DETERMINANTS OF AI ADOPTION IN FACILITIES MANAGEMENT: EVIDENCE FROM A SECOND-ORDER SYSTEMATIC REVIEW

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Resumo

O uso da Inteligência Artificial (IA) na Gestão de Facilities (GF) tem crescido significativamente, impulsionado pela busca por otimização de recursos, automação e maior eficiência operacional Apesar desse crescimento, a literatura existente ainda está em desenvolvimento, o que dificulta a compreensão aprofundada dos Fatores Críticos de Sucesso (FCS) que impactam a adoção da IA nesse campo Este estudo visa preencher essa lacuna realizando uma Revisão Sistemática de Segunda Ordem (RSSO) para identificar e sintetizar os principais FCS relacionados à adoção da IA em FM A análise segue o arcabouço teórico TOEH (Tecnologia–Organização–Ambiente–Humano), oferecendo uma visão abrangente dos diversos facilitadores e obstáculos Entre as principais preocupações estão a interoperabilidade dos sistemas, a integridade dos dados e a confiabilidade dos modelos, fatores agravados pela fragmentação tecnológica e pela falta de padronização, o que dificulta a implementação de soluções integradas Além disso, questões regulatórias relacionadas à privacidade de dados e governança, juntamente com a formação inadequada da força de trabalho, representam desafios à adoção em larga escala Por outro lado, avanços como gêmeos digitais, IA explicável, robótica e cibersegurança estão atuando como catalisadores da transformação Esses achados oferecem insights essenciais para gestores de FM, desenvolvedores de tecnologia e formuladores de políticas públicas.

Palavras-chave: Inteligência Artificial. Gestão de Facilities. Fatores Críticos de Sucesso

Abstract

The use of Artificial Intelligence (AI) in Facilities Management (FM) has significantly grown, driven by the pursuit of resource optimization, automation, and enhanced operational efficiency. Despite this growth, existing literature is still developing, which hampers a thorough understanding of the Critical Success Factors (CSFs) that impact AI adoption in this field. This study aims to fill that gap by performing a Second-Order Systematic Review (SOSR) to pinpoint and summarize the primary CSFs linked to AI adoption in FM. The analysis follows the TOEH theoretical framework (Technology–Organization–Environment–Human), offering a comprehensive view of the various facilitators and obstacles. Major concerns include system interoperability, data integrity, and model dependability, which are further complicated by technological fragmentation and a lack of standardization, making the rollout of integrated solutions more difficult. Additionally, regulatory issues related to data privacy and governance, alongside inadequate workforce training, pose challenges to widespread adoption. Conversely, advancements like digital twins, explainable AI, robotics, and cybersecurity are acting as catalysts for transformation. These findings offer crucial insights for FM managers, technology developers, and policymakers, aiding in the creation of effective organizational and regulatory approaches for the integration of AI in the FM sector.

Keywords: Artificial Intelligence. Facilities Management. Critical Success Factors.

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1. 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 and 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 well-being, including cleaning, security, reception, and workspace management. These activities are essential to ensure the operational continuity and efficiency of buildings, with Operations and Maintenance (OandM) 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 and 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 (Arsecularatne et al., 2024).

Recent studies have highlighted the benefits of such technologies. Abdelalim et al. (2025) identified a 25% reduction in maintenance costs and a 20% decrease in energy consumption through the use of digital twins (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 and 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.

In this context, identifying 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 TOEH model (Technology–Organisation–Environment–Human), an evolution of the TOE framework proposed by Tornatzky and 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 (Mishra et al., 2024; Lee et al., 2021). Environmentally, factors such as expected return on investment (ROI), regulations, and market conditions directly influence the feasibility of adoption (Marocco et al., 2024; Vaiste, 2020). 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:

