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REVIEW

The Use of Artificial Intelligence in Facilities Management: Potential Applications from Systematic Literature Review

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Abstract: The use of artificial intelligence (AI), which is in constant development, has impacted various spheres of society, profoundly reshaping how organizations conduct their business and bringing significant challenges. Understanding the applications and maturity levels of AI technologies is crucial for organizations seeking to harness the full potential of these innovations. The systematic literature review (SLR) revealed that while there are some models for stages of AI application, none have been specifically adapted and evaluated for the facilities management (FM) environment. FM is an operations area responsible for integrating people, spaces, processes, and technologies in built environments, aiming for optimal functionality throughout the life cycle. Additionally, the SLR revealed that AI applications in FM often rely on legacy platforms such as supervisory control and data acquisition for building maintenance activities and building information modeling for construction, as a form of adaptive technologies. Given this gap and the importance of this sector to companies, it is essential to identify which AI technologies are used and at what stages they are. The results indicated various potential AI applications in FM, which can present different maturity stages, underscoring the need for adapted models so that managers can categorize and subsequently direct managerial efforts in pursuit of operational excellence. The goal is to provide organizations with practical and adaptable insights to assess, enhance, and optimize AI applications, thereby increasing efficiency, productivity, and innovation in their operations. From an academic perspective, the study aims to fill the research gap on AI typologies and maturity levels in the context of FM, contributing to the advancement of FM theory.

Keywords: artificial intelligence, facilities management, technology adoption, adaptive innovations, maturity model

1. Introduction

Facilities management (FM) is a multidisciplinary field responsible for ensuring the efficient integration of people, spaces, processes, and technologies in built environments, aiming to optimize functionality and operational efficiency throughout their lifecycle, according to International Standard Organization 41001:2018. This broad scope encompasses various activities, including maintenance, construction, cleaning, security, food services, and transportation, making the integration of these services a significant challenge. FM's primary responsibility is to maintain the built environment's performance, where operational and maintenance (O&M) activities represent the largest share of total lifecycle costs, accounting for 80% to 85% [1].

The Architecture, Engineering, Construction, and Facilities Management sectors have seen uneven advancements in technological adoption. While the Architecture, Engineering, and Construction sectors have progressed significantly, FM has lagged behind, relying on manual and fragmented processes [2]. Efforts to integrate FM activities across the lifecycle of a facility are vital for improving operational efficiency, yet technological advancements in FM remain limited [3].

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Historically, the adoption of computational tools in FM can be traced back to the 1970s with the development of supervisory control and data acquisition (SCADA) systems. These systems allowed data collection from equipment and machinery, enabling decision-making based on real-time information [4]. However, despite the existence of these technologies, many FM processes still rely on manual, independent operations, which increase complexity [5]. This operational fragmentation has led facility managers to explore specialized tools and automated systems, which remain in the preliminary stages of adoption. These tools, though not fully integrated, are crucial for automating routine tasks, monitoring building performance, and supporting decision-making.

In recent years, artificial intelligence (AI) has emerged as a powerful tool to optimize FM activities. Its applications, including predictive maintenance, energy management, and real-time data analysis, have the potential to transform decision-making processes and operational efficiency in FM [6–9]. The rise of AI is also supported by advances in platforms such as building information modeling (BIM), which provides structured data inputs that are essential for AI-driven solutions [10]. In FM, AI can improve operational efficiency by facilitating predictive maintenance, optimizing resource allocation, and providing unbiased performance assessments [11].

In the United States alone, $50 billion is spent annually on O&M activities [12, 13], emphasizing the economic impact of optimizing these processes through technological solutions.

Despite these developments, there remains a critical gap in the application of AI in this sector, as evidenced by the limited number of scientific studies focused on AI adoption in this sector.

Given this context, this research aims to address the significant gap in AI adoption models specifically tailored for FM. While maturity-level models for AI applications exist, none have been adapted to meet the specific needs for this sector. This study was initiated by conducting a systematic literature review (SLR) to investigate the current state of AI applications in FM, identifying potential solutions, challenges, and gaps in existing literature. The research seeks to answer the following primary question: PQ1: What are the potential AI applications and their implications in FM activities?

By exploring and testing AI maturity models for FM, this study aims to provide a framework for assessing the maturity level of AI technologies within FM, facilitating continuous improvement in performance and operational efficiency. The AI maturity model proposed in this study is based on the results of the SLR, which identified a lack of practical diagnostic models for AI in FM. The reference matrix developed for this research draws on Lichtenthaler's [14] five-level AI maturity model and incorporates the AI technologies proposed by Benbya et al. [15], contextualized within the scope of FM activities. For the future field investigation stage, the adapted matrix was built, seeking to understand the main AI solutions used and their maturity levels, as well as the benefits and barriers to adoption.

2. Methods of the Systematic Literature Review (SLR)

The SLR was conducted to assess the current state of AI applications in FM and to identify key areas where AI could enhance FM practices. The review process was structured into two main sections: the first offering a historical perspective on the evolution of FM globally, and the second focusing on the use and application of AI within FM.

The SLR, as illustrated in Figure 1, followed a rigorous methodology, beginning with data collection from various scientific journal repositories, followed by a comprehensive analysis and synthesis of the results. The search terms employed were "Artificial Intelligence" AND "Facilities Management" OR "Facility Management," targeting works from the fields of Administration and Engineering, which are typical areas of FM practice. All articles were limited to English-language publications.

Six prominent scientific databases were used: SCOPUS and Web of Science (WoS) for the initial searches, analyzed using the Bibliometrix statistical package [16, 17]. The databases EBSCO, Science Direct, Emerald, and Google Scholar were also included, with data analyzed using RStudio software to ensure comprehensive coverage. A total of 130 initial articles were retrieved, but after eliminating duplicates, 98 relevant studies remained for detailed analysis. The articles were categorized and coded based on their content, providing a foundation for the development of the research instrument—a maturity levels matrix. This matrix aims to identify the AI applications in FM and their stages of maturity. The findings of this SLR serve as the basis for further investigation into how AI is utilized within FM and where gaps and opportunities exist for future advancements.

