	0	0	0	0	1	0
	Top Management Support	0	0	0	0	0	0	0	0	1	0	0	1	1
	Strategy Alignment	0	0	0	0	0	0	0	0	1	0	0	1	0
Environmental	Expected ROI & Costs	0	1	1	1	0	1	1	1	1	1	1	1	1
	External Economic Factors	0	0	0	1	0	1	1	1	1	1	1	1	0
	Governance & Compliance	0	0	0	0	0	0	1	1	1	0	0	1	0
Human	Workforce Training & Reskilling	0	1	1	1	0	1	1	1	1	1	1	1	1
	Knowledge Transfer	0	0	0	0	0	1	0	0	0	1	0	1	1
	End-User Engagement	0	0	1	0	1	1	1	1	1	1	1	1	1

Source: Prepared by the authors (2025)

Among the factors analyzed, Building Infrastructure and Data Availability stood out as the only CSFs unanimously identified across all 13 studies, highlighting how the diversity of building typologies, alongside effective information management and inter-organizational communication, represent central challenges and foundations for AI-driven digital transformation in FM. System Interoperability, IT Integration, Expected ROI & Costs, and Workforce Training & Reskilling were also frequently cited, highlighting the need for cohesive digital infrastructure, standardized interfaces, cross-platform connectivity, and investment in financial and human capital to enable the effective adoption of AI.

In the human dimension, CSFs related to End-User Engagement were widely cited, highlighting the critical role of user and employee participation in the successful assimilation of emerging technologies. Conversely, factors such as Strategic Alignment, Innovation Culture, and Top Management Support were observed less frequently. Although these factors hold contextual relevance, they have not yet been consolidated as universally recognized determinants in recent literature. Based on these findings, the adoption of AI in FM is shown to depend on three foundational pillars:

- A structured digital foundation, with compatible and interoperable infrastructure;
- The availability, quality, and fluidity of data, both technical and operational;
- A consistent organizational and human readiness to absorb and effectively utilize technological solutions.

This sociotechnical convergence should be understood as a strategic prerequisite for the sector's transition toward intelligent automation, data-driven management, and predictive decision-making. The SOSR approach adopted in this study offers methodological innovation through the critical aggregation of 1,200 secondary-level pieces of evidence drawn from consolidated systematic literature reviews (SLRs). This approach enabled the identification of cross-cutting patterns, mitigated the individual bias of primary studies, and supported the proposal of an integrative conceptual model with high external validity. The complementary analysis of SLRs reinforces the empirical insights from the first-order literature and validates the components of the final CSF model.

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Results

In light of the findings, which CSFs are relevant to AI adoption in FM and capable of guiding decision-makers (RQ4)? Table 2 was developed to present the CSFs organized according to the TOEH dimensions, concluding with the final conceptual model (Figure 4).