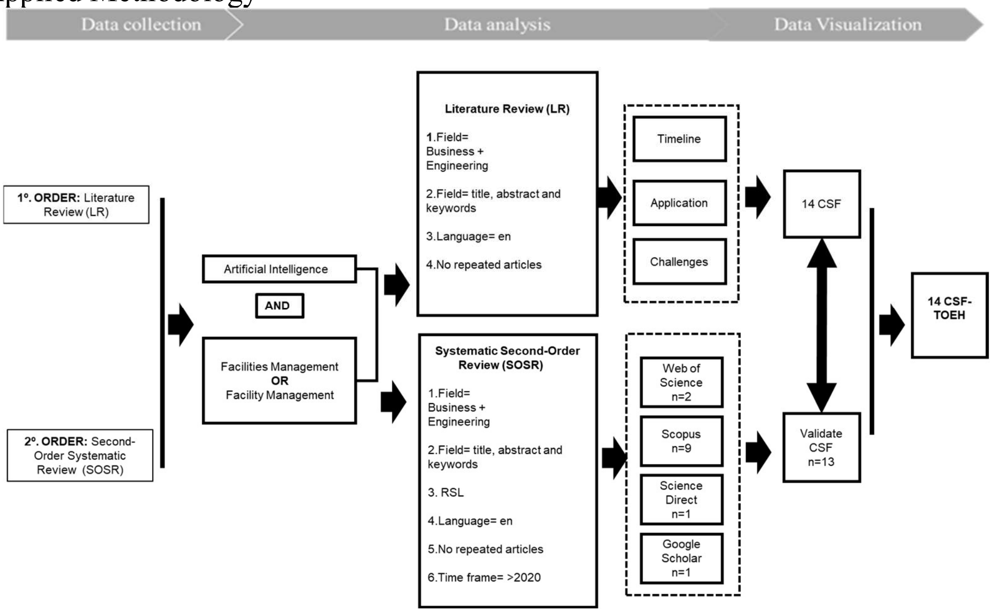
(RQ1) What is the chronological trajectory of AI applications in FM?
(RQ2) What are the emerging applications and future opportunities for the FM sector?
(RQ3) What are the main challenges faced in the adoption of these technologies?
(RQ4) What are the necessary conditions for the successful adoption of Artificial Intelligence in Facilities Management, based on a conceptual model of Critical Success Factors grounded in the TOEH framework?

2. Methodology

This study employs a Second-Order Systematic Review (SOSR) to validate Critical Success Factors (CSFs) for AI adoption in Facilities Management (FM), as shown in Figure 1. Unlike first-order SLRs or meta-analyses, SOSR analyzes SLRs themselves, ensuring methodological rigor, thematic relevance, and external validity. Although similar to umbrella reviews (Grant and Booth, 2009), this approach prioritizes conceptual validation over clinical consolidation, focusing specifically on AI applications in FM, such as sustainability, predictive maintenance, interoperability, and energy management. Following the protocols established by Schmid et al. (2024) and Barbosa et al. (2024), but with an emphasis on CSF robustness across contexts, the study selected 13 systematic literature reviews (SLRs) using databases such as Scopus and Web of

Science, adhering to strict inclusion criteria. The methodology combined a broad first-order review of AI applications in FM, based on recent and foundational literature, with second-order cross-referencing. The resulting conceptual model, structured by the TOEH framework, Technology (Nilashi et al., 2016); Organization (Wicaksono et al., 2022; Environment (Yadegaridehkordi et al., 2018); and Human (Orji et al., 2020), integrates theoretical bases from the TOE and HOT models, aiming to provide a replicable, multidimensional tool for guiding AI adoption strategies in FM.

Figure 1 – Applied Methodology



Source: Elaborated by the authors (2025)

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 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 and 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 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., 2020).

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.

3. Literature Review

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

As emphasized by Quinello and Nascimento (2025), it is essential to distinguish the chronology of AI applications in Facilities Management (FM) from the broader technological evolution of the sector. Technologies such as SCADA, BIM, BAS, CAFM, IoT, and RFID were widely adopted prior to the advent of AI. However, they lacked key attributes, including machine learning, autonomous decision-making, predictive inference, and the ability to process substantial amounts of data and unstructured information. The systematic application of AI in FM is relatively recent and can be divided into three periods: pre-2018, 2018–2021, and post-2021, following the definition of AI as systems simulating human intelligence through advanced algorithms (Russell and Norvig, 2020). The advent of generative AI in 2014, particularly through Pretrained Foundation Models (PFMs) like ChatGPT (Zhou et al., 2024), marked a significant turning point, enabling personalized decision-making and new human-machine interaction paradigms. However, interaction quality still relies on user expertise, a critical factor in FM.