3. Brief History of Facilities Management

The origins of FM as a formal managerial practice lack a single, universally agreed-upon date. However, Jensen's [18] longitudinal study of the Danish Broadcasting Corporation (DR) over 80 years of history, beginning in 1925, provides early evidence of formal services being provided for internal building operations and to customers using the spaces. These services, while essential, were not yet fully integrated under a single business area, as later studies on FM integration would propose [19–22].

In the early 20th century, FM activities were primarily reactive and focused on maintaining physical assets and critical infrastructure such as machinery, equipment, and systems. This reflected the industrial context of time, which demanded high levels of operational productivity. Concurrently, various associations were established in the United States to organize these efforts. These included the Association of Physical Plant Administrators in 1914, the Building Owners and Managers Association International in 1917, and the Association for Facilities Engineering in 1915. These early organizations laid the groundwork for the FM discipline, although they remained centered on machinery and technical services.

As the global workforce began migrating from industrial factories to urban corporate environments during the 20th century, the demand for complex real estate services in large cities increased. The expansion of corporate spaces required new technical and managerial skills. It was during the 1970s that the term FM first appeared in professional literature, such as an article in Computer World, which referenced FM as a new service modality. This was in response to the growing needs of corporate data processing buildings, particularly in the American banking sector. The article also introduced the concept of total FM, which encompassed all operations related to equipment and staff, later categorized into hard services (infrastructure maintenance) and soft services (user-centered services).

The 1970s to 1990s marked a period of growth for FM, with the emergence of specific professional and academic conferences on the discipline. This culminated in the establishment of organizations such as the International Facility Management Association in 1980 and the British Institute of Facilities Management in 1994. During this phase, FM began to be viewed as a more integrative and people-centered discipline, as described by Shiem-Shin Then during the CIB W70 2010 conference. Educational institutions such as Cornell University and Grand Valley State Colleges began offering FM programs in the 1980s [23]. The discipline expanded from the U.S. to Europe during this time, especially in the United Kingdom [24].

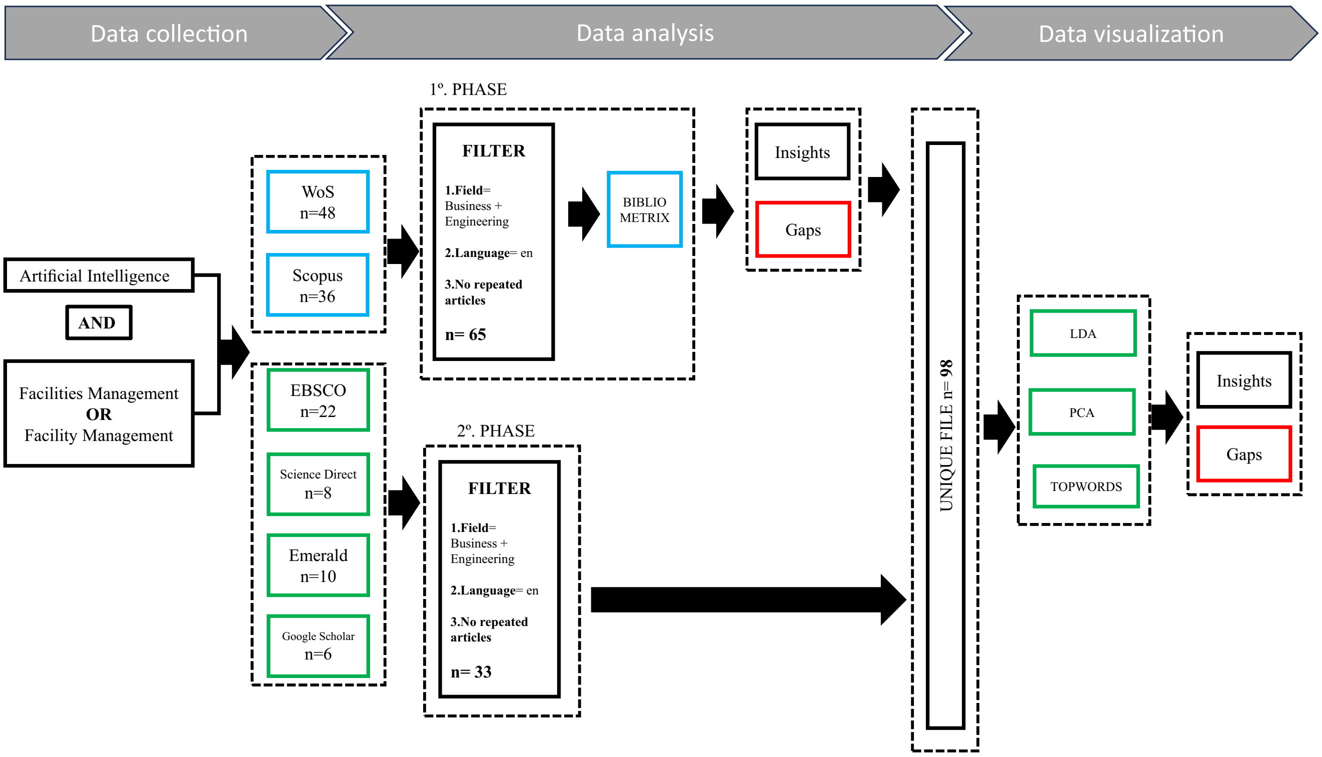
By the 1990s, environmental agendas started to play a more significant role in FM, driven by concerns over the high consumption of resources—such as energy and water—and the waste and carbon emissions generated by built environments. This sustainability movement, combined with the rise of digitalization and Industry 4.0 concepts [25], marked a shift in FM toward the use of innovative technologies [24]. Buildings were now increasingly automated, evolving into intelligent or green buildings that were partially integrated into broader smart city ecosystems [26, 27].

More recently, FM has begun to bridge the gap between public and private spaces, integrating urban neighborhoods into a single, cohesive ecosystem [13, 28–30]. This latest stage of FM evolution reflects the growing complexity of managing modern built environments, where the integration of advanced technologies such as AI and IoT can significantly enhance the functionality of both individual buildings and entire urban spaces.