Table 2. TOEH Dimensions and CSF Definitions for AI Adoption in FM

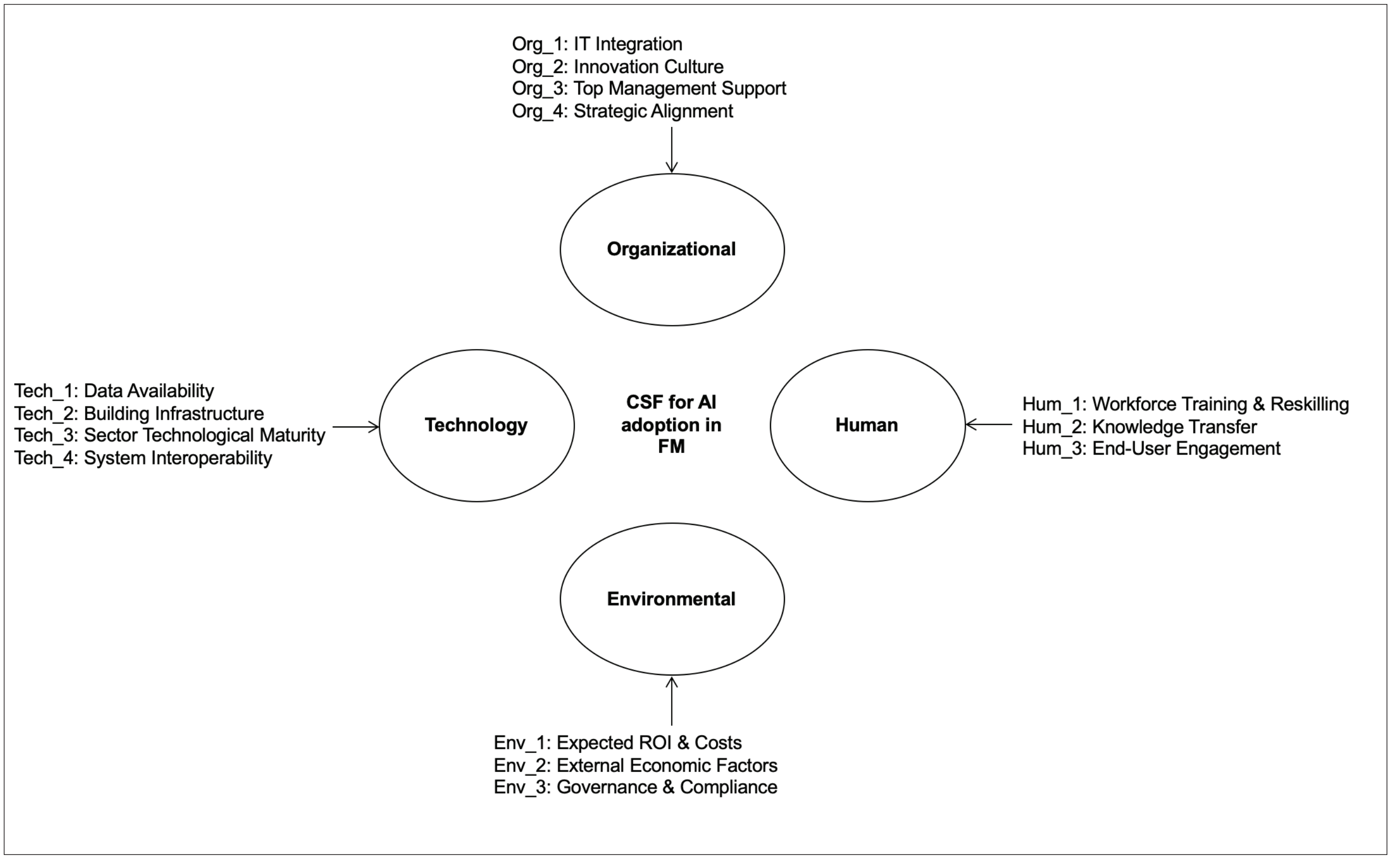
TOEH Dimension	CSF	Description	Justification
Technological	Data Availability	Accessibility and structuring of data for AI	Data quality and accessibility are crucial for the practical application of AI.
	Building Infrastructure	Suitability of infrastructure to support AI	The typology of buildings directly affects the feasibility of AI implementation.
	Sector Technological Maturity	Degree in innovative technology adoption	More advanced sectors more readily adopt AI solutions
	System Interoperability	Ability of AI systems to integrate with pre-existing platforms	Interoperability prevents data silos and enhances AI efficiency
Organizational	IT Integration	Level of collaboration between FM and IT departments	Communication between FM and IT is essential for successful AI implementation
	Innovation Culture	Organizational openness to adopting AI	Innovative organizations are more likely to adopt AI
	Top Management Support	Leadership commitment to AI adoption	Executive backing is critical to drive implementation
	Strategic Alignment	Ensuring that AI adoption aligns with corporate strategy	Organizations that embed AI in their strategic planning achieve more significant outcomes than those that adopt it in a fragmented manner
Environmental	Expected ROI & Costs	Financial benefits expected from AI implementation	The investment must yield tangible financial returns
	External Economic Factors	Influence of macroeconomic conditions on AI adoption	Economic downturns may hinder investments in emerging technologies
	Governance & Compliance	Regulatory barriers to AI adoption	Stringent data and safety regulations may restrict AI implementation
Human	Workforce Training and Reskilling	Level of workforce readiness to operate AI technologies	Skilled professionals reduce operational errors and resistance to AI
	Knowledge Transfer Among Stakeholders	Mechanisms for information sharing, training, and collaboration	Lack of structured knowledge sharing may compromise the effectiveness of AI-based decisions
	End-User Engagement	Involvement of internal users, customers, and service providers	End-user participation directly influences the adoption and use of AI systems in daily operations

The heatmap analysis (Table 1) reveals a significant imbalance in the emphasis placed on the different TOEH dimensions. While the Technological dimension is widely covered across the 13 reviewed articles, especially CSFs such as Data Availability, Building Infrastructure, and System Interoperability, the Organizational dimension shows considerably lower coverage.

Factors such as Governance & Compliance, Innovation Culture, Top Management Support, and Strategic Alignment are sparsely mentioned and are absent in over half of the studies. This pattern suggests that the literature has primarily focused on technical and structural barriers, while often neglecting organizational aspects that support governance, cultural transformation, and strategic alignment, all crucial for effective AI adoption in facilities management (FM).