Chronologically, scientific literature evolved as follows: (i) Pre-2018, limited and fragmented research, mainly in BIM and task scheduling, with scarce empirical validation (Cao et al., 2014; Pedral Sampaio et al., 2022; Vaiste, 2020); (ii) 2018–2021, technological integration with IoT and BIM, advances in predictive maintenance, HVAC systems (Cheng et al., 2020; Bouabdallaoui et al., 2021), early predictive modeling via DT (Dahanayake and Sumanarathna, 2022), and initiatives in energy efficiency (Yayla et al., 2020; Lu et al., 2021; Pedral Sampaio et al., 2022); and (iii) Post-2021, practical validations in maintenance and energy management (Olimat et al., 2023; Ajayi et al., 2024), regional adoption analyses (Moghayedi et al., 2024), ethical and governance concerns (Vaiste, 2020), and integration of blockchain, federated learning, and XAI (Beltrán et al., 2023), with quantitative results such as a 20% reduction in energy consumption through intelligent HVAC control (Hanafi et al., 2024).

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

The convergence of AI and FM has unleashed substantial innovation potential, leveraging advances in big data analytics, machine learning (ML), and the demand for greater efficiency and sustainability in the built environment. AI applications encompass predictive maintenance, intelligent energy management, space optimization, and advanced simulation technologies, providing disruptive enhancements to FM operations: (i) Predictive Maintenance and Asset Management: emerges as a key AI application, enabling real-time data analysis to anticipate failures and extend asset life, significantly reducing costs associated with unplanned downtimes (Pohl et al., 2022; Yan et al., 2022; Abdelalim et al., 2024; Pedral Sampaio et al., 2022). IoT sensors, combined with machine learning algorithms, forecast component degradation based on operational parameters such as temperature and vibration (Al-Aomar and Abel, 2023); (ii) Advanced AI Models: techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Convolutional Neural Networks (CNNs) have achieved high fault prediction accuracy in critical systems (Arsecularatne et al., 2024; Alijoyo, 2022), bolstered by time-series learning methods that enhance predictive capabilities and operational reliability; (iii)

Energy Efficiency and Sustainability: given that buildings consume nearly 48% of global energy, AI-driven systems optimize energy demand based on historical and environmental data (Marinakis et al., 2018; Zhu and Xiao, 2023; Rizvi, 2023; Abdelalim et al., 2024; Nainwal and Sharma, 2025), integrating weather forecasts and occupancy trends. Digital twins facilitate energy scenario simulations (Pedral Sampaio et al., 2022), while AI solutions integrate with renewable energy to maximize efficiency (Bin Abu Sofian et al., 2024; Ding et al., 2024); (iv) Space Optimization and Occupant Experience: AI enhances space utilization by dynamically adjusting layouts through real-time occupancy monitoring (Zeleny et al., 2024; Mena-Martinez et al., 2024). Environmental controls adapt to user feedback, improving comfort and productivity, particularly in post-COVID-19 contexts (Lok et al., 2022; Rafsanjani et al., 2023); (v) BIM, Digital Twins, and Simulation: the integration of AI with BIM and Digital Twins (DTs) enables continuous performance optimization and fault prediction, yielding up to 25% cost reductions (Wang and Chen, 2024; Abdelalim et al., 2024). Despite interoperability and cybersecurity challenges (Ige et al., 2024), the adoption of BIM-IoT-AI platforms demonstrates significant operational improvements (Arsecularatne et al., 2024); and (vi) Robotics and Augmented Reality: autonomous mobile robots (AMRs) and AI-enhanced drones streamline tasks such as cleaning and structural inspection (Lim et al., 2024), while Augmented Reality (AR) tools support technicians with real-time operational data visualization, increasing accuracy and reducing human error (Salman and Ahmad, 2025). This convergence advances the "FM 4.0" paradigm (Nota et al., 2021) intervention.

3.3. Constraints and Challenges to Emerging Technologies (RQ3)

Despite progress, the adoption of AI in FM faces multifaceted challenges related to human factors, data integration, modeling complexity, technological constraints, and regulatory frameworks.