3.1. The use of artificial intelligence in facilities management

The concept of AI originated in 1956 when John McCarthy, Marvin Minsky, Claude Shannon, and Nathaniel Rochester convened at Dartmouth College, USA, to explore the feasibility of machines simulating human intelligence [31]. Since then, AI has progressed

Figure 1
Systematic Literature Review (SLR)



significantly, evolving from laboratory experiments into practical applications, including OpenAI's ChatGPT, which launched in 2015 [32–34].

Recent advancements in AI across multiple sectors can be attributed to three primary factors: the exponential growth in data availability, enhancements in algorithms, and advancements in computational hardware [35]. Benbya et al. [15] define AI as intelligent systems that can learn, adapt, and function similarly to humans. These systems incorporate various technologies, including machine learning (with its subfields of deep learning and reinforcement learning), natural language processing, robotics, automation technologies, and expert systems. AI applications can be categorized as function-based, encompassing conversational, biometric, algorithmic, and robotic technologies. Furthermore, Mukhamediev et al. [36] classify AI into three categories: weak AI, strong AI, and artificial general intelligence, based on their degree of similarity to human intelligence.

In the context of FM, the historical application of AI can be segmented into three significant periods:

1) 1950 to 1970: FM focused on managing machines and factory equipment using isolated technologies, such as SCADA and computer-aided design. These systems provided limited simulations of intelligent characteristics for data interpretation from physical assets [4, 37].
2) Post-1970s: As the workforce transitioned to corporate environments, new applications like BIM emerged, capable of extracting and structuring data from various construction phases [38–40].
3) 2000s and Beyond: The rise of the Internet and the Internet of Things (IoT) led to the generation of vast amounts of data, which became the primary input for AI systems. Companies that adopt AI moderately now and plan for aggressive future implementations are likely to realize substantial benefits, akin to early adopters of data analytics [41–44].

The body of scientific literature on AI applications in FM is recent, primarily emerging after 2015. As illustrated in Figure 2 from the initial phase of the SLR, AI is poised to transform FM management by potentially replacing certain human-operated tasks with intelligent applications and autonomous devices [45]. AI applications span multiple domains, including security, energy control, predictive maintenance, and operational efficiency, affecting both hard and soft services.

Despite the broad potential of AI in FM, its applications are often isolated. Studies by Devold and Fjellheim [46], Neuroth et al. [47], Altohami et al. [48], and Pedral Sampaio et al. [5] emphasize that machine learning and expert systems primarily function within the BIM context, focusing on data processing, predictive modeling, and decision-making. For instance, autonomous operations in facilities such as oil and gas plants manage process safety and predictive analytics, reducing human presence while increasing safety and cost efficiency [46]. Integrating AI into building management systems allows for the coordinated control of HVAC systems, load balancing, and energy efficiency based on real-time occupancy and environmental conditions [49]. Balmer et al. [50] further identify applications in telecommunications and utilities that contribute to cost reduction, performance improvement, and enhanced customer service through predictive maintenance.

Wollenberg and Sakaguchi [51] demonstrate how technology enhances energy system operations by overcoming cognitive barriers during emergencies and supporting diagnostic processes. Moreover, Marzouk and Zaher [52] highlight the application of deep learning to classify and locate mechanical, electrical, and hydraulic elements, assisting technicians with initiative-taking maintenance. In corporate environments, research by Cao et al. [53] proposes models that incorporate occupant feedback in space management scheduling, optimizing task prioritization and resource allocation. Figure 3 illustrates the primary themes identified in 65