This gap presents a significant opportunity for future research. Organizational resistance, lack of executive sponsorship, and poor alignment with business objectives can be just as prohibitive as technical failures. By underemphasizing the organizational dimension, there is a risk of overestimating technical readiness while underestimating the human and institutional dynamics essential to digital transformation in FM.

Figure 4. Conceptual Model of CSFs for AI Adoption in FM



Source: Prepared by the authors (2025)

The conceptual model demonstrated strong convergence with the findings of Dora et al. (2022) and Merhi (2023), albeit in different industry sectors. CSFs such as data availability, interoperability, technological maturity, and integration with emerging technologies are widely recognized in the literature as fundamental enablers of effective AI implementation.

On the organizational front, FM–IT collaboration, innovation culture, and executive support are essential to ensure strategic alignment and adoption viability. Additionally, the environmental dimension highlights expected ROI and external market conditions as central elements in the decision-making process for AI investments.

Discussion

4.1. Theoretical Implications

This study contributes to the theoretical advancement of literature on the adoption of AI in FM, a domain that is still lacking consolidated conceptual frameworks and systematic empirical validation. Although prior research has investigated critical success factors (CSFs) in the adoption of digital technologies across various sectors, a clear gap remains in the structured identification of such factors within the FM context. This study addresses that gap through the following contributions:

- First, it represents one of the earliest attempts to extend CSF theory to the FM domain by proposing a conceptual model anchored in the TOEH framework. This integrative approach provides a systemic lens through which technological, organizational, environmental, and human factors are jointly examined in the adoption of AI in FM.

- Second, the proposed framework consolidates findings from an extensive literature review, including SLRs, aligning the CSFs with contemporary theoretical perspectives on digital transformation. By doing so, the study contributes to the growing body of knowledge on intelligent systems applied to building and infrastructure management.

- Third, this study introduces a SOSR as a methodological innovation for non-empirical validation, thereby expanding the traditional scope of literature reviews. This approach enables the triangulation of secondary evidence from multiple SLRs, capturing robust patterns and proposing a theoretically and externally valid model. In the FM domain, such a strategy remains underexplored, lending a pioneering character to this work.

- Fourth, the study builds upon and extends the works of Dora et al. (2022) and Merhi (2023), emphasizing that AI adoption transcends technical readiness; it also hinges on strategic alignment, leadership commitment, governance maturity, and professional reskilling. While CSFs such as data availability, IT integration, and expected ROI are widely acknowledged in the technological innovation literature, others, such as interoperability, knowledge transfer, and ethical compliance, emerge as context-specific and essential to FM.

- Fifth, the integration of the TOEH framework enables holistic analysis, linking the technological infrastructure of buildings with human capabilities and regulatory environments. This multidimensional perspective is particularly relevant in FM, given its operational complexity and the diversity of stakeholders involved.

Ultimately, the proposed model lays a theoretical foundation for future empirical validations, offering a structured set of observable variables that can be evaluated in field studies. By extending the TOEH perspective to an emerging domain and adopting SOSR as a methodological tool, this study underscores the importance of addressing contextual and sociotechnical dynamics in the digital transformation of facilities management.

4.2. Managerial Implications

The findings of this study demonstrate that ongoing technological transformations position the FM professional as a strategic actor. With deep expertise in the physical and operational conditions of building assets, this professional serves as a bridge between organizational demands and emerging technological solutions. In this regard, they assume the role of a "knowledge broker", as defined by Hargadon (2002), an agent who synthesizes internal and external knowledge to promote continuous cycles of innovation.

However, the effective adoption of AI in FM requires specific structural and strategic conditions. Key recommendations for industry professionals include:

- Workforce Training and Reskilling: Acquiring foundational knowledge in data science and analytics is crucial for facilities managers to comprehend the technological ecosystem and collaborate effectively with IT teams. This technical proficiency enhances operational data interpretation and strengthens their role in orchestrating digital initiatives.

- Building Infrastructure and Technical Feasibility: The typology of managed assets (e.g., brownfields vs. greenfields) must be considered when planning AI-driven solutions. Existing buildings may require significant technological retrofitting, whereas newly constructed facilities typically incorporate sensors, automation, and digital integration from inception, directly impacting investment scope and implementation complexity.

- Sector-Specific Technological Maturity: The feasibility of AI adoption varies across sectors. Industrial environments often demonstrate higher technical preparedness, whereas public administration and healthcare face additional challenges, including limited interoperability and stricter regulations. Assessing sectoral digital maturity is thus critical to informed investment decisions.