- Human and Organizational Barriers: the lack of data analytics competencies among FM professionals (Marocco et al., 2024; Mishra et al., 2024) and concerns over data privacy necessitate educational initiatives and governance frameworks. The integration of tacit knowledge and interdisciplinary collaboration is critical for overcoming institutional resistance (Dixit et al., 2019; Lok et al., 2023).
- Data Integration and Interoperability: fragmented data silos and limited interoperability between BIM, DTs, and operational systems hinder comprehensive analytics (Wong et al., 2018; Matarneh et al., 2019; Ozturk, 2020). Ontologies and taxonomies are proposed as solutions (Arsecularatne et al., 2024), but integration costs remain high, particularly for small and medium-sized enterprises (SMEs) (Lok et al., 2022; Asare et al., 2022).
- Data Quality and Availability: legacy infrastructures lacking modern sensors undermine AI performance (Ilter and Ergen, 2015; Arsecularatne et al., 2024). Smart sensors and DTs are recommended to standardize and govern data (Dahanayake and Sumanarathna, 2022; Lawal et al., 2025), yet challenges in privacy and cybersecurity persist (Hisamuddin et al., 2023).
- Modeling Complexity: buildings as cyber-physical systems present modeling difficulties. Hybrid physical-ML models show promise for enhanced diagnostics (Arsecularatne et al., 2024), while occupant behavior modeling remains an underexplored domain requiring interdisciplinary approaches (Antonino et al., 2022).
- Technological and Infrastructure Barriers: legacy buildings face challenges in accommodating AI due to infrastructure deficiencies (Ilter and Ergen, 2015), while

sensor reliability and data processing demands require advanced edge and cloud computing solutions (Arsecularatne et al., 2024). Vendor lock-in and fragmented standards complicate system integration (Wong et al., 2018).

- Methodological Gaps: current research is fragmented, lacking unified frameworks and standardized metrics beyond predictive accuracy (Pedral Sampaio et al., 2022). Explainable AI (XAI) is crucial for ensuring transparency (Hassija et al., 2024), and hybrid models that integrate expert knowledge are needed (Pedral Sampaio et al., 2022).
- Regulatory and Governance Challenges: the regulatory environment is nascent, with concerns about data privacy under frameworks like GDPR (European Commission, 2023). Cybersecurity and liability issues require urgent attention (Wong et al., 2018; Ige et al., 2024). Ethical governance models are advocated to ensure the responsible use of AI (Gupta and 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 is widely recognized as the structural foundation for predictive maintenance, energy optimization, and machine learning applications in Facilities Management (FM) (Pedral Sampaio et al., 2022; Abdelalim et al., 2024; Arsecularatne et al., 2024), while building infrastructure remains a critical physical barrier, particularly in legacy facilities lacking sensors and connectivity (Ilter and Ergen, 2015; Wong et al., 2018; Arsecularatne et al., 2024). The sector's low technological maturity is associated with early-stage digital transformation efforts and poor system interoperability (Pedral Sampaio et al., 2022; Lawal et al., 2025), with integration across BIM, DT, IoT sensors, and management platforms consistently cited as a key obstacle (Matarneh et al., 2019; Ozturk, 2020; Wong et al., 2018; Arsecularatne et al., 2024). Effective integration with IT infrastructures is necessary to ensure seamless communication across operational systems, middleware, and cloud or edge computing environments (Arsecularatne et al., 2024; Lok et al., 2022).

Organizational culture fostering innovation is essential to reduce internal resistance to AI adoption (Marocco et al., 2024; Mishra et al., 2024; Lok et al., 2023), supported by top management's commitment to resource allocation and institutional legitimacy (Mishra et al., 2024) and strategic alignment with organizational digital transformation goals (Pedral Sampaio et al., 2022; Mishra et al., 2024). Economic viability, as measured by expected ROI and cost analyses (Abdelalim et al., 2024; Lawal et al., 2025; Asare et al., 2022), and external financial factors, particularly the limitations faced by SMEs (Asare et al., 2022), also influence adoption. Governance and compliance, particularly about data protection, cybersecurity, and accountability within frameworks such as GDPR and LGPD (Wong et al., 2018; Ige et al., 2024; Gupta and Parmar, 2024), are increasingly emphasized. Training and reskilling initiatives are crucial to equip FM professionals with the competencies needed to manage AI-driven systems (Lok et al., 2023; Dixit et al., 2019), while effective knowledge transfer among stakeholders' bridges gaps between technical teams, managers, and technology vendors (Pedral Sampaio et al., 2022; Naghshbandi, 2022). Finally, user engagement remains critical for occupant-centric applications such as space optimization, thermal comfort, and adaptive environments (Rafsanjani et al., 2023; Lok et al., 2022)

3.4. 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 the Scopus, ScienceDirect, Web of Science, and Google Scholar databases, resulting in a final sample of 13 systematic literature reviews (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: 1 (one) indicates that the authors explicitly addressed the factor, and 0 (zero) means it was not.