Figure 2
AI scientific production in FM

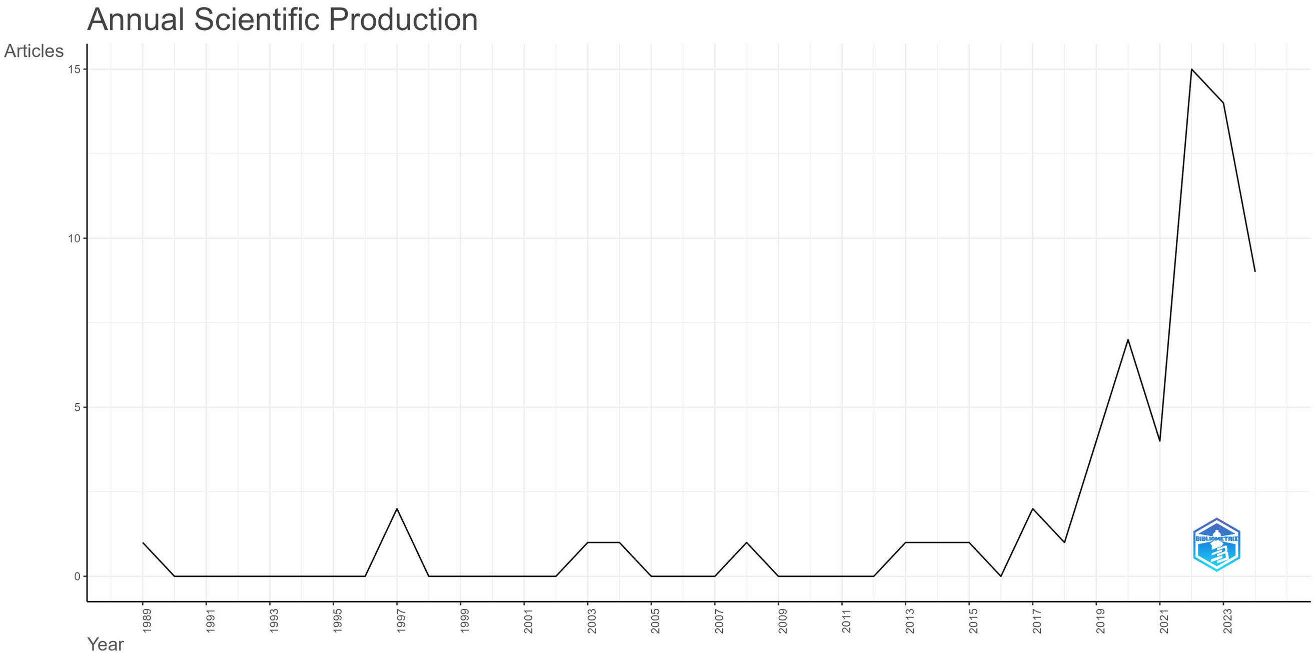


Figure 3
Emerging themes from the first SLR stage

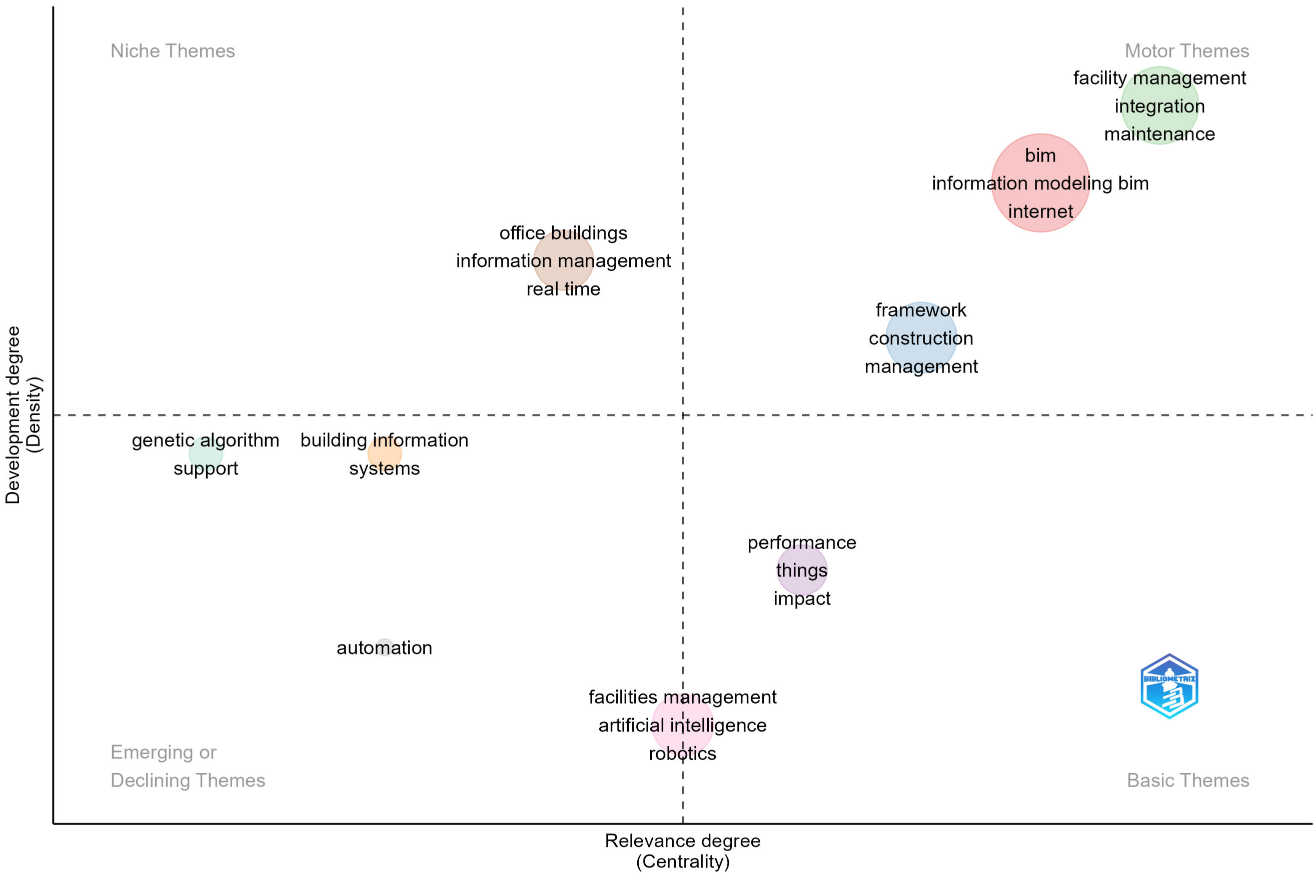
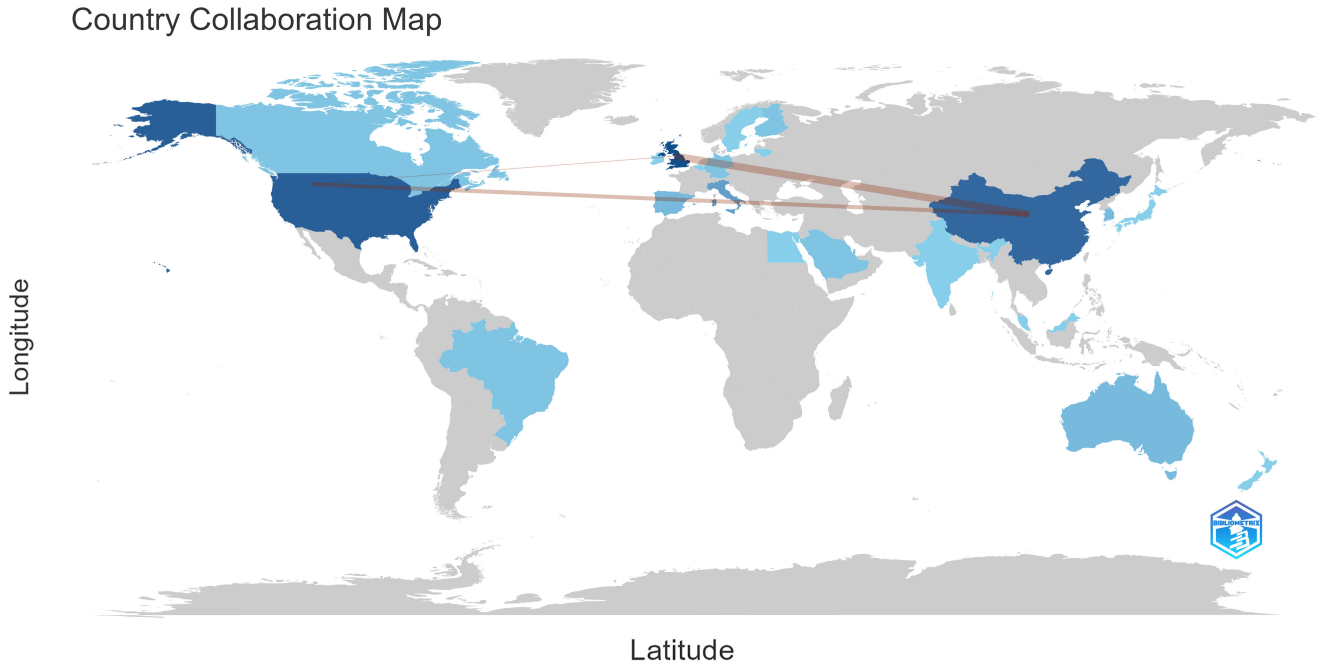