- Integration with IT Teams and Digital Governance: Collaboration between FM and IT should be structured as a strategic partnership, rather than ad hoc technical support. Establishing interdisciplinary committees can support decisions that address technical feasibility, data security, compliance, and return on investment in a more holistic manner.

AI adoption in FM should not be viewed merely as a technical innovation, but rather as a complex organizational transformation that requires cultural change, institutional learning, and maturity in digital governance. In this context, the facilities manager, acting as a "knowledge broker", becomes a key agent in digital transformation, ensuring that AI is implemented effectively, sustainably, and in alignment with the organization's strategic goals.

Conclusion

The growing convergence between Artificial Intelligence (AI) and Facilities Management (FM) marks a pivotal moment in the evolution of building operations, enabling significant advances in operational efficiency, energy sustainability, and occupant experience. However, as this study has demonstrated, AI adoption in the sector still faces substantial technical, methodological, and regulatory challenges.

Among the key obstacles are difficulties related to system interoperability, the maturity of digital governance, and the reliability of predictive models, which hinder the scalability and effectiveness of AI applications in real-world scenarios. These barriers compromise the transition of FM toward a fully digital, data-driven operational model.

Nonetheless, the potential benefits of AI in FM are unequivocal. Technologies such as DT, predictive maintenance, automated energy optimization, and multi-agent systems have already demonstrated tangible impacts, including reduced operational costs, improved environmental performance, and enhanced real-time decision support. The scientific literature reviewed suggests that the success of these technologies depends not only on structural enablers, such as digital infrastructure, but also, and perhaps more critically, on organizational and human factors, including technical training, professional engagement, and regulatory clarity.

This study employed an exploratory and interpretive approach, grounded in a Second-Order Systematic Review (SOSR), to identify and validate the Critical Success Factors (CSFs) for AI adoption in Facilities Management (FM). The proposed conceptual model, structured through the TOEH framework (Technology, Organization, Environment, and Human), provides a solid theoretical foundation for guiding future research and practical applications. However, some limitations should be acknowledged:

- Lack of empirical validation: Although this study is based on high-quality scientific literature, the absence of real-world experimentation limits the direct measurement of AI's impact on FM;

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- Sectoral and regional variability: The implementation of AI in FM varies significantly across sectors (industrial, commercial, healthcare) and geographic regions, aspects that were not explored in depth in this article;

- Binary classification methods in second-order reviews: Recognize the inherent challenge in strictly coding the explicit presence of CSFs due to semantic variations and diverse reporting styles in the literature.

In light of these limitations, future research is encouraged to explore the following directions:

- Empirical validation of the CSF–TOEH model: Investigate how the 14 CSFs manifest across different contexts through case studies, surveys, or quantitative analyses;

- Binary classification methods in second-order reviews: Future studies should consider more nuanced, graded, or qualitative approaches for mapping CSFs in systematic reviews of reviews;

- Hybrid prediction models: Integrate machine learning with physical models and engineering rules to enhance the accuracy and reliability of intelligent systems;

- Development of AI governance and ethics frameworks: Create guidelines to ensure transparency, fairness, and accountability in the use of sensitive data and automated decisions;

- Comparative impact assessment: Conduct empirical comparisons of buildings with and without AI to evaluate differences in energy performance, operational costs, and occupant comfort;
- Multidimensional evaluation metrics: Develop indicators that go beyond predictive accuracy to include sustainability, ROI, cybersecurity, and usability;

- Organizational impact and role transformation: Study how AI changes the required competencies, roles, and decision-making processes of FM professionals;

- Testing multi-agent system architectures: Experimentally assesses the effectiveness of autonomous and distributed systems for the automation and interoperability of smart buildings.

The advancement of AI in FM is an irreversible phenomenon, driven by the increasing digitization of built environments and the ongoing demand for operational efficiency, sustainability, and transparency. However, its full-scale adoption depends on overcoming technical barriers, continuously training professionals, and establishing a robust and up-to-date regulatory framework.

To ensure that this transition is both successful and sustainable, it will be essential for academia, industry, and regulatory bodies to collaborate in defining technological standards, empirically validating AI solutions, and strengthening digital governance. As research continues to evolve, AI is expected to move from a peripheral role in building operations to becoming a central pillar of intelligent and sustainable facilities management.

Conflict of Interest Statement

The authors declare that there is no conflict of interest.

Data Availability Statement

All datasets supporting the findings of this study are provided within the article itself.

Generative AI disclosure statement

During the preparation of this work, the author(s) used ChatGPT version 4o to improve language and readability. Following the use of this tool, the author(s) reviewed and edited the content as needed and took full responsibility for the final content of the publication.

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