Table 1 – Results from the Second-Order Systematic Review

		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	0	1	1	1	1	1	1
	Building Infraestructure	0	0	0	0	1	1	0	0	0	1	1	0	1
	Sector Technological Maturity	1	1	1	1	1	1	0	1	1	1	1	1	1
	Systems Interoperability	1	1	1	1	1	1	0	1	0	1	1	1	1
Organizational	IT Integration	1	1	1	1	1	1	0	1	0	1	1	1	1
	Innovation Culture	1	0	1	1	1	0	0	0	1	0	1	0	0
	Top Management Support	0	0	0	0	0	0	1	0	1	0	0	0	0
	Strategy Alignment	0	0	0	0	0	0	1	0	1	0	0	0	0
Environmental	Expected ROI & Costs	0	0	1	0	0	0	1	0	1	0	0	1	1
	External Economic Factors	0	0	0	0	0	0	1	0	0	0	0	0	0
	Governance & Compliance	0	0	0	0	0	0	1	0	0	0	0	0	0
Human	Workforce Training & Reskilling	1	0	0	1	0	1	1	1	1	1	1	0	1
	Knowledge Transfer	1	1	1	1	1	1	1	1	1	1	1	1	1
	End-User Engagement	0	0	0	0	1	1	1	0	0	1	1	1	1

Source: Prepared by the authors (2025)

Among the factors analyzed, Data Availability was the only CSF unanimously identified across all 13 studies, highlighting the centrality of information management and cross-institutional communication as structural pillars of digital transformation in FM. Factors such as Data Availability, Sector Technological Maturity, System Interoperability, and Integration with IT also appeared with high frequency, underscoring the importance of cohesive digital infrastructure, standardized interfaces, and cross-platform connectivity for the effective adoption of AI.

In the human dimension, CSFs related to workforce training and end-user engagement were widely cited, demonstrating the importance of cultural, educational, and operational aspects in the assimilation of emerging technologies.

Conversely, factors such as Top Management Support, Strategic Alignment, Expected ROI and Costs, and External Economic Factors 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; and 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.

3.5. 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 2).

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

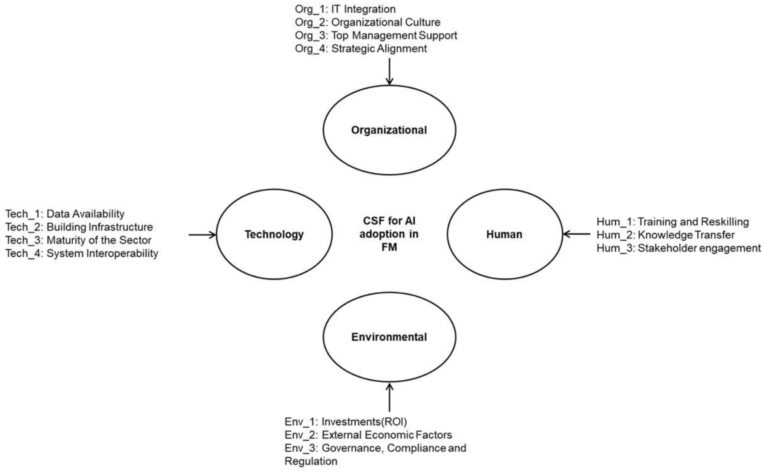
TOEH Dimension	**CSF**	**Description**	**Justification**
Technological	Data Availability	Accessibility and structuring of data for AI	Data quality and accessibility are crucial for the practical application of AI.
	Building Infrastructure	Suitability of infrastructure to support AI	The typology of buildings directly affects the feasibility of AI implementation.
	Technological Maturity of the Sector	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	Integration with IT	The level of collaboration between the 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	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, and Regulation	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, System Interoperability, and Sector Technological Maturity, the Organizational dimension shows considerably lower coverage.

Factors such as Integration with IT, 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 2 – 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 the expected return on investment (ROI) and external market conditions as central elements in the decision-making process for AI investments.

4. Discussion

4.1. Theoretical Implications

This study advances the theoretical understanding of AI adoption in Facilities Management (FM), a domain that remains lacking in consolidated conceptual frameworks and systematic empirical validation. Although previous research has explored critical success factors (CSFs) for digital technologies in other sectors, a structured identification specific to FM remains absent. This research addresses that gap by proposing a conceptual model grounded in the TOEH framework, enabling a systematic analysis of the technological, organizational, environmental, and human dimensions. The framework consolidates evidence from extensive literature reviews, including systematic literature reviews (SLRs), aligning CSFs with contemporary digital transformation theories, and contributing to the growing body of knowledge on intelligent systems in building and infrastructure management. Methodologically, the study introduces a Second-Order Systematic Review (SOSR) to triangulate evidence from multiple SLRs, offering a theoretically and externally valid model, a pioneering approach within FM research.