Figure 4
Academic production by region



articles located in SCOPUS and WoS, which predominantly focus on built environments, including BIM and maintenance.

It is essential to note that the majority of scientific production in this field is concentrated in the Global North, specifically the USA, China, and the UK, as shown in Figure 4.

In conclusion, the application of AI in FM is multifaceted, encompassing predictive maintenance, autonomous operations, energy management, and occupant-centered decision-making. However, numerous challenges remain regarding its adoption. Wugofski and Hengstebeck [54] pointed out the difficulty in identifying appropriate problems for AI solutions due to the reliance on specialized professionals, who are still scarce. This gap exists because the terminology and language used in research often differ from those employed by practitioners seeking to resolve real-world issues.

Atkin and Bildsten [45] emphasize the need for facility/property managers to establish and maintain development plans that gradually incorporate IoT and AI technologies into their operations. Bouabdallaoui et al. [55] highlight a significant gap in data in the building environment are diverse in terms of sources and in terms of nature. Data within the building environment are highly diverse, both in terms of their sources and their nature. They originate from human activities indoors, various building systems (mechanical, electrical, electronic, etc.), and the structure of the building itself. However, the majority of these data remain uncollected and unstored. Furthermore, unlike many other industries, there is a notable absence of open databases dedicated to building-related data, with the exception of a few that primarily focus on energy consumption.

Tambe et al. [56] and Gélinas et al. [57] stress the importance of ethical and legal considerations when obtaining sensitive data, particularly concerning asset security, underscoring the need for validation of these data sources. Furthermore, Orooje and Latifi [58] reinforce the challenges faced in facility maintenance, such as slow and nonintegrated implementation processes and insufficient data for as-built digital models, emphasizing the necessity for optimized data collection and management for effective BIM-IoT integration.

The findings from the initial stage of the SLR were enriched during the second phase, incorporating 33 additional articles from four scientific journal databases—EBSCO, Science Direct, Emerald, and Google Scholar—resulting in a total of 98 analyzed works. At this point, the most frequently used keywords were evaluated through linear discriminant analysis (LDA) and principal component analysis (PCA). LDA was employed for classification, while PCA facilitated dimensionality reduction, revealing two main dimensions. The most cited terms included data, digital, BIM, buildings, maintenance, and construction, as confirmed by the results shown in Table 1.

In cluster analysis, as ilustrando in Figure 5, the identified key terms formed two main clusters (>0.8), with the first cluster focusing on maintenance systems and the second on construction applications. This finding underscores the potential for these technologies to support AI's role in enhancing FM practices.

Additionally, the most cited articles in the SLR were analyzed, summarizing key concepts and findings, as illustrated in Table 2.

Table 1
Recurring words in LDA

Topic 1	Topic 2
"data"	"data"
"systems"	"construction"
"bim"	"digital"
"information"	"industry"
"building"	"technologies"
"healthcare"	"building"
"maintenance"	"system"
"system"	"technology"
"digital"	"information"

Figure 5
Dendrogram of keyword clusters

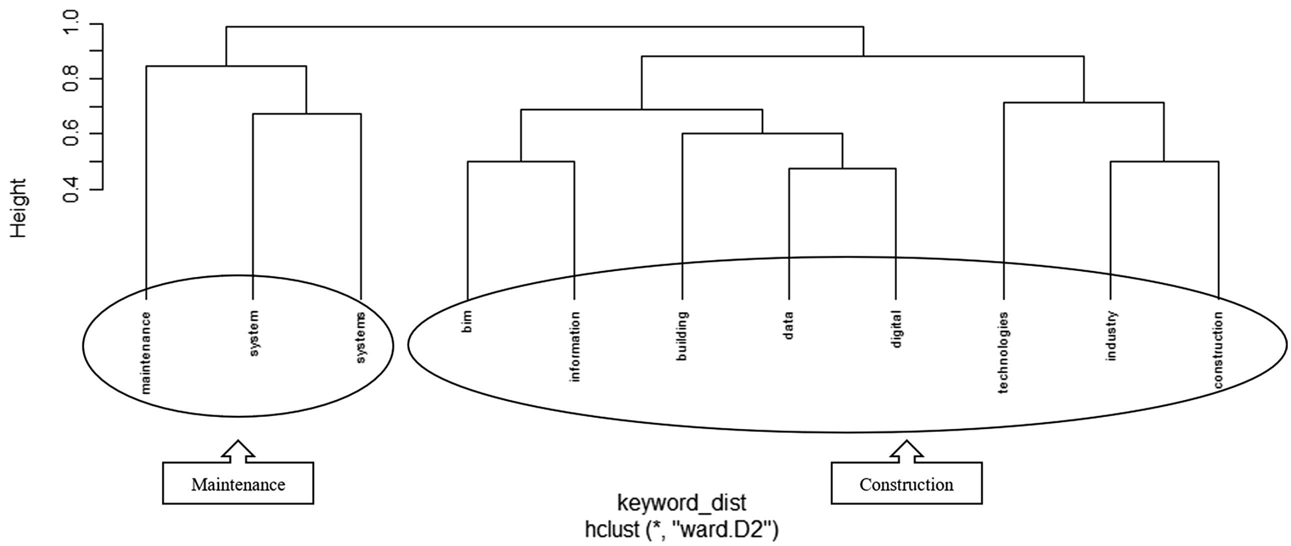


Table 2
Most cited articles in the SLR

Year	Authors	Summary	Key Concept(s)
1997	Clark and Mehta [49]	Emphasis on integrating building systems through centralized BMS. Proposes a methodology for data integration using multimedia networks and knowledge-based systems to enhance HVAC control.	Building system integration, building management, knowledge-based systems
2017	Atkin and Bildsten [45]	Discussion on current trends in facilities management and the impact of disruptive technologies like IoT and AI.	Facilities management, Internet of Things (IoT), artificial intelligence (AI)
2018	Bruno et al. [59]	Focus on BIM and cognitive automation for historical asset preservation, proposes a new modeling method for automated diagnosis and performance assessment.	Building information modelling (BIM), cognitive automation
2020	Lu et al. [60]	Review of research impacting BIM and asset management in the O&M phase, proposing a framework for smart asset management integrating digital twin concepts.	Asset management, digital twin (DT)
2021	Yadav and Paul [4]	Review of SCADA systems, highlighting vulnerabilities and proposing security enhancement techniques.	SCADA security, intrusion detection
2021	Marocco and Garofolo [61]	Literature review on disruptive technologies in FM, identifying trends and research gaps.	Disruptive technologies, facilities management
2021	Khan et al. [62]	Review of immersive technologies (VR, AR, and MR) in the AEC sector, discussing the integration with BIM and identifying future directions for adoption.	Immersive technologies, building information modelling (BIM), systematic review, Industrial Revolution 4.0
2022	Huseien and Shah [63]	Examination of 5G technology's application in smart buildings, focusing on enhancing connectivity and data transmission for real-time monitoring and automation.	5G technology, smart buildings
2023	Arsiwala et al. [64]	Presents a digital twin solution to monitor CO_2-eq emissions in buildings, integrating IoT, BIM, and AI to predict emissions based on indoor air quality.	Digital twins, internet of things (IoT), building information modeling (BIM), carbon emissions

In summary, there is a clear trend toward exploring the potential of derivative technologies such as digital twin, BIM, SCADA, and IoT integrated with AI. These combinations aim to enhance asset and facility management across various domains, from cybersecurity to historic preservation and carbon emission reduction. This convergence of technologies, once achieved, would bring benefits such as leveraging existing technological environments and significant improvements in operational efficiency and decision-making in complex environments like smart buildings and industrial infrastructures.

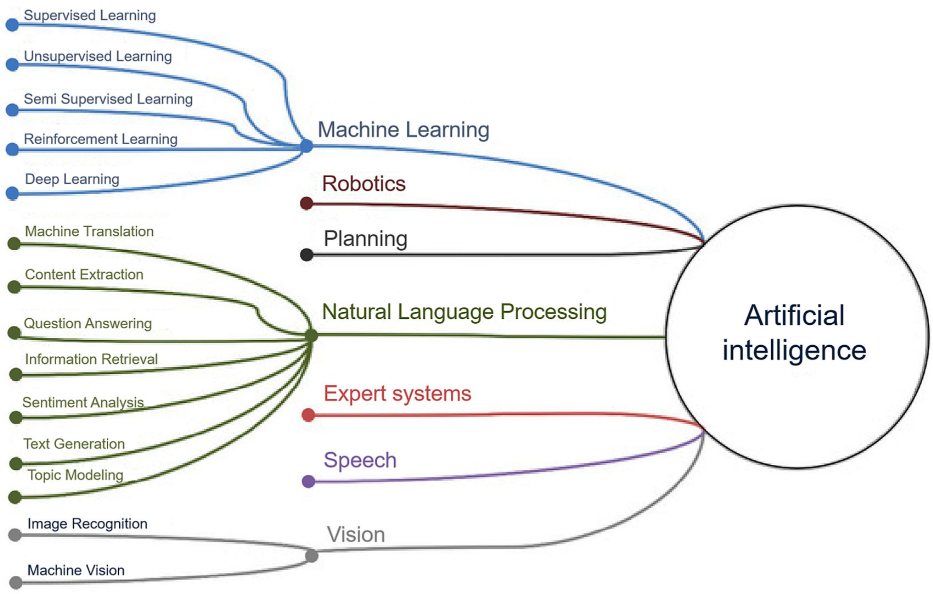
Table 3
Lichtenthaler's model adapted to FM

Level	Definitions	Impact on FM Management	Potential impacts in FM, based on SLR
0-Isolated Ignorance	Ignorance of the growing relevance of AI; strategic emphasis on other topics and value generators, at least in the short term; current inactivity regarding AI.	Non-existent	- No research initiatives or studies in the area.
1- Initial Intent	Initial steps of experimentation with selected AI technologies; exploration of feasibility and sustainability; limited implementation in uncertain contexts.	Initial	- Conducting research and feasibility studies; participation in AI events and workshops; identifying AI use cases in FM.
2-Independent Initiative	Continuous AI initiatives; typical emphasis on advanced automation and process efficiency improvement; often initiated in selected organizational units.	Basic	- Automation of repetitive tasks such as scheduling work orders and generating reports. - Using AI to analyze sensor data and identify potential anomalies. - Implementation of chatbots to provide basic customer support.
3-Interactive Deployment	Exploration of multiple AI solutions; sometimes combined interdependencies of human intelligence and AI; often coordination across multiple organizational units.	Moderate	- Implementing AI-based predictive maintenance systems to reduce downtime and maintenance costs. - Using AI to optimize space layout and improve facility utilization. - Implementing AI-based energy management systems to reduce energy consumption and costs.
4- Interdependent Innovation	Emphasis on AI for innovation beyond efficiency; sometimes combined and sequential interdependencies of human intelligence and AI; often corporate orchestration for synergies.	Significant	- Using AI to automate repetitive tasks and manual labor, freeing up time for employees to focus on strategic activities. - Developing new AI-based products and services for facility management. - Implementing chatbots and virtual assistants to automate customer service and resolve technical issues.
5-Integrated Intelligence	Renewal and recombination of human intelligence and AI; leveraging combined, sequential, and reciprocal interdependencies for completely new solutions.	Transformative	-Renewal and recombination of human intelligence and AI; leveraging combined, sequential, and reciprocal interdependencies for completely innovative solutions. - Using AI to optimize energy usage, reduce costs, and improve sustainability. - Developing new business models based on AI data and insights.
+Intuitive Intelligence	Shared management of human intelligence and AI; self-aware systems with some consciousness, emotional intelligence, and ingenuity (future only).	Revolutionary	-Shared management of human intelligence and AI; self-aware systems with some consciousness, emotional intelligence, and ingenuity (future only). - Smart work environments that adapt to individual occupants' needs. - Virtual assistants providing personalized support to tenants and automatically resolving issues.