Furthermore, this study builds upon the works of Dora et al. (2022) and Merhi (2023), demonstrating that AI adoption extends beyond technical readiness and requires strategic alignment, leadership commitment, governance maturity, and professional reskilling. While factors such as data availability, IT integration, and expected ROI are recognized in the innovation literature, others, such as interoperability, knowledge transfer, and ethical compliance, emerge as FM-specific priorities. By integrating the TOEH framework, the study adopts a holistic lens, linking building infrastructure to human capabilities and regulatory environments, which is particularly relevant given the operational complexity and stakeholder diversity of FM. Ultimately, the proposed model establishes a theoretical foundation for future empirical validations and highlights the necessity of considering sociotechnical dynamics in FM's digital transformation.

4.2. Managerial Implications

The findings reveal that ongoing technological transformations elevate FM professionals as strategic actors who bridge organizational needs with technological solutions. With deep expertise in building operations, facilities managers become "knowledge brokers" (Hargadon, 2002), synthesizing internal and external knowledge to foster continuous innovation. However, successful AI adoption demands specific structural and strategic conditions. Key recommendations include investing in workforce training and reskilling, as well as equipping managers with a foundational knowledge of data science and analytics to enhance their collaboration with IT teams and their ability to interpret operational data. Additionally, attention must be given to the typology of managed assets: while retrofitting existing buildings may be costly and complex, newly constructed facilities offer integrated digital infrastructures from inception. Sectoral technological maturity also influences AI feasibility, with industrial sectors being more advanced compared to healthcare and public administration, where regulatory and interoperability challenges are more prominent.

Moreover, fostering structured collaboration between the FM and IT departments is crucial, with interdisciplinary committees recommended to comprehensively address technical feasibility, data security, compliance, and return on investment. AI adoption in FM should not be perceived merely as a technological innovation but as a broader organizational transformation requiring cultural change, institutional learning, and maturity in digital governance. Within this context, the facilities manager, acting as a knowledge broker, plays a pivotal role in ensuring that AI initiatives are implemented effectively, sustainably, and strategically aligned with the organization's long-term goals.

5. Conclusion

The growing convergence between Artificial Intelligence (AI) and Facilities Management (FM) marks a critical juncture in the evolution of building operations, fostering advances in operational efficiency, energy sustainability, and occupant experience. However, as evidenced by this study, the adoption of AI remains constrained by substantial technical, methodological, and regulatory challenges. Issues such as system interoperability, the maturity of digital governance, and the reliability of predictive models continue to limit the scalability and effectiveness of AI applications in real-world FM environments. Despite these obstacles, the potential benefits of AI are unequivocal. Technologies such as digital twins, predictive maintenance, automated energy optimization, and multi-agent systems have demonstrated measurable improvements in operational cost reduction, environmental performance, and real-time decision support. Notably, the literature highlights that successful AI adoption depends not only on structural enablers, such as digital infrastructure, but also on organizational and human dimensions, including technical training, workforce engagement, and regulatory clarity.

Grounded in a Second-Order Systematic Review (SOSR), this study proposed a conceptual model structured around the TOEH framework (Technology, Organization, Environment, and Human), offering a solid theoretical foundation for future empirical validation and practical application. Nevertheless, limitations must be acknowledged, including the lack of empirical validation and the exclusion of sectoral and regional variability, which may influence AI adoption patterns. To address these gaps, future research should focus on empirical validation of the TOEH-CSF model across diverse contexts, the integration of hybrid predictive models, the development of AI governance and ethics frameworks, and comparative assessments of AI-enabled and conventional buildings. Additional efforts are warranted in constructing multidimensional evaluation metrics, analyzing organizational transformations, and experimentally testing multi-agent system architectures.

The advancement of AI in FM is an irreversible phenomenon, propelled by the digitization of built environments and increasing demands for efficiency, sustainability, and transparency. Achieving large-scale, sustainable adoption will require coordinated efforts among academia, industry, and regulatory bodies to define technological standards, validate AI solutions empirically, and strengthen digital governance. As research progresses, AI is poised to transition from a peripheral technology to a central pillar in the intelligent and sustainable management of facilities.

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.

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