4. Findings: Potential AI Applications

Based on the SLR, it became evident that within the FM domain, few studies offer concrete models or matrices that categorize the types and maturity levels of AI applications. The current technologies adopted in FM often do not adhere to a structured framework, but instead, are progressively integrated ("grafted") into existing systems. Predominantly, studies describe isolated AI applications without an integrated approach. Therefore, it was necessary to develop an adapted matrix with two axes: types of AI applications and levels of technological maturity.

Figure 6
IA types



For this research, several existing models from related domains were explored, including those by authors such as Burgess [65], Gentsch [66], Ellefsen et al. [67], Lichtenthaler [14], Sadiq et al. [68], and Oliveira [69]. While these models provide frameworks for understanding AI maturity, they are not specifically tailored to FM. Nonetheless, they offer valuable insights into developing a model suited to FM.

Similarly, Burgess [65] outlines five levels of automation, starting from manual processing to end-to-end automation. Ellefsen et al. [67] present a Pringle & Zoller model with four phases, beginning with an exploratory stage (where companies are unprepared for AI) and culminating in an advanced stage where AI is deeply embedded, with proven results. Lichtenthaler [14] offers a five-level model particularly suited for adaptation to FM, which consists of:

1) Isolated Ignorance: A lack of knowledge about AI, with no strategic plans for AI adoption.
2) Initial Intent: Interest in AI, with exploration of potential benefits, but no concrete implementations.
3) Independent Initiative: Initial implementations of AI in specific areas, focusing on automation and efficiency.
4) Interdependent Innovation: AI is integrated across different areas, promoting synergies and innovation.
5) Integrated Intelligence: AI is fully embedded in the organization, driving digital transformation and industry leadership.

These models collectively depict a spectrum ranging from pre-AI adoption to advanced AI deployment, making them relevant for FM. Given this, Lichtenthaler's model was adapted for this research to fit the operational context of FM. This adaptation allows FM professionals to understand AI's maturity levels during field investigation, as shown in Table 3.

4.1. AI typologies and domains in facilities management

Another important line of research in AI has focused on typologies or domains, as seen in the works of Davenport [70] and Mukhamediev et al. [36, 71]. This classification is a constantly evolving field, often interdisciplinary, with new categories and subcategories emerging as technology advances, yet crucial for both technical and managerial understanding of potential applications. These authors converge on typologies (with the exception of voice application, proposed by Mukhamediev et al. [71], as illustrated in Figure 6 and Table 4.

4.2. Proposed AI maturity matrix for FM

These aforementioned studies contributed to the final formatting of a matrix proposal, featuring two axes that combine AI typologies and levels of technological maturity within the scope of FM. This matrix could be tested in future research to validate its effectiveness and applicability. Using the insights from the reviewed literature and typologies, a hypothetical AI maturity matrix for FM was developed. This matrix incorporates Lichtenthaler's maturity levels and combines them with AI typologies to create a practical framework that could be evaluated in the next stage.

The proposed matrix, as illustraded in Table 5, is a theoretical framework designed to categorize AI typologies and their maturity levels within the FM sector. Its refinement and validation through empirical research will allow FM professionals to assess their organization's AI maturity and identify opportunities for growth. In future studies, this hypothetical matrix—which integrates AI typologies (e.g., computer vision, NLP, and machine learning) with maturity levels ranging from "Isolated Ignorance" to "Integrated Intelligence" will be tested. Surveys, interviews, and case studies conducted with FM organizations at different maturity stages will provide both quantitative and qualitative insights to evaluate the matrix's alignment with real-world AI adoption. This process will lead to its refinement, ensuring its practicality and effectiveness as a tool to guide AI integration in FM.

Table 4
Relating typologies from Mukhamediev et al. and Davenport, adapted to FM

Technology/Domain	Definitions	Potential applications in FM, based on SLR
Computer vision (CV)	Involves machine vision and image recognition. Systems can analyze objects and people in images or videos without human intervention.	– Security monitoring through surveillance cameras. – Fault detection in equipment and infrastructure. – Access control via facial recognition for enhanced security.
Natural language processing (NLP)	Enables machines to understand and interpret human language, translating speech to text and vice versa.	– Automated customer service through AI chatbots. – Analysis of feedback and opinions from social media for service improvement. – Monitoring social media to identify trends and demands in FM services.
Expert systems	Uses specialized knowledge and rules to simulate human expert reasoning in specific domains.	– Predictive maintenance systems based on historical data. – Intelligent energy management that adjusts consumption based on occupancy. – Optimized cleaning and maintenance routes based on real-time needs.
Machine learning	Algorithms that learn from data, identifying patterns and making predictions without explicit programming.	– Predictive failure analysis for facility systems. – Optimization of inventory and logistics based on demand forecasting. – Personalized user services based on behavioral data and preferences.
Robotics	Integration of robotic technologies with AI, enabling robots to perform tasks autonomously or semi-autonomously.	– Autonomous robots for cleaning and maintenance in commercial or residential spaces. – Remote inspection of infrastructure via drones. – Autonomous delivery systems with large facilities.
Planning technology	AI that finds optimal sequences of actions to achieve goals, optimizing for performance, cost, and efficiency.	– Task scheduling for maintenance and cleaning. – Optimized routing of work teams. – Preventive maintenance scheduling based on performance data.
Voice technology	Systems that process and understand human speech, converting speech to text and offering voice-driven interfaces.	– Voice assistants for controlling building automation systems. – Real-time status reporting for facilities management. – Interactive voice assistants for guidance and instruction in operational procedures.

Table 5
Hypothetical matrix

Maturity level / Typologies	0-Isolated Ignorance	1-Initial Intent	2-Independent Initiative	3-Interactive Deployment	4-Interdependent Innovation	5-Integrated Intelligence	+ Intuitive Intelligence
Computer vision (CV)				TO BE TESTED			
Natural language processing (NLP)							
Expert systems							
Machine learning							
Robotics							
Planning technology							
Voice							

5. Conclusion

Based on the findings and models presented, it is evident that FM is progressively adopting AI at varying levels of integration and technological maturity. The proposed matrix and typologies highlight key dimensions of this transformation, offering valuable insights into the future trajectory of AI in FM. Below are the key takeaways:

1) Adoption Spectrum: the spectrum of AI adoption within FM spans from initial exploration (Level 1) to full integration and transformative AI-driven solutions (Level 5). At the initial stages, organizations experiment with AI by automating basic tasks and improving operational efficiency. As AI adoption matures, FM shifts toward innovative and complex solutions where human intelligence works synergistically with AI capabilities, driving strategic decision-making and value creation. The transition from basic automation to intuitive AI systems (Level +) marks the progression toward more advanced, self-aware, and adaptive technologies that can operate with minimal human intervention.

2) Impact on FM Practices: AI is significantly reshaping FM practices at each stage of adoption. At the lower levels (1–3), AI is focused on improving operational efficiency through predictive maintenance, energy management, and customer service automation. These early applications help FM managers reduce costs and streamline processes. At the higher levels (4–5), AI fosters not only operational improvements but also drives innovation in service delivery, business model development, and strategic decision-making. AI's capacity to transform data into actionable insights provides FM professionals with the tools needed to enhance the quality of services and optimize resource utilization.
3) Technological Evolution: the evolution of AI in FM reflects a shift from basic, rule-based automation to more sophisticated systems that demonstrate advanced capabilities, such as self-correcting equipment failures, adaptive workspaces, and personalized tenant services. The highest levels of AI adoption envision systems that integrate human intelligence with intuitive, AI-driven solutions, capable of providing real-time responses, personalized support, and enhanced decision-making. This technological evolution promises to revolutionize FM operations, making them more intelligent, responsive, and efficient.
4) Strategic Imperative: the integration of AI into FM is not just a technological upgrade; it is a strategic imperative. AI enables FM professionals to leverage data-driven insights, optimize asset and resource allocation, and enhance service delivery. By utilizing AI for predictive analytics, automation, and decision support, organizations can achieve higher levels of operational excellence, tenant satisfaction, and sustainability. The strategic use of AI helps FM professionals address complex challenges, including cost management, resource optimization, and regulatory compliance, while driving innovation and growth.
5) Future Prospects: looking ahead, FM's journey with AI is poised for continued growth and innovation. As AI technologies mature and organizations become more adept at harnessing their potential, we can expect significant advancements in areas such as sustainability, occupant experience, and operational efficiency. The adoption of AI will likely expand to encompass more intuitive systems that anticipate and respond to real-time needs, creating smarter, more adaptive built environments. Additionally, AI will play an increasing role in enhancing energy efficiency, reducing the carbon footprint of facilities, and optimizing the lifecycle management of buildings.

5.1. Research contributions and limitations

This study offers a preliminary framework for understanding AI applications in FM, providing a roadmap for organizations looking to enhance their operational capabilities through AI technologies. The hypothetical matrix presented serves as a conceptual guide for assessing AI maturity levels and typologies within FM. However, it is important to acknowledge the limitations of this research:

1) Lack of Empirical Validation: the proposed AI maturity matrix has yet to undergo empirical testing, which could offer more concrete insights into its applicability and practical effectiveness across different FM environments. Field research, such as case studies or pilot projects, would be essential for refining and validating the matrix.
2) Conceptual Focus: this study primarily focuses on the conceptual implications of AI in FM. While the theoretical foundation is strong, the study lacks extensive real-world validation. Future research should aim to bridge this gap by applying the proposed models in practical settings and measuring the impact of AI integration on operational outcomes.
3) Longitudinal Studies: further research should also include longitudinal studies to track the long-term impact of AI adoption in FM. By examining how AI technologies evolve and interact with FM practices over time, researchers can provide deeper insights into the sustainability, scalability, and adaptability of AI solutions.
4) Ethical and Social Implications: as AI becomes more integrated into FM, it is critical to explore the ethical and social implications, including concerns about data privacy, security, and potential job displacement. Research in this area should focus on developing ethical guidelines for AI implementation in FM, ensuring that data collection and usage comply with privacy laws and that AI-driven automation does not negatively impact the workforce.

5.2. Final remarks

In conclusion, AI is becoming an increasingly integral part of the future of FM. It offers unprecedented opportunities for organizations to enhance their capabilities, improve service quality, and achieve greater efficiency in managing built environments. The progression through distinct levels of AI adoption, from basic automation to fully integrated, intuitive systems, underscores FM's evolution towards more intelligent, adaptive, and responsive practices. As AI technologies continue to advance, FM professionals must remain proactive in understanding and implementing these innovations to stay competitive and meet the growing demands of modern facilities. The future of FM lies in harnessing the power of AI to drive operational excellence, sustainability, and enhanced occupant experiences.

Recommendations

This study provides a preliminary framework for understanding AI applications in FM, but it is not without limitations. The hypothetical matrix proposed has yet to be empirically tested, which could provide more concrete insights into its applicability and effectiveness. Additionally, the study primarily focuses on conceptual implications without extensive real-world validation. Future research should aim to validate this matrix through case studies and practical applications across different FM environments. Moreover, longitudinal studies could provide insights into the long-term impact of AI integration on FM practices and outcomes. Finally, exploring the ethical and social implications of AI in FM, including data privacy and job displacement concerns, would be valuable areas for further investigation.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Robson Quinello: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, supervision, Project administration. **Paulo Tromboni de Souza Nascimento:** Conceptualization.

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